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Measuring on Physiological Parameters and Its Applications: A Review

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ABSTRACT

In providing patient care, it is essential to know the patient's status to avoid incorrect treatment. Patient status includes various physiological parameters such as heart rate, blood oxygen saturation, blood pressure, body temperature, and respiratory rate. Measuring each physiological parameter requires data collection and analysis. Data acquisition in measuring physiological parameters can be categorized into contact methods, non-contact methods, invasive methods, and non-invasive methods. After data collection, it is crucial to analyze the collected data to ensure accurate and reliable measurements. This analysis can utilize RF signals, PPG signals, machine learning, and deep learning, depending on the specific needs and objectives of the study. This paper aims to identify studies based on types of data acquisition and analysis methods developed. These studies will be reviewed to understand the limitations of the data acquisition methods and analysis methods used. Additionally, this paper will discuss and classify the types of applications developed in these studies over the last five years, focusing on functionality, device design, and body-to-device connectivity. This review will identify whether the studies developed wearable or portable, wired or wireless devices, and their purpose whether for diagnosis, monitoring, or both. This review will also highlight the limitations and provide a brief perspective on future developments.

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1. INTRODUCTION

Knowing a person's health status is related to the value of physiological parameters that are measured. It is frequently discovered in people receiving outpatient or inpatient care. Physiological parameters are characteristics that refer to humans, which describe the physiological processes that occur in the body. Physiological parameters processes in the human body are associated with electrical, chemical, kinematic, and acoustic changes. The results of this process will be shown in the form of data such as numbers, graphs, etc [1].

Characteristics of the human body consist of more than one characteristic, representing a physiological process that occurs in the human body. Hence, there are different types of physiological parameters like heart rate (HR), body temperature, NIBP (non-invasive blood pressure), electrocardiogram (ECG), and pulse rate. Each of these parameters has a different interpretation, such as ECG, which will interpret electrical activity in the heart [2]. These parameters are essential for monitoring an individual's health status and can provide valuable insights into their overall well-being and potential health risks [3], [4].

Knowing physiological parameters is crucial because they reflect an individual's state of health at that particular moment. For this reason, they are frequently utilized as one of the key indicators that need to be observed when a patient is receiving therapy. By monitoring changes in the patient's health on a minute basis, the doctor's analysis can be facilitated by changes in these physiological signs that are related to changes in time [5].

Although these measurements may not allow for direct physiological assessment or diagnosis, they provide valuable information about human activity and physiology. This information is particularly useful when monitoring anatomical systems in the human body, such as the cardiovascular and respiratory systems. Additionally, physiological parameters are essential for assessing the impact of environmental factors on health, such as the adverse effects of ambient pollutants on vital signs and physiological parameters. Furthermore, physiological parameters play a crucial role in personalized and continuous health monitoring, allowing for the detection of abnormalities and tracking of changes in an individual's health status over time [5], [6].

Therefore, to know physiological parameters, there are several methods for performing physiological measurements, among them the non-contact method, the contact method, the invasive method, and the non-invasive method. We refer to these methods as data acquisition methods. The difference between these methods is how to measure physiological parameters to obtain the required values or data. For example, the non-contact method works by limiting direct physical touch between sensors or devices and the human body. This method is only utilized when it is required, when discrete measures are taken, when the patient is in a small area, or in another place where their health condition needs to be secured. to secure their health status [7]. These methods are followed by different analysis methods as needed. The analysis methods that are often applied in measuring physiological parameters are signal processing (PPG signal, RF signal) and machine learning, or a combination of both. For example, Nishan *et al*. (2024) use machine learning with SVR models and PPG signal optimization as a non-contact and non-invasive method to measure blood pressure [8].

The medical devices currently available are very diverse and have different functions depending on their specifications. There are many medical devices intended to measure physiological parameters, such as pulse oximetry to measure blood oxygen saturation and pulse rate in the body, thermometers to measure body temperature, and sphygmomanometers to measure non-invasively blood pressure, etc. The use of these medical devices is to assist medical officers in making decisions regarding further patient care and obtaining important information regarding the patient's health status according to the measured physiological parameters. In addition to these devices, there are types of medical devices that can measure more than one parameter, namely vital sign monitor and patient monitor. Both devices have the same function of measuring several physiological parameters at a time; the difference is the number of parameters that can be measured [9]. The Vital Sign Monitor can measure basic vitals, i.e., heart rate, respiratory rate, blood pressure, and body temperature, while the Patient Monitor can track more than basic vitals. They can also record ECG (electrocardiogram), $ETCO_2$ (end-tidal carbon dioxide), SPO_2 (blood oxygen saturation), EMG (electromyography), IBP (invasive blood pressure), and more. So in its use, the Patient Monitor is often used for comprehensive and continuous monitoring of critically ill or unstable patients, and the Vital Monitor is more frequently used for routine checks and monitoring of stable patients [9], [10].

Many research studies have been performed during the last five years to optimize physiological parameter monitoring or diagnosing. These research studies can be defined by applying them to patients or working specifically on research methods. Zhang *et al*. (2023), use the non-contact method to detect heart rate and respiratory rate by using an RF signal. The signal is structured into a photonic radar system with fiber optics (laser, photodetector, etc.) as the medium of transmission of RF signals. The research has been tested on human breathing simulators and cane toads as human proxies and has not been tested on humans in person, but use with this system can reach resolutions up to a 13,7 micrometer (mm) scale, so it can detect motion on objects and reduce gaps in heart rate and respiratory rate measurement data [11]. Subsequent research involves the use of PPG signals in the continuous measurement of arterial blood pressure by involving machine learning to develop methods that can monitor arterial blood pressure, as carried out by Ma *et al*. (2024). The type of model used in this study is the SE-MSResUNet model to create an effective approach to non-invasive blood pressure monitoring and contact methods that enable packaging in wearable devices [12]. Similar research has been carried out by Nishan *et al*. (2024) to do continuous blood pressure measurements with PPG signals and using machine learning. The model used is the SVR model to obtain the values of SBP (systolic blood pressure), MAP (mean arterial pressure), and DBP (diastolic blood pressure) by measuring cuffless (non-contact) and non-invasive [8]. From these studies, many types of data acquisition and analysis methods can be studied and tested for measuring physiological parameters, both as diagnosis and as monitoring, according to the needs or purpose of the research. The other related works to the detection of physiological parameters will be described in this paper.

This research reviews the physiological parameters, including blood pressure, respiratory rate, heart rate, body temperature, blood oxygen saturation, and how to measure it. The measurement of physiological parameters will be seen from data acquisition methods (non-contact, contact, invasive, and non-invasive methods) and analysis methods (PPG signal, RF signal, deep learning, and machine learning). Furthermore, it will discuss the implementation of techniques over the past 5 years in measuring physiological parameters, both for diagnosing and monitoring, based on the studies carried out. In this paper, we reviewed related research in the last 5 years related to data acquisition, analysis methods, and their implementation related to physiological parameters and compiled it in a literature review.

2. PHYSIOLOGICAL PARAMETER TYPES

Physiological parameters are quantifiable measures of a person's health and functioning. These parameters provide valuable information about various aspects of the body's physical and biochemical processes [1]. Each of these physiological parameters interprets how different body parts work, making it useful as assessment data to assess a person's health. Following are the various types of essential physiological parameters, along with their definition, uses, and measuring techniques, that will be reviewed in this section.

2.1. Blood Pressure

The force of blood against artery walls during a heartbeat is known as blood pressure and is expressed in mmHg. It is essential for the early diagnosis of cardiovascular illnesses, which are the world's largest cause of death and morbidity. Blood pressure will be expressed in systolic and diastolic terms; while diastolic pressure measures the pressure in the arteries in between heartbeats, systolic pressure measures pressure in the arteries throughout a heartbeat. A normal blood pressure reading is 120/80 mmHg, though this might vary based on factors like age, gender, and physical condition. If the blood pressure value exceeds this, it is known as hypertension. Hypertension, a disease where the strain against artery walls is continuously too high and can result in major health issues, is frequently linked to blood pressure monitoring [13], [14].

An inflatable cuff attached to a pressure gauge is called a sphygmomanometer, and it is used to measure blood pressure. This non-invasive technique is based on the conventional stethoscope auscultation of the brachial arteries, without causing direct harm to the patient. Oscillometric approaches are used to enhance non-invasive blood pressure measures. During cuff deflation, the software analyzes oscillometric waveforms and estimates blood pressure using sensors and algorithms [15], [16].

2.2. Respiratory Rate (RR)

One of the most important physiological markers for identifying anomalies in the human body is respiratory rate. An essential physiological measure that indicates the effectiveness of the respiratory system is the respiratory rate (RR), which is obtained from the number of breaths someone takes in a minute. The normal respiratory rate in an adult is 12-18 bpm. The measurement of this parameter is performed by the medical officer by counting the patient's breathing for 1 minute (60 seconds), taking into consideration other factors including the patient's condition [17]. Moreover, it may be integrated into wearable technology and monitor respiration rates using machine learning and signal processing techniques like PPG signals [18], [19].

Respiratory rate measuring can be used to detect abnormalities in breathing patterns that may be signs of diagnosis or intervention. Measurements of respiratory rate also provide important on the respiratory health and recovery status of a patient [20]. This measure is particularly helpful for keeping an eye on high-risk patients who have diseases like asthma or Chronic Obstructive Pulmonary Disease (COPD), where early identification of acute breathing pattern abnormalities is essential for timely treatment [18].

2.3. Heart Rate

Heart rate (HR), which rises with increased exercise intensity and responds to body movement, is an essential indicator for diagnosing and evaluating health. It is connected to a lifetime and controlled by the autonomic nervous system. Weak heart response can raise the risk of death in some patient populations, such as those with heart failure [21]. Adults typically have a heart rate between 60 and 100 bpm; a cardiac rhythm above 100 bpm at rest is referred to as tachycardia, and a rhythm below 60 bpm at rest is referred to as bradycardia [22].

Some methods used for measuring heart rate are arterial pulse count, photoplethysmography (PPG) signal, electrocardiograph (ECG), ballistocardiograph, acoustic methods, temperature monitoring, and echocardiography [23], [24]. Traditional procedures, including arterial pulse count, were used before the development of more contemporary techniques. ECG-based methods quantify cardiac electrical activity; ballistocardiograph records mechanical pulses; and high-resolution temperature monitoring records heart rate and respiration [24]. In addition, heart rate data is measured and displayed in real-time by optical sensors or electrical signals in heart rate monitors, smartphones, and wearable fitness trackers. Furthermore, they combine elements like fitness bands and smartwatches and save the data for further research [21].

2.4. Body Temperature

The internal temperature which is produced by the body's metabolism and controlled by the thermoregulation system is known as body temperature. Human body temperature normally varies between 36.1-37.2 °C. Although it varies from person to person, a normal body temperature is often maintained within the range necessary for the best possible physiological functioning [25]. Time, environment, gender, and age all have an impact on body temperature [26].

Hyperthermia, or a high body temperature, and hypothermia, or a low body temperature, are the two types of abnormal temperature that can impact organ function, and metabolic processes, and potentially cause tissue damage [27]. There are several ways to take an adult's body temperature, and one of them is placing non-contact infrared thermometers in the forehead or the inner corner of the eye [25].

2.5. Blood Oxygen Saturation (SpO_2)

Blood oxygen saturation (SpO_2) is one of the most significant indicators of oxygen transfer from the lungs to the body's tissue. It determines the fraction of total hemoglobin that is oxygen-bound to hemoglobin in the blood. Values between 95% and 100% are regarded as normal, whereas those under 90% suggest hypoxemia. In medical settings like the ICU and the operating room, it is vital to keep an eye on a patient's SpO_2. It is a crucial sign of how well oxygen leaves the lungs and reaches the body's tissues [28].

There are several methods for measuring blood oxygen saturation, but one of the most common and non-invasive methods is pulse oximetry. Pulse oximetry uses photoplethysmography (PPG) that can measure how much light is absorbed or reflected by the tissue to estimate its oxygen saturation level [29], [30]. The device detects the difference in red and infrared light absorption between oxygenated and deoxygenated blood. Certain methods, including arterial blood gas analysis and co-oximetry, are more intrusive and therefore to be reserved for critical medical situations [31].

These physiological parameters are commonly found in medical devices for the diagnosis and monitoring of patients. Other parameters like ECG and $ETCO_2$ are currently present in patient monitors that are used for higher-level patient surveillance and inspection in hospitals, such as an ICU (Intensive Care Unit) [9], [10].

3. DATA ACQUISITION METHODS

Depending on the type of physiological parameter to be measured, different data collection and analysis methods can be used to obtain measurement results on physiological parameters. The term "data acquisition" refers to various types of data collection techniques, including contact, non-contact, invasive, and non-invasive methods for physiological parameters, as shown in Fig. 1.

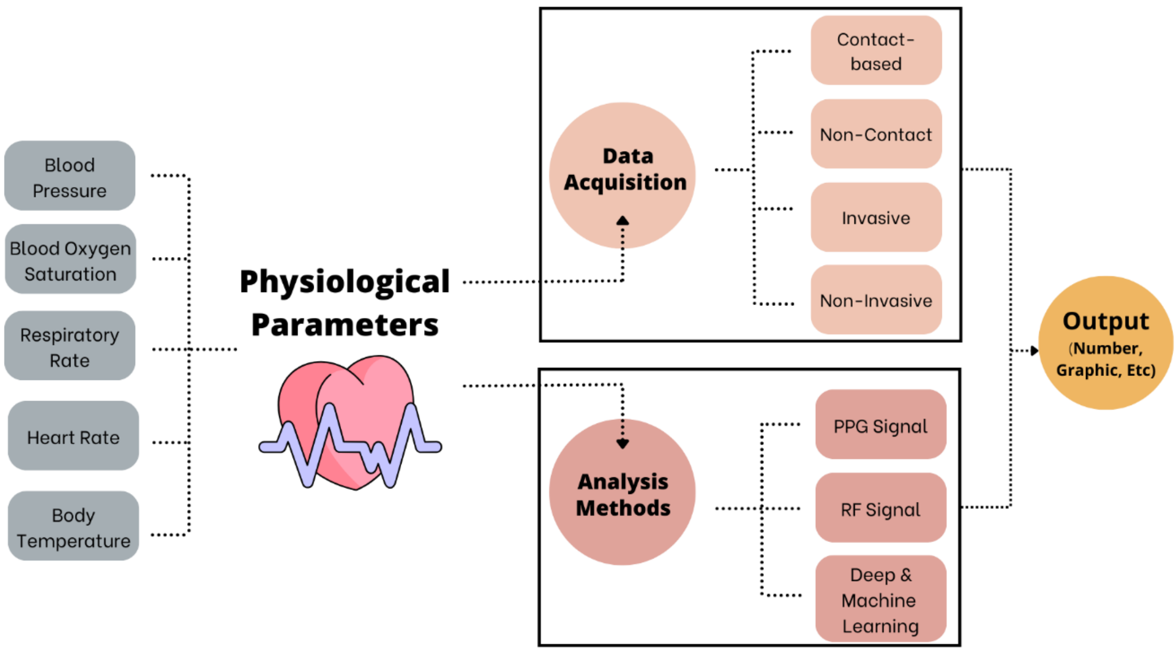

Fig. 1. Measurement Methods of Physiological Parameters

This section will analyze the comprehension of this method, give examples of how it has been used in previous research, evaluate the advantages and disadvantages of each method, and present tables showcasing research from the past 5 years categorizing the types of data acquisition methods used to measure physiological parameters, as illustrated in Table 1.

Table 1. Type of Acquisition Data Methods for Measuring Physiological Parameters Based on Latest Research

Author	**Type of Physiological Parameters**	**Type of Data Acquisition Methods**				**Ref**
		Contact Methods	**Non-Contact Methods**	**Invasive Methods**	**Non-Invasive Methods**	
Nishan *et al.*	Blood Pressure		√		√	[8]
Zhang *et al.*	Heart Rate Respiratory Rate		√		√	[11]
Ma *et al.*	Blood Pressure		√		√	[12]
Zanoguera *et al.*	Electrocardiogram	√			√	[32]
Motin *et al.*	Blood Oxygen Saturation Heart Rate	√			√	[33]
Rong *et al.*	Heart Rate		√		√	[34]
Marathe *et al.*	Blood Oxygen Saturation Blood Pressure Body Temperature Electrocardiogram	√			√	[35]
Nwibor *et al.*	Blood Pressure Heart Rate Blood Oxygen Saturation	√			√	[36]
Ahmad *et al.*	Blood Oxygen Saturation Heart Rate Body Temperature	√	√		√	[37]
Morishima *et al.*	Body Temperature		√		√	[38]
Muralidharan *et al.*	Blood Oxygen Saturation Heart Rate	√			√	[39]
Chamim *et al.*	Heart Rate Body Temperature	√	√		√	[40]
Hoseinzadeh *et al.*	Body Temperature Blood Oxygen Saturation	√			√	[41]
Sarbaras *et al.* Moller *et al.* Rahman *et al.* Naranjo *et al.*	Electrocardiogram	√			√	[42] [43] [44] [45]
Edwan *et al.*	Blood Pressure	√			√	[46]
Ali *et al.*	Heart Rate Blood Oxygen Saturation Body Temperature	√			√	[47]
Zahra *et al.*	Respiration Rate Body Temperature	√			√	[48]
Jhora *et al.*	Body Temperature		√		√	[49]
Azhari *et al.*	Body Temperature		√		√	[50]
Ahmed *et al.*	Pulse Rate Blood Oxygen Monitor	√			√	[51]
Khan *et al.*	Pulse Rate	√			√	[52]
Dubey *et al.*	Body Temperature Blood Oxygen Saturation Electrocardiogram	√ √	√		√	[53]
Zhou *et al.*	Heart Rate Blood Oxygen Saturation	√			√	[54]
Cinel *et al.*	Respiratory Rate		√		√	[55]
Sharma *et al.*	Heart Rate Respiratory Rate	√			√	[56]
Sahrul *et al.*	Blood Oxygen Saturation Body Temperature	√			√	[57]
Boonsong *et al.*	Body Temperature		√		√	[58]
Sriraam *et al.*	ECG	√			√	[59]
Lyra *et al.*	Body Temperature		√		√	[60]

In Table 1, several studies only measure a single type of physiological parameter. For example, Sriraam *et al.* (2023) conducted a study in which they developed a 3-lead ECG. They used the AD8232 sensor, and the prototype is attached to the chest using a belt-like concept. This research is classified as using the contact method and non-invasive method for measurement [59].

In addition, research has been conducted by Ahmad *et al.* (2022) to develop a method for measuring multiple physiological parameters. Their study measures three physiological parameters - blood oxygen saturation and heart rate using the MAX30102 sensor, and body temperature using the MLX90614 sensor. The research utilized three different acquisition methods for a single prototype. The measurement of blood oxygen saturation and heart rate was done using both contact and non-invasive methods, while body temperature was measured using non-contact and non-invasive methods. The information about the type of sensor used in the study indicates that the MAX30102 sensor requires the finger to be placed on it, whereas the MLX90614 sensor needs to be placed at a certain distance on the forehead, mouth, or ear [37].

Table 1 indicates that most of these studies utilized contact or non-contact methods, with some even using a combination of non-invasive techniques. This approach may be attributed to the focus on creating user-friendly studies that pose minimal risks and side effects for long-term measurement of physiological parameters.

3.1. Contact Methods

The contact method is a measurement method that involves sensors or sensor elements placed directly on the subject's body to obtain the necessary data or information. For example, in respiratory rate measurement, this method is aimed at monitoring and measuring a person's respiratory activity with accuracy and in real-time in a variety of conditions and activities [20].

Many studies have used the contact method to measure the physiological parameters listed in Table 1. Zanoguera *et al.* (2020) developed a portable ECG measurement using the AFE AD8232 microchip. The purpose of this open-source research is to these components to generate 3-lead (LA, RA, and RL) output). To the sensor to continuously record ECG signals and save them on a microSD card, this research uses the contact method, attaching each electrode to the left arm, right arm, and right leg then connecting it to the prototype [32]. Another example of research using contact methods is research by Motin *et al.* (2021). They created a compact pulse oximeter for measuring and monitoring blood oxygen saturation and heart rate. This prototype can be used at home and remotely because it has a Bluetooth feature that allows measurement data to be transferred to a mobile application. The MAX30102 sensor was used in this research's contact method, which makes it simple for users to place one finger directly on the prototype's MAX30102 sensor [33].

There are some advantages and disadvantages of using contact methods for measuring physiological parameters, as mentioned in Table 2. These can be affected by the patient's condition, the environment, or the way of use. This type is usually provides more accurate data because it makes direct contact, though the patient may feel uncomfortable during the measurement. Furthermore, the prototype's low-cost testing and calibration techniques and its ability to minimize motion artifacts must be considered in the development process [20].

3.2. Non-Contact Methods

Methods of measuring physiological parameters that do not involve making direct contact with the person's body are referred to as non-contact methods. In this case, technology like cameras is used to get the required data measurements, reducing the need to contact the patient directly. This non-contact method eliminates the need for physical sensors attached to the person's body and allows for effortless, non-invasive measurements to be taken from a distance [61].

Table 2. Pros and Cons of Contact Method in Measuring Physiological Parameters

Contact Method of Measuring Physiological Parameters	
Pros (+)	**Cons (-)**
Accuracy: This method often provides more accurate results, like respiratory measurements because the sensor is in direct contact with the body.	**Intrusive**: The use of sensors in direct contact with the body may be considered disturbing or intrusive to the patient, especially in situations where freedom of movement is important.
Real-time monitoring: This method allows real-time monitoring of physiological parameters such as respiratory rate, which is important in situations where a quick response is required.	**Potential for motion artifacts**: body movement or physical activity can cause interference or noise in physiological parameters, like respiratory rate measured using contact methods.
Sensitivity: This method can be more sensitive in detecting changes such as breathing patterns and respiratory activity for respiratory rate.	**Sensor position limitations**: Some contact methods may require placing the sensor in a specific position on the body, which may limit flexibility of use.
Wide applications: Contact methods are applicable in a variety of settings, such as clinical environments, workplaces, and sports.	**Cost and maintenance**: Additional expenses for sensor calibration and maintenance may be needed for some contact methods.

Similar to the contact method, non-contact methods are often used in research to measure physiological parameters. For example, Rong *et al.*'s research (2021) is listed in Table 1. In their research, they developed impulse signals for microwave ultra-wideband (UWB) radar systems, which use radio frequency (RF) signals. The objective of this system is to identify tiny movements on the skin that are brought on by breathing and heart rate when an RGB camera catches them up. Therefore, all the patient has to do is sit in front of the camera that is attached to the device that measures heart rate [34].

This method can make patients feel more comfortable because it is done remotely, like using an infrared sensor for body temperature measurement [62], [63]. However, due to its dependence on several factors, including the measuring position, the size of the area being measured, or the environment around it, its use may be less accurate than that of the contact method, as explained in Table 3 regarding the advantages and disadvantages of non-contact methods in measuring physiological parameters like heart rate measurements [61], [34].

Table 3. Pros and Cons of Non-Contact Method in Measuring Physiological Parameters

Non-Contact Method for Measuring Physiological Parameters	
Pros (+)	**Cons (-)**
Convenience and Comfort: These methods are more user-friendly because they don't require any physical sensors to be attached to the body.	**Sensitivity to Environmental Conditions:** These methods may be influenced by lighting conditions, motion artifacts, and other environmental factors, which could affect the accuracy and reliability of the measurements.
Hygiene: This method reduces the possibility of infection and cross-contamination, which is especially crucial in clinical environments.	**Complexity of Signal Processing:** These methods often require complex algorithms and signal processing techniques to extract accurate physiological parameters, such as heart rate data from video or radar signals, which can increase the computational load.
Continuous Monitoring: This method allows for long-term, continuous monitoring without putting the user through discomfort, which is helpful for applications such as stress or sleep monitoring.	**Cost and Equipment:** While some non-contact methods can be implemented with common devices such as cameras, others, such as those using radar, may require specialized and potentially expensive equipment.
Application in Diverse Settings: This method can be applied in a range of situations, such as clinical environments, remote monitoring, and even regular things like smartphones.	**Limited Accuracy in Motion:** Non-contact methods may struggle to maintain accuracy when the subject is in motion, as movement can introduce significant noise and artifacts into the signal.

3.3. Invasive Methods

An invasive method is a technique that includes entering the body through the tissue, organs, or skin to try to collect information or deliver the treatment. An invasive method of measuring physiological parameters usually involves inserting a device or sensor in the body to get accurate and direct data from the source [64], [65]. While using this method may cause pain or discomfort because the samples are obtained directly from the patient's body, they can also provide highly precise and accurate data. However, there is a risk of infection or tissue damage, so proceed with caution and precision, as listed in Table 4 regarding the advantages and disadvantages of this method [64], [66].

Table 4. Pros and Cons of Invasive Method in Physiological Parameters

Invasive Method for Measuring Physiological Parameters	
Pros (+)	**Cons (-)**
High Accuracy: Data obtained from direct pressure measurement from within the ventricle or artery is highly accurate.	**Risk of Infection:** Involves entering the body to perform procedures that carry a risk of complications, such as bleeding or infection.
Comprehensive: Capable of considering all factors affecting SEVR, such as LV isometric contraction, LV isometric relaxation, and intraventricular diastolic pressure.	**Intrusive:** During the application of these methods, patients may experience pain or discomfort.
Responsive: Accurate measurement of arterial blood pressure allows for quick and sensitive detection of changes, enabling prompt medical intervention.	**Cost and Resources:** It is more costly and requires additional resources due to the need for specialized equipment and medical staff.

In a study by Jiang *et al*. (2024), a comparison was made between invasive and non-invasive methods for measuring arterial blood pressure in patients with sepsis. The invasive method involved inserting an arterial catheter directly into the patient's arterial blood vessel to assess blood pressure. This method requires a medical professional to perform an invasive procedure by introducing a catheter into the patient's artery, usually the femoral or radial artery. A pressure monitor attached to the artery catheter allows for fast and accurate blood pressure readings. Due to its high accuracy, this invasive method is considered the clinical reference standard for blood pressure measurement in critically ill patients.

For non-invasive blood pressure measurement, the oscillometric method uses a cuff placed on the patient's arm. Non-invasive blood pressure monitoring using oscillometric measurement is commonly used in various clinical settings, including intensive care units. This method involves attaching a cuff to the patient's arm and then measuring the changes in arterial pressure as the cuff is compressed. The data obtained from this process can be used to determine the mean, diastolic, and systolic blood pressure values. Accurate arterial blood pressure data was obtained using the invasive method compared to the non-invasive method. This illustrates one of the advantages of invasive methods, while non-invasive methods are more suitable for general clinical needs [66].

3.4. Non-Invasive Methods

"Non-invasive methods" refer to approaches or procedures that do not penetrate or enter the patient's body. Non-invasive blood pressure monitoring, for example, does not require any penetration of the skin or blood vessels. This means that methods such as non-invasive blood pressure measures do not involve puncturing the skin or implanting a catheter. Instead, they can be carried out using a blood pressure cuff on the arm or a sensor on a finger [67], [68]. To ensure that patients feel safe and secure while using this method, which is also easier to use, it demonstrates the benefits of utilizing this method despite its accuracy being lower than invasive methods. As a result, according to Table 5, this method is better suited for routine measurement rather than for assessment in critically ill patients. Table 5 presents the advantages and disadvantages of using non-invasive methods in measuring physiological parameters [67].

Several studies utilize non-invasive methods, as detailed in Table 1. One such study was conducted by Marathe *et al*. (2019). In their research, they developed a wireless prototype for measuring ECG, blood oxygen saturation (SpO2), blood pressure, and body temperature using non-invasive methods. This can be observed from the types of sensors employed, such as the AD8232 sensor for ECG and MAX30100 sensors for blood oxygen saturation (SpO2) [35]. Nwibor *et al*. (2023) conducted further research and developed a prototype to measure blood pressure, heart rate, and blood oxygen saturation (SpO2) using a non-invasive and contact method. They used the MAX30102 sensor to measure blood oxygen saturation and heart rate, and the MAX32644D sensor to measure blood pressure [36]. Overall, as shown in Table 1, measurements using non-invasive methods can be combined with either contact or non-contact methods.

4. ANALYSIS METHODS

As seen in Fig. 1, there are data acquisition methods as well as analysis methods for measuring physiological parameters. Analysis methods aim to evaluate the information gathered by data acquisition methods in order to assess the physiological parameter values that were measured. The analysis methods for measuring physiological parameters (PPG signal, RF signal, machine learning, and deep learning) will be reviewed in this section. The introduction of each analysis method is followed by examples of studies that used it and a table including studies from the previous five years that have utilized this kind of analysis method. The studies are categorized by the kind of sensor or algorithm that was used, the kind of physiological parameters that were measured, and the research results that are listed in Table 6.

Table 5. Pros and Cons of Non-Invasive Methods in Physiological Parameters

Non-Invasive Methods for Measuring Physiological Parameters	
Pros (+)	**Cons (-)**
Convenience and Comfort: Because these methods do not require skin entry or puncture, the patient is not bothered during physiological measurements, such as blood pressure monitoring.	**Accuracy Differences:** Non-invasive and invasive methods may differ in terms of accuracy, particularly in clinical settings when highly accurate blood pressure measurements are necessary, such as in patients who are critically ill.
Low Risk of Infection: This method has a lower risk of infection compared to invasive methods that require punctures or catheter insertion, as it does not involve skin penetration.	**Subject to External Interference:** This method is vulnerable to outside interference, such as body motion or incorrect sensor alignment, which could skew the test results.
Useful: This method is suitable for long-term monitoring as it can be regularly performed without the risk of harm or consequences and is easy to use.	**Limited Information Detail:** When it comes to extra hemodynamic parameters required in certain clinical situations, these methods may not always offer the same level of detail as invasive methods.
Suitable for Routine Measurement: This method does not involve difficult or intrusive procedures; it is appropriate for routine physiological parameter measurements, such as blood pressure.	**Limitations in Special Conditions:** Patients with specific or physically challenging conditions may not be able to use these methods, requiring the use of an invasive approach to accurately monitor blood pressure.

Table 6. Type of Analysis Method for Measuring Physiological Parameters Based on Latest Research

Author	Type of Physiological Parameter	Type of Analysis Method	Sensor/Component	Algorithm	Parameter	Result	Ref
Nishan *et al.*	Blood Pressure	Machine Learning	-	SVR, KNR, DTR, RF	MAE	2.49 mmHg (sys) 1.43 mmHg (dias)	[8]
Zhang *et al.*	Heart Rate Respiratory Rate	RF Signal	Photonic Radar	-	Resolution Correlation Coefficient (r)	13.7 mm 0.746	[11]
Ma *et al.*	Blood Pressure	PPG Signal & Machine Learning	-	SE-MSResUNet	MAE±SD	3.88±6.17 mmHg (sys) 2.16±3.75 mmHg (dias)	[12]
Shuzan *et al.*	Respiratory Rate SpO_2	PPG & Machine Learning	-	SVR, GPR ET, LR, DT	MAE	0.89 bpm 0.57%	[19]
Morishima *et al.*	Body Temperature	Machine Learning	-	LSTM	RMSE	0.90%	[38]
Ahmad *et al.*	Blood Oxygen Heart Rate Body Temperature	PPG Signal Infrared	MAX30102 MLX90614	-	Accuracy	98% 89% 95%	[37]
Nwibor *et al.*	Blood Pressure Heart Rate Blood Oxygen	PPG Signal	MAX32664D MAX30102	-	Accuracy	3 mmHg 98.7% 99.5%	[36]
Hoseinzadeh *et al.*	Body Temperature Heart Rate SpO_2	ADC PPG Signal	MAX30205 MAX30102	-	Standard Deviation	0.6°C 1.84 bpm 0.75%	[41]
Jhora *et al.*	Body Temperature	RF Signal	Infrared Array SensorGrid-EYE	-	Error	0,18%	[49]
Ahmed *et al.*	Pulse Rate Blood Oxygen	PPG Signal	MAX30100	-	Deviation	0.8175% 0.425%	[51]
Sharma *et al.*	Respiratory rate Heart Rate	RF Signal	NCS	-	Correlation coefficient (r)	0,93 0,95	[56]
Tazarv *et al.*	Blood Pressure	PPG signal & Deep Learning	-	CNN, RNN, & MLP	MAE±SD	0.21±6.27 mmHg (sys) 0.24±3.40 mmHg (dias)	[69]
Schlesinger *et al.*	Blood Pressure	Deep Learning	-	CNN	MAE	5.95 mmHg (sys) 3.41 mmHg (dias)	[70]
Bian *et al.*	Respiratory Rate SpO_2	Deep Learning	-	RNN	MAE±SD	2.5±0.6 brpm 0.94±0.56%	[71]
Wang *et al.*	Blood Pressure	PPG Signal	AFE IC nRF52832	N/A	ME±SD	-2.10±7.07 mmHg (sys) 0.04±7.34 mmHg (dias)	[72]
Nabavi *et al.*	Heart Rate Respiratory Rate SpO_2 Body Temperature	PPG Signal	MAX30102	N/A	MAE	2.75 bpm 1.25 breaths/min 0.64% 0.22°C	[73]

4.1. PPG Signal

Photoplethysmography is a non-invasive optical technique that measures blood volume variations in peripheral blood vessels. PPG uses light to detect variations in the way tissue reflects or absorbs light [74], [75]. Since the blood volume flowing through the vessel is proportionate to the voltage signal from the PPG, even minute changes in blood volume can be detected using this method. The PPG waveforms consist of a pulsatile (AC) component caused by cardiac coordinated increases in blood volume with each pulse, and a slowly changing (DC) baseline with several low-frequency components [29], [76]. In both pathological and non-pathological analytical applications, photoplethysmography (PPG) is an affordable bio-optical sensing technique that allows for the non-invasive, contact method or contactless monitoring of physiological parameters and real-time quality assessment [77].

PPG signals are utilized as an analysis method in some of the latest research shown in Table 6 for the measurement of physiological parameters, including studies conducted by Ahmad *et al*. (2022) and Hoseinzadeh *et al*. (2022). The MAX30102 sensor, which utilizes PPG and LED-based technologies, is employed in both studies to measure heart rate and blood oxygen saturation. The sensor emits LED light into the skin to measure heart rate. Blood vessels in the skin absorb and reflect some of this light. The sensor detects changes in light absorption due to the pulsing effect of the heartbeat on blood flow. The PPG signal is derived from the systolic and diastolic peaks. Beats per minute (BPM) are calculated by counting the number of peaks over a predetermined time interval, typically one second, and multiplying this count accordingly.

In detecting blood oxygen saturation, the sensor uses two LEDs (red and infrared) to measure changes in light absorption in oxygenated and deoxygenated blood. Oxyhemoglobin absorbs more infrared light (950nm), while deoxyhemoglobin absorbs more red light (650nm). By calculating the ratio of absorption between these two wavelengths (red/infrared), the sensor determines the SpO2 level using a pre-determined equation involving constants derived from comparative measurements with medical-grade SpO2 sensors [37], [41].

The two studies used different parameters in attaching test results to blood oxygen saturation and heart rate, as listed in Table 6. In the research by Ahmad *et al*. (2022), they evaluated accuracy by comparing the prototype with a commercial product (Philips IntelliVue X3), where the blood oxygen saturation reached 98% and the heart rate reached 89% [37]. The research by Hoseinzadeh *et al*. (2022) focused on the standard deviation, which measures the variation or dispersion of heart rate and blood oxygen saturation values between the prototype and the comparison of the tool, with blood oxygen saturation reaching 0.75% and heart rate reaching 1.84 bpm [41]. Both studies concluded that the MAX30102 sensor can effectively measure blood oxygen saturation and heart rate, making it a reliable monitoring device.

When using the MAX30102 sensor in these studies, several shortcomings need to be considered. The PPG signal generated by the MAX30102 sensor can sometimes experience noise due to various factors such as dense optics and the length of the illuminated network path. This can make it difficult to identify the systolic and diastolic peaks of the resulting signal. Additionally, during the heart rate measurement, there is a possibility of motion artifacts that can affect the accuracy of the readings. This is especially true when the user makes movements or changes position during the measurement, which can interfere with the final measurement results. The accuracy of PPG measurements is also greatly affected by the proper placement of the sensor on the user's body. If the sensor is not placed correctly, this can result in inaccurate readings. For better development, improvements need to be made to ensure the accuracy and consistency of readings between the prototype and the tested medical device [37].

This method commonly utilized in wearable technology, such as pulse oximetry and fitness trackers, to monitor physiological parameters continuously. Integrating PPG acquisition functionally into wearable devices enables discreet physiological parameter tracking suitable for ongoing patient status monitoring [78].

4.2. RF Signal (Radio Frequency Signal)

An electromagnetic wave known as an RF signal, which is useful in the medical field, enables wireless data transfer [79]. An RF sensor is a device that tracks and detects a range of factors, such as a person's motions, activities, and physiological data. RF sensors have many applications, including Wi-Fi, RFID technology, and active or passive radar systems. These sensors have the potential to improve patient autonomy and quality of life in the healthcare sector by facilitating remote monitoring of patients with chronic conditions [80], [81]. Radio-frequency (RF) sensors are a possible technology for supporting living in the medical area since they can be utilized as an inexpensive, non-intrusive, and real-time data source [81].

There are several studies that use RF signals as an analysis method in measuring physiological parameters listed in Table 6, one of which is the research by Sharma *et al*. (2020) that uses NCS in detecting heart rate and respiration rate. NCS (near-field coherent sensing) employs the principle of radio frequency (RF). It involves the near-field coupling of ultra-high frequency waves with dielectric boundary motion. With a transmitter and receiver on the body, the sensor detects motion on the surface as well as movements within boundaries. The

UHF waves are modulated by the mobility of the internal dielectric boundary during respiration and heartbeat, and the receiver then picks them up. The NCS sensor records physical alterations in organs related to breathing and heartbeat and offers non-invasive physiological parameter data. Compared to direct far-field reflection, it is less susceptible to environmental changes and provides better signal isolation from interferences and inter-sensor collisions. In this research, the NCS sensor was placed on the chests of twenty volunteers with a range of genders and BMI indices. According to the study's test result, the correlation coefficients (r) for heart rate and respiratory rate were 0.95 and 0.93, respectively. Although it can detect heart rate and respiration rate, this study highlights the possibility of errors or low data quality in the respiration and heart rate data from the sensors used. These issues can lead to low consistency in respiratory rate and heart rate measurements, thereby reducing their accuracy [56].

Furthermore, there is research from Zhang *et al*. (2023) which uses photonic radar in detecting the same parameters are heart rate and respiratory rate. Photonic radar systems generate RF signals in the form of stepped-frequency (SF) signals with a bandwidth of 10 GHz in the Ka-band (26.5-40 GHz). These RF signals are used to reflect electromagnetic waves from moving objects, such as the human chest or experimental animals. The RF signals reflected from the moving object are recorded and analyzed by the photonic radar system. Changes in these reflected RF signals provide information about body movements, including changes in chest volume associated with breathing and heart rate. By analyzing these changes, the photonic radar system can extract physiological parameters information such as heart rate and respiratory rate. The detected changes in RF signals can be converted into numerical information representing heart rate and respiratory rate.

The photonic radar system can achieve high distance resolution (13.7 mm) and micrometer-level accuracy in detecting respiratory activity, with a correlation coefficient of 0.746, as shown in Table 6. This allows the system to detect small changes in body movements associated with heart rate and respiration with a high degree of accuracy. By using RF signals and photonic technology, this radar system can provide accurate and non-contact physiological parameters detection, suitable for real-time monitoring in various settings.

Although photonic radar systems are capable of achieving high distance resolution and good detection accuracy, the information obtained from detecting physiological parameters such as heart rate and respiratory rate may need confirmation by other methods or integration with additional clinical data to gain a more comprehensive understanding of a person's health condition. While this study successfully demonstrated the ability of the photonic radar system to detect physiological parameters in experimental animals, such as frogs used as human models, the use of animals as test subjects may have limitation in representing the full response of the human body. Therefore, the results obtained from animal testing need to be further verified in humans to ensure their applicability in clinical applications and to explore wider health applications [11].

4.3. Deep Learning and Machine Learning

The development of advanced technical systems that can carry out complex activities that have historically required human ability is known as artificial intelligence (AI). AI includes subfields like computer vision, machine learning, deep learning, and natural language processing [82], [83]. Deep learning, a type of artificial intelligence, uses algorithms modeled after the architecture and operations of neural networks found in the human brain. These algorithms are designed to learn from massive volumes of data without being explicitly programmed, allowing them to spot patterns and draw conclusions based on data [84]. Physiological parameter identification often makes use of deep learning and machine learning, optimizing measurements within time limits and using strategies such as PPG signals, as shown in Table 6 [85].

Based on Table 6, there are several studies that use machine learning or deep learning in measuring physiological parameters. One example is the research by Tazarv *et al*. (2021), which uses deep learning to develop a method for measuring blood pressure. The research uses PPG signals that have been preprocessed before being included in the model, which utilizes Multi-Layer-Perceptrons (MLP), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) by using MIMIC II and UQVSD datasets. Furthermore, the trainable weights in the CNN are optimized to extract the most informative features for blood pressure value estimation. The model is trained using the leave-one-window-out validation method, where the one-time window is tested separately from the rest of the data. The performance of the model was evaluated using the mean absolute error (MAE) and standard deviation (SD) metrics, with 0.21±6.27 mmHg for systolic and 0.24±3.40 mmHg for diastolic [69].

Ma *et al*. (2024) conducted research that uses a combination of PPG and machine learning, as shown in Table 6. This research aims to create an accurate and efficient method for continuous, non-invasive monitoring of arterial blood pressure using the SE-MSResUNet network by processing PPG data and predicting blood pressure. The work process starts with data collection, where PPG data is recorded from sensors placed on the skin to detect optical signals from changes in blood volume. Next, the raw PPG data is processed to remove noise, normalize the signal, and prepare the data for further analysis, which is called the data preprocessing stage. Then, feature extraction is performed on the PPG data, extracting time features, frequency, statistics, and other physiological features that can provide information about blood pressure. Machine learning models such as neural networks, convolutional neural networks (CNN), or other models are then trained using the PPG data along with the corresponding blood pressure labels. After training, the machine learning model can be used to predict blood pressure values from new PPG data. It is then evaluated using mean absolute error (MAE) and standard deviation (SD) metrics, yielding values of 3.88±6.17 mmHg for systolic and 2.16±3.75 mmHg for diastolic blood pressure.

The research conducted by Tazarv *et al*. (2021) used many datasets, including MIMIC-II and UQVSD, but Ma *et al*. (2024) only used one dataset, MIMIC-II. However, this the one explanation for different metric evaluation results aside from different algorithm usage. In both of these studies, several weaknesses were identified, including dependence on training data, as the performance of machine learning models is strongly influenced by the quality and representation of the training data used. If not properly addressed, the model may experience overfitting or underfitting. Additionally, it was mentioned that the model's performance on external validation datasets (such as MIMIC-II) may be low due to poor data quality or individual differences. Therefore, it is necessary to focus on external validation to ensure the model's reliability outside the training dataset. Limitations in the amount of data or variations in the dataset may affect the model's ability to produce generalized and accurate predictions. In addition, both studies require large computing resources and long training times, making them difficult to apply in the environment quickly. Thus, further evaluation and development are needed using varied datasets with a sufficient amount and high-quality data [12], [69].

Both deep learning and machine learning can be used as analytical methods for measuring physiological parameters. These models may include detection, diagnosis, and monitoring. However, for these models to be used as needed, they must be constructed from the data used, processing steps, assessment model, and security data.

5. DISCUSSION

The previous studies discussed various methods for data acquisition and analysis in the measurement of physiological parameters, as detailed in Table 1 and Table 6. These methods included different types of applications, functions, device designs, and device-to-body connectivity, as illustrated in Fig. 2. The studies had various objectives, including diagnosis, monitoring, and both. Moreover, they used different types of device designs, such as portable and wearable devices, each offering different body connectivity options, such as wired or wireless, tailored to the specific study's needs.

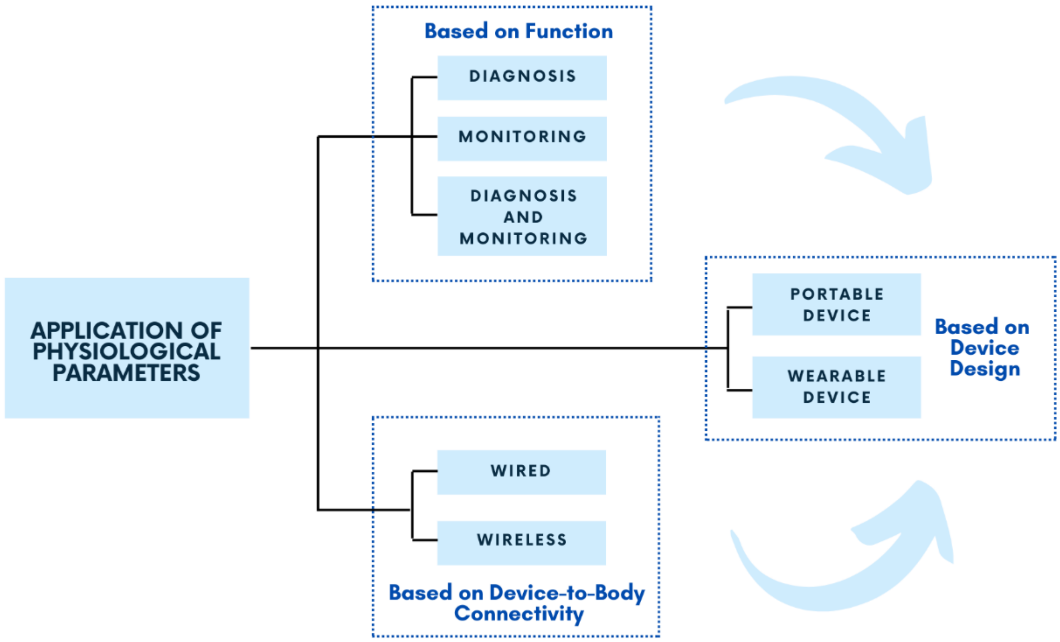

Fig. 2. Types of Applications for Measuring Physiological Parameters

The information in Table 7 presents studies on the measurement of physiological parameters, categorized by application as shown in Fig. 2. The table includes the type of function, device design, and device-to-body connectivity for the past 5 years. It also outlines the physiological parameters studied, which include heart rate (HR), pulse rate (PR), blood oxygen saturation (SpO2), blood pressure (BP), body temperature, respiratory rate (RR), electrocardiograph (ECG), and end-tidal carbon dioxide (ETCO2), which are identified in each study.

5.1. Diagnosis in Physiological Parameters

Physiological parameters are measured in the research indicated in Table 7 to aid in monitoring and diagnosing, as measuring physiological parameters is necessary for accurate diagnosis. Fig. 2 shows the different types of applications according to their functions: wearable devices and portable device.

A portable device is a type of lightweight and compact device that is designed to be easily carried around. This design is often used by healthcare businesses for their medical devices to make them more appealing and convenient for users. Portable devices are usually powered by batteries, only power sources, or both. Battery systems enable the measurement of physiological parameters without needing a direct connection to a fixed power source. One of the studies that implements a portable device for diagnosing physiological parameters is the research by Muralidharan *et al*. (2023), as listed in Table 7. This research involved developing a prototype to detect blood oxygen saturation (SpO2) and heart rate using the MAX30100 sensor. The device is designed to be portable because the components used are small in size without compromising performance. The components used in this study include an Arduino Nano as a microcontroller and an LCD I2C 16x2 as a displa.

In addition to portable devices, there is a type of wearable device found in the studies in Table 7. This type allows the device to be worn on the body or clothing and is essential for disease prevention, monitoring physiological parameters, and diagnosing [102]. The devices have multiple applications in healthcare, ranging from being skin-based to biofluidic-based. These adaptable devices can conform to physiological parameters and help in treating diseases by providing insights into physiological changes. Research often involves the use of textile and skin-based wearable devices [103]. One of the studies that utilized wearable devices for diagnosing physiological parameters in Table 7 is by Wang *et al*. (2022). They used AFE ICs and PPG signals in their prototype, to detect physiological parameters, including blood pressure, heart rate, and blood oxygen saturation. Due to its watch-like design, this research is classified as a wireless type, and the device ensures accurate and safe results [72].

According to the ease of use category wearable and portable devices are easy to use and comfortable due to their everyday design that doesn't interfere with daily activities. These devices can be used for continuous and real-time monitoring based on the user's needs. However, the available features are not as extensive as those in medical devices such as patient monitors and accuracy systems, so they are not as advanced as those found in clinical settings. Because of this, these devices can be used in a way that best suits the user's needs.

5.2. Monitoring in Physiological Parameters

Monitoring applications on physiological parameters is an effort to make the measurement process on physiological parameters take place continuously for early diagnosis, monitoring of chronic diseases, and others. The form of monitoring physiological parameters can be utilized to build a system on a module connected to the prototype. For example, Rahmat *et al*. (2019) as shown in Table 7, developed a monitoring system with the Bluetooth HC-05 module in their prototype. This makes it possible to use an application using Bluetooth to remotely observe the ECG measurement results from the prototype. The weakness of this prototype is that it cannot be used for remote monitoring due to the limitations of Bluetooth features. Therefore, it is necessary to develop remote monitoring using other features such as WiFi or by developing an application or web platform [44].

Telemedicine, a form of remote health monitoring, can diagnose and treat patients to optimize the monitoring of physiological parameters. Medical professionals can analyze, diagnose, and treat patients by using technology including secure messaging, phone calls, alarm systems, and video conferencing [104]. This item is very useful in remote areas and during the COVID-19 pandemic [105], [106].

Ding *et al*. (2020) analyzed the concept of telemedicine, which uses cellular communications and embedded technology to enable real-time remote data and alarm signal transmission over the Internet. This prototype collects and displays a wide range of physiological parameters, including blood oxygen saturation, heart rate, NiBP (non-invasive blood pressure), and body temperature. Telemedicine monitoring systems can monitor physiological parameters in real time by connecting to medical devices and transmitting the data via wireless GPRS or the internet. This technology helps medical professionals understand patient's health status and safeguards patient's safety. However, there are a few weaknesses such as the lack of an appropriate alert module, which reduces the system's ability to warn users when physiological parameters surpass the standard of measurement. Since the home environment is the focus of this research, its applicability in larger medical settings, such as hospitals, may not be fully maximized [2].

Additionally, Antor *et al*. (2021) studied a web-based telemedicine system for COVID-19 patients, including hospital integration, doctor registration, remote consultations, communication between doctors and patients, a user-friendly interface, and connectivity with Google Maps. Patients may obtain medications, keep medical records, and have remote consultations with doctors because of this system. Furthermore, by allowing medical professionals to register and designate specialists for specific departments, it enhances accessibility and the user experience. Meanwhile, a very safe password protection system is needed to safeguard patient and medical professionals data and ensure reliable network access that can be accessed from anywhere [105].

Table 7. Application in Multi-Physiological Parameters Based on Recent Research

Author	**Function**	**Categories**		**Physiological Parameter**								**Ref**
		PD/WD	**W/WL**	**HR**	**PR**	**SpO_2**	**BP**	**Body Temp**	**RR**	**ECG**	**$ETCO_2$**	
Chu *et al.*	Diagnosis	WD	W						√			[18]
Buekers *et al.*	Diagnosis	WD	W		√	√						[31]
Motin *et al.*	Diagnosis	PD	W	√		√						[33]
Marathe *et al.*	Diagnosis	PD	W			√	√	√		√		[35]
Muralidharan *et al.*	Diagnosis	PD	WL	√		√						[39]
Moller *et al.*	Diagnosis	PD	W							√		[43]
Cinel *et al.*	Diagnosis	WD	WL						√			[55]
Sharma *et al.*	Diagnosis	WD	W	√					√			[56]
Sahrul *et al.*	Diagnosis	PD	W			√		√				[57]
Sriraam *et al.*	Diagnosis	WD	W							√		[59]
Wang *et al.*	Diagnosis	WD	WL	√		√	√					[72]
Kuzubasoglu *et al.*	Diagnosis	WD	WL					√				[86]
Long *et al.*	Diagnosis	WD	W	√		√						[87]
Passler *et al.*	Diagnosis	WD	WL		√							[88]
Davies *et al.*	Diagnosis	WD	WL			√						[89]
Ding *et al.*	Monitoring	-	WL	√		√	√	√				[2]
Andrade *et al.*	Monitoring	-	WL	√		√	√			√	√	[9]
Nduka *et al.*	Monitoring	-	WL					√				[90]
Nemcova *et al.*	Monitoring	-	WL	√		√	√					[91]
Wei *et al.*	Monitoring	-	WL					√				[92]
Nishan *et al.*	Diagnosis and Monitoring	WD	WL				√					[8]
Zhang *et al.*	Diagnosis and Monitoring	PD	WL	√					√			[11]
Ma *et al.*	Diagnosis and Monitoring	WD	WL				√					[12]
Zanoguera *et al.*	Diagnosis and Monitoring	PD	W							√		[32]
Nwibor *et al.*	Diagnosis and Monitoring	WD	WL	√		√	√					[36]
Hoseinzadeh *et al.*	Diagnosis and Monitoring	PD	WL			√		√				[41]
Sarbaras *et al.*	Diagnosis and Monitoring	PD	W							√		[42]
Rahman *et al.*	Diagnosis and Monitoring	PD	W							√		[44]
Naranjo *et al.*	Diagnosis and Monitoring	WD	W							√		[45]
Edwan *et al.*	Diagnosis and Monitoring	PD	W				√					[46]

Author	Function	Categories		Physiological Parameter								Ref
		PD/WD	W/WL	HR	PR	SpO_2	BP	Body Temp	RR	ECG	$ETCO_2$	
Ali *et al.*	Diagnosis and Monitoring	PD	W	√	√	√		√				[47]
Azhari *et al.*	Diagnosis and Monitoring	PD	WL					√				[50]
Dubey *et al.*	Diagnosis and Monitoring	PD	WL			√		√		√		[53]
Zhou *et al.*	Diagnosis and Monitoring	WD	WL	√		√						[54]
Boonsong *et al.*	Diagnosis and Monitoring	PD	WL					√				[58]
Ghassemi *et al.*	Diagnosis and Monitoring	WD	WL					√				[93]
Bakar *et al.*	Diagnosis and Monitoring	PD	W	√				√				[94]
Fazio *et al.*	Diagnosis and Monitoring	WD	W						√			[95]
Naggar *et al.*	Diagnosis and Monitoring	PD	W	√		√		√	√	√		[96]
Alam *et al.*	Diagnosis and Monitoring	WD	WL						√			[97]
Bae *et al.*	Diagnosis and Monitoring	PD	W	√		√	√	√	√	√		[98]
Wong *et al.*	Diagnosis and Monitoring	WD	WL	√		√		√	√	√		[99]
Jamil *et al.*	Diagnosis and Monitoring	PD	W	√		√	√	√		√		[100]
Fan *et al.*	Diagnosis and Monitoring	WD	W		√	√	√	√				[101]

Note: *PD (Portable Device); WD (Wearable Device); W(Wired); WL(Wireless)*

Based on Table 7, overall, there are studies that use both wired and wireless body-to-device connectivity in the prototypes they develop. for example, Marathe *et al.* (2019) used the wired type in their prototypes because it employs electrodes as intermediaries between the AD8232 sensor and the human body to measure ECG, categorizing it using the contact method as stated in Table 1 [35]. Conversely, research by Lyra et a. (2021) utilized the wireless type, employing deep learning to detect body temperature and using a camera to take measurements. Therefore, this study used a non-contact method to measure body temperature, as shown in Table 1 [60].

The use of wired and wireless types in prototypes for measuring physiological parameters each have distinct advantages and developmental needs. Wired prototypes, such as those using electrodes connected to an AD8232 sensor, offer stable and reliable data transmission, making them ideal for controlled environments like hospitals. However, their main drawback is the limitation on user mobility and comfort due to the physical connections. Development in this area could focus on making wired systems more flexible and less intrusive, perhaps by using more ergonomic designs and materials that reduce discomfort for users or patients [35]. On the other hand, wireless prototypes provide greater flexibility and convenience, allowing for continuous monitoring without the constraints of physical cables. This is particularly beneficial for applications requiring patient mobility, such as wearable health monitors for daily activities or remote patient monitoring systems. However, wireless systems can face challenges with data transmission reliability, battery life, and potential interference from other wireless devices. Future developments could aim at enhancing the battery efficiency, data security, and minimizing latency in data transmission to ensure accurate and uninterrupted monitoring [60]. Both types have seen advancements in recent years, but there is a continuous need for innovations to address their respective limitations. For wired systems, integrating more advanced sensors that require less invasive connections could improve user experience. For wireless systems, improving wireless protocols and power management technologies can enhance performance and reliability, making them more suitable for a wider range of applications in healthcare.

6. CONCLUSION

According to this review paper, physiological parameters are essential for understanding an individual's health condition. Each physiological parameter represents specific characteristics that reflect the body's functions. For example, blood oxygen saturation and respiration rate are related to the respiratory system, heart and blood pressure are associated with the cardiovascular system, and body temperature indicated the heat level of the body. Different measurement methods are used to determine physiological parameters, depending on the type of parameter being measured. These measurement methods are divided based on data collection techniques and analysis methods, chosen according to specific needs. Data acquisition methods for physiological parameters include contact methods, non-contact methods, invasive methods, and non-invasive methods. Contact and non-contact methods pertain to whether the measurement is taken directly or indirectly using sensors, while invasive and non-invasive methods relate to whether the measurement involves penetrating the body. These four methods are interrelated, such as contact and invasive, contact and non-invasive, or non-contact and non-invasive, as shown in Table 1.

Various methods measure physiological parameters, including RF signals, PPG signals, machine learning, and deep learning. PPG signals use optical technology, RF signals use electromagnetic waves, and machine learning and deep learning create non-contact, non-invasive for measurements. Ma et. Al (2024) combined PPG and machine learning to develop a continuous, non-invasive method for monitoring arterial blood pressure using the SE-MSResUNet network. The model predicted blood pressure with MAE and SD values of 3.88±6.17 mmHg for systolic and 2.16±3.75 mmHg for diastolic blood pressure. However, ensuring model reliability remains a challenge due to issues such as data variability and computational demands. Further research is needed to optimize these technologies for widespread clinical use, focusing on improving accuracy, reliability, and practical deployment in diverse healthcare settings.

Based on research from the past five years, several aspects can be classified in these studies, including function, device design, and device-to-body connectivity. Physiological parameters are essential for accurate diagnosis and monitoring, with portable and wearable devices serving these purposes effectively. Portable devices, like those in Muralidharan *et al.*'s (2023) study, offer user-friendly solutions for continuous health monitoring in heart rate and blood oxygen saturation. These devices, while convenient and adaptable to daily life, may lack the extensive features and precision of traditional medical equipment, making them suitable primarily for personal use and early intervention.

Monitoring applications for physiological parameters enables continuous monitoring measurement for early diagnosis and chronic disease management. Rahmat *et al.* (2019) developed a system using the Bluetooth HC-05 module to remotely observe ECG measurements, but its limited range necessitates further development using WiFi or web platforms for better remote monitoring. In conclusion, ongoing advancements in physiological parameters technologies present exciting opportunities for personalized healthcare. However, addressing challenges such as data quality, mode reliability, and practical integration into clinical practice remains crucial. Future research should prioritize refining these technologies to enhance accuracy, usability, and impact on patient outcomes across diverse healthcare environments.

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REFERENCES

[1] V. Selvaraju *et al.*, "Continuous Monitoring of Vital Signs Using Cameras: A Systematic Review," *Sensors*, vol. 22, no. 11, p. 4097, 2022, https://doi.org/10.3390/s22114097.
[2] S. Ding and X. Wang, "Medical Remote Monitoring of Multiple Physiological Parameters Based on Wireless Embedded Internet," *IEEE Access*, vol. 8, pp. 78279-78292, 2020, https://doi.org/10.1109/ACCESS.2020.2990167.
[3] Z. Xu *et al.*, "Simultaneous Monitoring of Multiple People's Vital Sign Leveraging a Single Phased-MIMO Radar," in *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 6, no. 3, pp. 311-320, 2022, https://doi.org/10.1109/JERM.2022.3143431.
[4] S. Benedetto, C. Caldato, D. C. Greenwood, N. Bartoli, V. Pensabene, and P. Actis, "Remote Heart Rate Monitoring

- Assessment of the Facereader rPPg by Noldus," *PLoS One*, vol. 14, no. 11, p. e0225592, 2019, https://doi.org/10.1371/journal.pone.0225592.
[5] M. Haghi *et al.*, "A Flexible and Pervasive IoT-Based Healthcare Platform for Physiological and Environmental Parameters Monitoring," *IEEE Internet of Things Journal*, vol. 7, no. 6, pp. 5628-5647, 2020, https://doi.org/10.1109/JIOT.2020.2980432.
[6] I. J. Brekke, L. H. Puntervoll, P. B. Pedersen, J. Kellett, and M. Brabrand, "The Value of Vital Sign Trends in Predicting and Monitoring Clinical Deterioration: A Systematic Review," *PLoS One*, vol. 14, no. 1, p. e0210875, 2019, https://doi.org/10.1371/journal.pone.0210875.
[7] J. K V and T. Jayanthi, "Non-Contact methods for assessment of respiratory parameters," *2023 International Conference on Innovations in Engineering and Technology (ICIET)*, pp. 1-6, 2023, https://doi.org/10.1109/ICIET57285.2023.10220744.
[8] A. Nishan *et al.*, "A Continuous Cuffless Blood Pressure Measurement from Optimal PPG Characteristic Features using Machine Learning Algorithms," *Heliyon*, vol. 10, no. 6, p. E27779, 2024, https://doi.org/10.1016/j.heliyon.2024.e27779.
[9] E. Andrade *et al.*, "Novel Interface Designs for Patient Monitoring Applications in Critical Care Medicine: Human Factors Review," *JMIR Human Factors*, vol. 7, no. 3, p. e15052, 2020, https://doi.org/10.2196/15052.
[10] D. Bibbo, J. Kijonka, P. Kudrna, M. Penhaker, P. Vavra, and P. Zonca, "Design and Development of a Novel Invasive Blood Pressure Simulator for Patient's Monitor Testing," *Sensors*, vol. 20, no. 1, p. 259, 2020, https://doi.org/10.3390/s20010259.
[11] Z. Zhang, Y. Liu, T. Stephens, and B. J. Eggleton, "Photonic Radar for Contactless Vital Sign Detection," *Nature Photonics*, vol. 17, no. 9, pp. 791-797, 2023, https://doi.org/10.1038/s41566-023-01245-6.
[12] K. Ma, L. Zou, F. Yang, C. A. Zhan, Y. Gong, and D. Huang, "Continuous Non-Invasive Arterial Blood Pressure Monitoring with Photoplethysmography via SE-MSResUNet Network," *Biomedical Signal Processing and Control*, vol. 90, p. 105862, 2024, https://doi.org/10.1016/j.bspc.2023.105862.
[13] P. Muntner *et al.*, "Blood Pressure Assessment in Adults in Clinical Practice and Clinic-Based Research: JACC Scientific Expert Panel," *Journal of the American College of Cardiology*, vol. 73, no. 3, pp. 317-335, 2019, https://doi.org/10.1016/j.jacc.2018.10.069.
[14] S. P. Juraschek *et al.*, "Effects of Intensive Blood Pressure Treatment on Orthostatic Hypotension : A Systematic Review and Individual Participant-based Meta-analysis," *Annals of Internal Medicine*, vol. 174, no. 1, pp. 58–68, 2021, https://doi.org/10.7326/M20-4298.
[15] P. Muntner *et al.*, "Measurement of Blood Pressure in Humans: A Scientific Statement From the American Heart Association," *Hypertension*, vol. 73, no. 5, pp. E35–E66, 2019, https://doi.org/10.1161/HYP.0000000000000087.
[16] N. D. Agham and U. M. Chaskar, "Learning and Non-Learning Algorithms for Cuffless Blood Pressure Measurement: a Review," *Medical & Biological Engineering & Computing*, vol. 59, no. 6, pp. 1201-1222, 2021, https://doi.org/10.1007/s11517-021-02362-6.
[17] B. Hill and S. H. Annesley, "Monitoring Respiratory Rate in Adults," *Practice Nursing*, vol. 31, no. 5, pp. 12–16, 2020, https://doi.org/10.12968/pnur.2020.31.5.206.
[18] M. Chu *et al.*, "Respiration Rate and Volume Measurements Using Wearable Strain Sensors," *npj Digital Medicine*, vol. 2, no. 1, pp. 1–9, 2019, https://doi.org/10.1038/s41746-019-0083-3.
[19] M. N. I. Shuzan *et al.*, "Machine Learning-Based Respiration Rate and Blood Oxygen Saturation Estimation Using Photoplethysmogram Signals," *Bioengineering*, vol. 10, no. 2, p. 167, 2023, https://doi.org/10.3390/bioengineering10020167.
[20] C. Massaroni, A. Nicolò, D. Lo Presti, M. Sacchetti, S. Silvestri, and E. Schena, "Contact-Based Methods for Measuring Respiratory Rate," *Sensors*, vol. 19, no. 4, p. 908, 2019, https://doi.org/10.3390/s19040908.
[21] M. Almeida, A. Bottino, P. Ramos, and C. G. Araujo, "Measuring Heart Rate During Exercise: From Artery Palpation to Monitors and Apps," *International Journal of Cardiovascular Sciences*, vol. 32, no. 4, pp. 396-407, 2019, https://doi.org/10.5935/2359-4802.20190061.
[22] A. Galli, R. J. H. Montree, S. Que, E. Peri, and R. Vullings, "An Overview of the Sensors for Heart Rate Monitoring Used in Extramural Applications," *Sensors*, vol. 22, no. 11, p. 4035, 2022, https://doi.org/10.3390/s22114035.
[23] Z. Yu, W. Peng, X. Li, X. Hong and G. Zhao, "Remote Heart Rate Measurement From Highly Compressed Facial Videos: An End-to-End Deep Learning Solution With Video Enhancement," *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 151-160, 2019, https://doi.org/10.1109/ICCV.2019.00024.
[24] N. De Pinho Ferreira, C. Gehin, and B. Massot, "A Review of Methods for Non-Invasive Heart Rate Measurement on Wrist," *IRBM*, vol. 42, no. 1, pp. 4–18, 2021, https://doi.org/10.1016/j.irbm.2020.04.001.
[25] J. Foster, A. B. Lloyd, and G. Havenith, "Non-Contact Infrared Assessment of Human Body Temperature: The Journal Temperature Toolbox," *Temperature*, vol. 8, no. 4, pp. 306-319, 2021, https://doi.org/10.1080/23328940.2021.1899546.
[26] I. I. Geneva, B. Cuzzo, T. Fazili, and W. Javaid, "Normal Body Temperature: A Systematic Review," *Open Forum Infectious Diseases*, vol. 6, no. 4, pp. 1–7, 2019, https://doi.org/10.1093/ofid/ofz032.
[27] W. Chen, "Thermometry and Interpretation of Body Temperature," *Biomedical Engineering Letters*, vol. 9, no. 1, pp. 3–17, 2019, https://doi.org/10.1007/s13534-019-00102-2.
[28] S. K. Longmore, G. Y. Lui, G. Naik, P. P. Breen, B. Jalaludin, and G. D. Gargiulo, "A Comparison of Reflective Photoplethysmography for Detection of Heart Rate, Blood Oxygen Saturation, and Respiration Rate at Various Anatomical Locations," *Sensors*, vol. 19, no. 8, p. 1874, 2019, https://doi.org/10.3390/s19081874.

[29] C. A. Haque, S. Hossain, T. -H. Kwon and K. -D. Kim, "Comparison of Different Methods to Estimate Blood Oxygen Saturation using PPG," *2021 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 792-794, 2021, https://doi.org/10.1109/ICTC52510.2021.9621142.

[30] G. Casalino, G. Castellano and G. Zaza, "A mHealth solution for contact-less self-monitoring of blood oxygen saturation," *2020 IEEE Symposium on Computers and Communications (ISCC)*, pp. 1-7, 2020, https://doi.org/10.1109/ISCC50000.2020.9219718.

[31] J. Buekers *et al.*, “Wearable Finger Pulse Oximetry for Continuous Oxygen Saturation Measurements During Daily Home Routines of Patients with Chronic Obstructive Pulmonary Disease (COPD) Over One Week: Observational Study,” *JMIR mHealth uHealth*, vol. 7, no. 6, pp. 1-15, 2019, https://doi.org/10.1109/ICTC52510.2021.9621142.

[32] M. Bravo-Zanoguera, D. Cuevas-Gonzalez, M. A. Reyna, J. P. Garcia-Vazquez, “Fabricating a Portable ECG Device Using AD823X Analog Front-End Microchips and Open-Source Development Validation,” *Sensors*, vol. 20, p. 5962, 2020, https://doi.org/10.3390/s20205962.

[33] M. A. Motin, P. P. Das, C. K. Karmakar and M. Palaniswami, "Compact Pulse Oximeter Designed for Blood Oxygen Saturation and Heart Rate Monitoring," *2021 3rd International Conference on Electrical & Electronic Engineering (ICEEE)*, pp. 125-128, 2021, https://doi.org/10.1109/ICEEE54059.2021.9718773.

[34] Y. Rong, A. Dutta, A. Chiriyath, and D. W. Bliss, “Motion-Tolerant Non-Contact Heart-Rate Measurements from Radar Sensor Fusion,” *Sensors*, vol. 21, no. 5, p. 1774, 2021, https://doi.org/10.1109/ICEEE54059.2021.9718773.

[35] S. Marathe, D. Zeeshan, T. Thomas and S. Vidhya, "A Wireless Patient Monitoring System using Integrated ECG module, Pulse Oximeter, Blood Pressure and Temperature Sensor," *2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, pp. 1-4, 2019, https://doi.org/10.1109/ViTECoN.2019.8899541.

[36] C. Nwibor *et al*., "Remote Health Monitoring System for the Estimation of Blood Pressure, Heart Rate, and Blood Oxygen Saturation Level," in *IEEE Sensors Journal*, vol. 23, no. 5, pp. 5401-5411, 2023, https://doi.org/10.1109/JSEN.2023.3235977.

[37] R. Ahmad, H. M. Kaidi, M. N. Nordin, A. F. Ramli, M. A. Abu and Y. Kadase, "Development of Blood Oxygen Level, Heart Rate And Temperature Monitoring System by Using ESP32," *2022 4th International Conference on Smart Sensors and Application (ICSSA)*, pp. 167-172, 2022, https://doi.org/10.1109/ICSSA54161.2022.9870943.

[38] S. Morishima, Y. Xu, A. Urashima, and T. Toriyama, “Human Body Skin Temperature Prediction Based on Machine Learning,” *Artif. Life Robot.*, vol. 26, no. 1, pp. 103–108, 2021, https://doi.org/10.1007/s10015-020-00632-4.

[39] M. J, S. S, S. A, Y. K and S. K, "Detecting the Oxygen Saturation level and Heart Rate using MAX30100 Sensor," *2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN)*, pp. 1-5, 2023, https://doi.org/10.1109/ViTECoN58111.2023.10157171.

[40] A. N. Nazilah Chamim, J. Rinaldi, Y. Ardiyanto, I. Iswanto and A. Ma’arif, "Heart Rate and Body Temperature Monitoring Based on Android Operating System," *2020 2nd International Conference on Industrial Electrical and Electronics (ICIEE)*, pp. 143-148, 2020, https://doi.org/10.1109/ICIEE49813.2020.9276750.

[41] M. S. Hoseinzadeh and A. Ekhlasi, "A Wireless Body Temperature and Oxygen Saturation Monitoring system based on Android Smartphones," *2022 Sixth International Conference on Smart Cities, Internet of Things and Applications (SCIoT)*, pp. 1-5, 2022, https://doi.org/10.1109/SCIoT56583.2022.9953654.

[42] S. J. S. Suhaim and I. Ali, "A Portable Android Based ECG System for Long-Time Heart Monitoring," *2022 IEEE Delhi Section Conference (DELCON)*, pp. 1-6, 2022, https://doi.org/10.1109/DELCON54057.2022.9752906.

[43] T. Möller, Y. Georgie, M. Voss and L. Kaltwasser, "An Arduino Based Heartbeat Detection Device (ArdMob-ECG) for Real-Time ECG Analysis," *2022 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, pp. 1-3, 2022, https://doi.org/10.1109/SPMB55497.2022.10014819.

[44] M. M. Rahman, M. A. H. Rimon, M. A. Hoque and M. R. Sammir, "Affordable Smart ECG Monitoring Using Arduino & Bluetooth Module," *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, pp. 1-4, 2019, https://doi.org/10.1109/ICASERT.2019.8934498.

[45] D. Naranjo *et al*., "Wearable Telemedicine System for Real-Time Monitoring of Electrocardiographic Signals," *2019 Sixth International Conference on eDemocracy & eGovernment (ICEDEG)*, pp. 69-75, 2019, https://doi.org/10.1109/ICEDEG.2019.8734294.

[46] E. Edwan, M. Abu-Musameh and A. Alsabah, "Blood Pressure Monitoring Using Arduino-Android Platform," *2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech)*, pp. 87-91, 2020, https://doi.org/10.1109/iCareTech49914.2020.00024.

[47] M. M. Ali, S. Haxha, M. M. Alam, C. Nwibor, and M. Sakel, “Design of Internet of Things (IoT) and Android Based Low Cost Health Monitoring Embedded System Wearable Sensor for Measuring SpO2, Heart Rate and Body Temperature Simultaneously,” *Wirel. Pers. Commun.*, vol. 111, pp. 2449-2463, 2019, https://doi.org/10.1007/s11277-019-06995-7.

[48] I. F. Zahra, I. D. G. H. Wisana, P. C. Nugraha, and H. J. Hassaballah, “Design a Monitoring Device for Heart-Attack Early Detection Based on Respiration Rate and Body Temperature Parameters,” *Indones. J. Electron. Electromed. Eng. Med. informatics*, vol. 3, no. 3, pp. 114–120, 2021, https://doi.org/10.35882/ijeeemi.v3i3.5.

[49] F. U. Jhora and Mairizwan, “Skin Temperature Monitoring with an Instrument Infrared Sensors Measuring Based on Direction and Distance,” *J. Phys. Conf. Ser.*, vol. 1876, no. 1, pp. 1–11, 2021, https://doi.org/10.1088/1742-6596/1876/1/012023.

[50] H. Marbun, R. Karolina, and L. Hakim, “Design of Room Capacity Measurement and Body Temperature Detection Based on Atmega328 Microcontroller,” *J. Phys. Conf. Ser.*, vol. 2193, no. 1, pp. 1–10, 2022,

https://doi.org/10.1088/1742-6596/2193/1/012014.
[51] N. B. Ahmed, S. Khan, N. A. Haque and M. S. Hossain, "Pulse Rate and Blood Oxygen Monitor to Help Detect Covid-19: Implementation and Performance," *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, pp. 1-5, 2021, https://doi.org/10.1109/IEMTRONICS52119.2021.9422520.
[52] M. M. Khan, T. Tazin, and T. Hossain, "Development of Wireless Monitoring System for Pulse Rate: A New Approach," *Proceedings*, vol. 67, no. 1, p. 13, 2020, https://doi.org/10.3390/ASEC2020-07524.
[53] T. Dubey, M. T. Hossain, M. I. Hossain, K. M. S. Hossain and M. M. Khan, "Development of Wireless Electrocardiogram, Body Temperature and Blood Oxygen Level Monitoring System," *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 394-399, 2022, https://doi.org/10.1109/ICCMC53470.2022.9753852.
[54] X. Zhou, X. Yi, Y. Liu, S. Xu, Z. Liu and Z. Yan, "Design of Intelligent Wearable Device Based on Embedded System," *2022 9th International Forum on Electrical Engineering and Automation (IFEEA)*, pp. 202-205, 2022, https://doi.org/10.1109/IFEEA57288.2022.10037788.
[55] G. Cinel, E. A. Tarim and H. C. Tekin, "Wearable respiratory rate sensor technology for diagnosis of sleep apnea," *2020 Medical Technologies Congress (TIPTEKNO)*, pp. 1-4, 2020, https://doi.org/10.1109/TIPTEKNO50054.2020.9299255.
[56] P. Sharma, X. Hui, J. Zhou, T. B. Conroy, and E. C. Kan, "Wearable Radio-Frequency Sensing of Respiratory Rate, Respiratory Volume, and Heart Rate," *npj Digit. Med.*, vol. 3, pp. 1–10, 2020, https://doi.org/10.1038/s41746-020-0307-6.
[57] M. S. T. P. Sahrul, Triwiyanto, and Torib Hamzah, "Patient Monitor for SpO2 and Temperature Parameters," *J. Electron. Electromed. Eng. Med. Informatics*, vol. 1, no. 2, pp. 7–12, 2019, https://doi.org/10.35882/jeeemi.v1i2.2.
[58] W. Boonsong, N. Senajit, and P. Prasongchan, "Contactless Body Temperature Monitoring of In-Patient Department (IPD) Using 2.4 GHz Microwave Frequency via the Internet of Things (IoT) Network," *Wirel. Pers. Commun.*, vol. 124, no. 3, pp. 1961–1976, 2022, https://doi.org/10.1007/s11277-021-09438-4.
[59] N. Sriraam, A. Srinivasulu and V. S. Prakash, "A Low-Cost, Low-Power Flexible Single-Lead ECG Textile Sensor for Continuous Monitoring of Cardiac Signals," *IEEE Sensors Journal*, vol. 23, no. 17, pp. 20189-20198, 2023, https://doi.org/10.1109/JSEN.2023.3296512.
[60] S. Lyra *et al.*, "A Deep Learning-Based Camera Approach for Vital Sign Monitoring Using Thermography Images for ICU Patients," *Sensors*, vol. 21, no. 4, p. 1495, 2021, https://doi.org/10.3390/s21041495.
[61] H. Rahman, M. U. Ahmed and S. Begum, "Non-Contact Physiological Parameters Extraction Using Facial Video Considering Illumination, Motion, Movement and Vibration," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 1, pp. 88-98, 2020, https://doi.org/10.1109/TBME.2019.2908349.
[62] H. Y. Chen, A. Chen, and C. Chen, "Investigation of the Impact of Infrared Sensors on Core Body Temperature Monitoring by Comparing Measurement Sites," *Sensors*, vol. 20, no. 10, p. 2885, 2020, https://doi.org/10.3390/s20102885.
[63] Y. Zhao and J. H. M. Bergmann, "Non-Contact Infrared Thermometers and Thermal Scanners for Human Body Temperature Monitoring: A Systematic Review," *Sensors*, vol. 23, no. 17, p. 7439, 2023, https://doi.org/10.3390/s23177439.
[64] P. Salvi *et al.*, "Comparison between invasive and noninvasive methods to estimate subendocardial oxygen supply and demand imbalance," *J. Am. Heart Assoc.*, vol. 10, no. 17, pp. 1–19, 2021, https://doi.org/10.1161/JAHA.121.021207.
[65] S. Manga *et al.*, "Estimation of Physiologic Pressures: Invasive and Non-Invasive Techniques, AI Models, and Future Perspectives," *Sensors*, vol. 23, no. 12, p. 5744, 2023, https://doi.org/10.3390/s23125744.
[66] Z. Jiang *et al.*, "A Comparison of Invasive Arterial Blood Pressure Measurement with Oscillometric Non-Invasive Blood Pressure Measurement in Patients with Sepsis," *J. Anesth.*, vol. 38, no. 2, pp. 222–231, 2024, https://doi.org/10.1007/s00540-023-03304-2.
[67] J. Fortin *et al.*, "A Novel Art of Continuous Noninvasive Blood Pressure Measurement," *Nat. Commun.*, vol. 12, no. 1, pp. 1–14, 2021, https://doi.org/10.1038/s41467-021-21271-8.
[68] D. Konstantinidis *et al.*, "Wearable Blood Pressure Measurement Devices and New Approaches in Hypertension Management: The Digital Era," *J. Hum. Hypertens. Nat.*, vol. 36, no. 11, pp. 945–951, 2022, https://doi.org/10.1038/s41371-022-00675-z.
[69] A. Tazarv and M. Levorato, "A Deep Learning Approach to Predict Blood Pressure from PPG Signals," *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 5658-5662, 2021, https://doi.org/10.1109/EMBC46164.2021.9629687.
[70] O. Schlesinger, N. Vigderhouse, D. Eytan and Y. Moshe, "Blood Pressure Estimation From PPG Signals Using Convolutional Neural Networks And Siamese Network," *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1135-1139, 2020, https://doi.org/10.1109/ICASSP40776.2020.9053446.
[71] D. Bian, P. Mehta and N. Selvaraj, "Respiratory Rate Estimation using PPG: A Deep Learning Approach," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 5948-5952, 2020, https://doi.org/10.1109/EMBC44109.2020.9176231.
[72] Y. Wang, F. Miao, Q. An, Z. Liu, C. Chen and Y. Li, "Wearable Multimodal Vital Sign Monitoring Sensor With Fully Integrated Analog Front End," *IEEE Sensors Journal*, vol. 22, no. 13, pp. 13462-13471, 2022, https://doi.org/10.1109/JSEN.2022.3177205.

[73] S. Nabavi and S. Bhadra, "Design and Development of a Wristband for Continuous Vital Signs Monitoring of COVID-19 Patients," *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 6845-6850, 2021, https://doi.org/10.1109/EMBC46164.2021.9630299.
[74] R. G. Priyadarshini, M. Kalimuthu, S. Nikesh, and M. Bhuvaneshwari, "Review of PPG signal using Machine Learning Algorithms for Blood Pressure and Glucose Estimation," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1084, no. 1, p. 012031, 2021, https://doi.org/10.1088/1757-899X/1084/1/012031.
[75] S. S. Abdulkader and U. A. Qidwai, "A Review on PPG Compression Techniques and Implementations," *2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pp. 511-516, 2021, https://doi.org/10.1109/IECBES48179.2021.9398812.
[76] J. Park, H. S. Seok, S. S. Kim, and H. Shin, "Photoplethysmogram Analysis and Applications: An Integrative Review," *Front. Physiol.*, vol. 12, pp. 1–23, 2022, https://doi.org/10.3389/fphys.2021.808451.
[77] G. Narendra Kumar Reddy, M. Sabarimalai Manikandan and N. V. L. Narasimha Murty, "On-Device Integrated PPG Quality Assessment and Sensor Disconnection/Saturation Detection System for IoT Health Monitoring," in *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 9, pp. 6351-6361, 2020, https://doi.org/10.1109/TIM.2020.2971132.
[78] M. Krizea, J. Gialelis, A. Kladas, G. Theodorou, G. Protopsaltis and S. Koubias, "Accurate Detection of Heart Rate and Blood Oxygen Saturation in Reflective Photoplethysmography," *2020 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, pp. 1-4, 2020, https://doi.org/10.1109/ISSPIT51521.2020.9408845.
[79] J. -K. Park *et al*., "Noncontact RF Vital Sign Sensor for Continuous Monitoring of Driver Status," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 3, pp. 493-502, 2019, https://doi.org/10.1109/TBCAS.2019.2908198.
[80] X. Liu, J. Yin, Y. Liu, S. Zhang, S. Guo and K. Wang, "Vital Signs Monitoring with RFID: Opportunities and Challenges," in *IEEE Network*, vol. 33, no. 4, pp. 126-132, 2019, https://doi.org/10.1109/MNET.2019.1800014.
[81] S. A. Shah and F. Fioranelli, "RF Sensing Technologies for Assisted Daily Living in Healthcare: A Comprehensive Review," *IEEE Aerospace and Electronic Systems Magazine*, vol. 34, no. 11, pp. 26-44, 2019, https://doi.org/10.1109/MAES.2019.2933971.
[82] S. Secinaro, D. Calandra, A. Secinaro, V. Muthurangu, and P. Biancone, "The Role of Artificial Intelligence in Healthcare: a Structured Literature Review," *BMC Med. Inform. Decis. Mak.*, vol. 21, no. 1, pp. 1–23, 2021, https://doi.org/10.1186/s12911-021-01488-9.
[83] M. Coccia, "Artificial intelligence technology in cancer imaging: Clinical challenges for detection of lung and breast cancer," *Journal of Social and Administrative Sciences*, vol. 6, no. 2, pp. 82-98, 2019, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3424072.
[84] F. Esgalhado, B. Fernandes, V. Vassilenko, A. Batista, and S. Russo, "The Application of Deep Learning Algorithms for PPG Signal Processing and Classification," *Computers*, vol. 10, no. 12, p. 158, 2021, https://doi.org/10.3390/computers10120158.
[85] H. Rohmetra, N. Raghunath, P. Narang, V. Chamola, M. Guizani, and N. R. Lakkaniga, "AI-Enabled Remote Monitoring of Vital Signs for COVID-19: Methods, Prospects and Challenges," *Computing*, vol. 105, no. 4, pp. 783–809, 2023, https://doi.org/10.1007/s00607-021-00937-7.
[86] B. A. Kuzubasoglu, E. Sayar, C. Cochrane, V. Koncar, and S. K. Bahadir, "Wearable Temperature Sensor for Human Body Temperature Detection," *J. Mater. Sci. Mater. Electron.*, vol. 32, no. 4, pp. 4784–4797, 2021, https://doi.org/10.1007/s10854-020-05217-2.
[87] N. M. H. Long and W. -Y. Chung, "Wearable Wrist Photoplethysmography for Optimal Monitoring of Vital Signs: A Unified Perspective on Pulse Waveforms," *IEEE Photonics Journal*, vol. 14, no. 2, pp. 1-17, 2022, https://doi.org/10.1109/JPHOT.2022.3153506.
[88] S. Passler, N. Müller, and V. Senner, "In-Ear Pulse Rate Measurement: A Valid Alternative to Heart Rate Derived from Electrocardiography?," *Sensors*, vol. 19, no. 17, p. 3641, 2019, https://doi.org/10.3390/s19173641.
[89] H. J. Davies *et al*., "In-Ear SpO_2 for Classification of Cognitive Workload," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 15, no. 2, pp. 950-958, 2023, https://doi.org/10.1109/TCDS.2022.3196841.
[90] A. Nduka, J. Samual, S. Elango, S. Divakaran, U. Umar and R. SenthilPrabha, "Internet of Things Based Remote Health Monitoring System Using Arduino," *2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, pp. 572-576, 2019, https://doi.org/10.1109/I-SMAC47947.2019.9032438.
[91] A. Nemcova *et al.*, "Monitoring of Heart Rate, Blood Oxygen Saturation, and Blood Pressure using a Smartphone," *Biomed. Signal Process. Control*, vol. 59, p. 101928, 2020, https://doi.org/10.1016/j.bspc.2020.101928.
[92] Q. Wei, H. J. Park, and J. H. Lee, "Development of a Wireless Health Monitoring System for Measuring Core Body Temperature from the Back of the Body," *J. Healthc. Eng.*, pp. 1–8, 2019, https://doi.org/10.1155/2019/8936121.
[93] F. Ghassemi, M. S. Hoseinzadeh and A. Ekhlasi, "Design and Implementation of Wireless Body Temperature Monitor with warning system via SMS," *2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)*, pp. 1-5, 2020, https://doi.org/10.1109/ICSPIS51611.2020.9349541.
[94] A. A. Bakar, S. S. A. Rahim, A. R. Razali, E. Noorsal, R. Radzali, and A. F. A. Rahim, "Wearable Heart Rate and Body Temperature Monitoring Device for Healthcare," *J. Phys. Conf. Ser.*, vol. 1535, no. 1, pp. 1–9, 2020, https://doi.org/10.1088/1742-6596/1535/1/012002.
[95] R. De Fazio, M. Stabile, M. De Vittorio, and R. Vel, "An Overview of Wearable Piezoresistive and Inertial Sensors for Respiration Rate Monitoring," *Electronics*, vol. 10, no. 17, p. 2178, 2021,

https://doi.org/10.3390/electronics10172178.
[96] N. Q. Al-Naggar, H. M. Al-Hammadi, A. M. Al-Fusail, and Z. A. Al-Shaebi, "Design of a Remote Real-Time Monitoring System for Multiple Physiological Parameters Based on Smartphone," *J. Healthc. Eng.*, vol. 2019, pp. 1–13, 2019, https://doi.org/10.1155/2019/5674673.
[97] M. M. Alam, M. Hussain and M. A. Amin, "A Novel Design of a Respiratory Rate Monitoring System using a Push Switch Circuit and Arduino Micocontroller," *2019 International Conference on Robotics,Electrical and Signal Processing Techniques (ICREST)*, pp. 470-473, 2019, https://doi.org/10.1109/ICREST.2019.8644282.
[98] T. W. Bae, K. K. Kwon, and K. H. Kim, "Vital Block and Vital Sign Server for ECG and Vital Sign Monitoring in a Portable u-Vital System," *Sensors*, vol. 20, no. 4, p. 1089, 2020, https://doi.org/10.3390/s20041089.
[99] D. L. T. Wong *et al.*, "An Integrated Wearable Wireless Vital Signs Biosensor for Continuous Inpatient Monitoring," in *IEEE Sensors Journal*, vol. 20, no. 1, pp. 448-462, 2020, https://doi.org/10.1109/JSEN.2019.2942099.
[100] F. Jamil, S. Ahmad, N. Iqbal, and D. H. Kim, "Towards a Remote Monitoring of Patient Vital Signs Based on IoT-Based Blockchain Integrity Management Platforms in Smart Hospitals," *Sensors*, vol. 20, no. 8, p. 2195, 2020, https://doi.org/10.3390/s20082195.
[101] Y. Fan, P. Xu, H. Jin, J. Ma and L. Qin, "Vital Sign Measurement in Telemedicine Rehabilitation Based on Intelligent Wearable Medical Devices," in *IEEE Access*, vol. 7, pp. 54819-54823, 2019, https://doi.org/10.1109/ACCESS.2019.2913189.
[102] B. Bent, B. A. Goldstein, W. A. Kibbe, and J. P. Dunn, "Investigating Sources of Inaccuracy in Wearable Optical Heart Rate Sensors," *npj Digit. Med.*, vol. 3, no. 1, pp. 1–9, 2020, https://doi.org/10.1038/s41746-020-0226-6.
[103] S. M. A. Iqbal, I. Mahgoub, E. Du, M. A. Leavitt, and W. Asghar, "Advances in Healthcare Wearable Devices," *npj Flex. Electron.*, vol. 5, no. 9, pp. 1–14, 2021, https://doi.org/10.1038/s41528-021-00107-x.
[104] M. C. van Rossum *et al.*, "Adaptive Threshold-Based Alarm Strategies for Continuous Vital Signs Monitoring," *J. Clin. Monit. Comput.*, vol. 36, no. 2, pp. 407–417, 2022, https://doi.org/10.1007/s10877-021-00666-4.
[105] M. B. Antor, A. H. M. Shafayet Jamil, M. Mamtaz, M. M. Khan, S. S. Alshamrani, and M. Masud, "Development of a Web-Based Telemedicine System for Covid-19 Patients," *Intell. Autom. Soft Comput.*, vol. 30, no. 3, pp. 899–915, 2021, https://doi.org/10.32604/iasc.2021.018914.
[106] N. Kagiyama *et al.*, "Validation of Telemedicine-Based Self-Assessment of Vital Signs for Patients with COVID-19: A Pilot Study," *J. Telemed. Telecare*, vol. 29, no. 8, pp. 600–606, 2021, https://doi.org/10.1177/1357633X211011825.

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