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Leveraging the accelerometer data for precise blood pressure assessment and management

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ABSTRACT

In recent years, the use of accelerometer data in biosensors, which tracks physical activity levels and mobility, has gained more attention. Accelerometers offer enormous promise in the field of blood pressure measurement in addition to being utilized for physical activity monitoring. It is possible to utilize it as a sensor to measure ballistocardiograms (BCG) and seismocardiograms (SCG), which can be used to forecast blood pressure. Accelerated plethysmograms can also be monitored in real-time with accelerometer-based devices. More importantly, three-dimensional accelerometer data can provide physiological information and can therefore be used to forecast blood pressure. Other research claims to be able to measure pulse transit time (PTT) and, consequently, blood pressure using opto-accelerometers. The data produced by the accelerometer can be used as contextual information in blood pressure prediction models and is essential for preventing motion artifact in physiological signals. These appealing factors lead us to investigate the importance of accelerometer data in this field. This review intends to explore the significance of accelerometer data in blood pressure monitoring, emphasizing its possible effects on clinical practice and public health.

1. Introduction

Cardiovascular illness is largely brought on by hypertension, which is becoming more commonplace worldwide [1,2]. Auscultatory or oscillometric devices, which offer a snapshot of blood pressure at a certain time, are common methods used to measure blood pressure [3]. These measures, however, might not be an accurate representation of a person's blood pressure throughout the day, as blood pressure can vary considerably depending on physical activity, stress, the time of day etc. [4]. In order to track physical activity and sleep, accelerometer devices that measure acceleration or movement in three dimensions have found widespread application in wearable technology, mobile phones, and smartwatches [5,6].

Accelerometers were first created and studied as a way to gauge acceleration and gait velocity in the 1950s [7]. The acceleration meter used to measure human motion was the subject of in-depth research in the 1970s [7]. Furthermore, research showed that accelerometers have advantages over competing techniques for quantitatively and precisely measuring human movement [7]. Accelerometer data offer important information on a person's activity level, length, intensity, and movement patterns, which can represent their general lifestyle and health behaviours [8–14]. The accelerometer is employed in several healthcare applications, including blood pressure measurement, fall detection, lung sound monitoring, heart rate monitoring, and more [11,15–19].

Accelerometer data can be used to monitor the effectiveness of blood pressure medications and lifestyle interventions. For instance, if a patient is prescribed a medication to lower their blood pressure, the accelerometer data can be used to monitor their physical activity levels and ensure that the medication is having the desired effect [20]. Similarly, if a patient is advised to make lifestyle changes, such as increasing their physical activity, the accelerometer data can be used to monitor their progress and provide feedback on their adherence to the recommended changes [20]. Utilizing accelerometers, certain studies explored the impact of motion, particularly on localized blood pressure (BP), and related this to potential effects of the autonomic nervous system (ANS) and hemodynamic pressure changes. Information on the impact of motion will be crucial for reducing the impact of motion artifacts on physiological signals produced by the human body in the future [21].

Studies employing a hydrostatic pressure approach to cuffless blood

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pressure monitoring have shown the creation of a non-invasive modality that allows for patient arterial blood pressure to be monitored remotely without the need for a high-pressure cuff [22]. The hydrostatic pressure approach makes use of the accelerometer to measure blood pressure at different positions. Additionally, The blood pressure measuring device can be calibrated using an accelerometer [23]. Moreover, a recent study found that accelerometer data could possibly be used to predict blood pressure levels. Some studies used accelerometers as ballistocardigram (BCG), seismocardiogram (SCG) sensors and others used them to measure Pulse Transit Time (PTT) [19]. Besides, direct acceleration plethysmograph (APG) detection using an accelerometer is another interesting study area [24,70]. Accelerometer data can be utilized to make accurate measurement of blood pressure, identify risk factors for high blood pressure, track the success of therapies, and ultimately improve patient outcomes. The use of accelerometer data in healthcare, especially the measurement of blood pressure, is projected to enhance as wearable technology grows further. Since there haven't been any reviews in this field published to our knowledge, we made the decision to investigate the significance of the accelerometer in blood pressure measurement.

1.1. Accelerometers and their sensing mechanisms

An accelerometer is a sensor that combines electromechanical components to detect and measure acceleration an object along one, two, or three axes. [25]. Particularly, the structure of an accelerometer carrying the mechanical elements measures physical deformation and converted those movements into an electrical signal for further processing [25–27]. Mems-based Accelerometer (MEMS) technology has immense commercial importance because of its numerous attractive attributes, including a tiny footprint, low power consumption, high sensitivity as well as reliability, and many functionalities [8,9]. MEMS accelerometers are utilized for inertial guidance, vibration monitoring, seismology, micro-gravity measurements, healthcare etc. [25,28–30] applications of accelerometer in healthcare are expanding nowadays, and fulfilling the arising demands and necessities, particularly, in terms of customization, power consumption, size of device and performance. Different types of accelerometers and schematic illustrations of Various sensing mechanisms are shown in Fig. 2 and Fig. 3 respectively. (See Fig. 1.)

The piezoelectric accelerometer is a type of accelerometer that relies on the piezoelectric effect present in specific materials to produce an electric charge when subjected to mechanical stress, including acceleration or vibration. These accelerometers are commonly used in wearable devices due to their small size and minimal power consumption. Additionally, they offer advantages such as a reduced number of moving components, a wide operating range, and low noise levels [31,32]. On the other hand, capacitive accelerometers function by detecting changes in capacitance between two plates when subjected to acceleration. They exhibit excellent sensitivity and provide precise measurements, capable of capturing constant, periodic, and transient accelerations. Furthermore, capacitive accelerometers possess advantages such as high-temperature stability and enhanced sensitivity. However, they are susceptible to interference from electromagnetic sources and have a limited frequency range of application [33,34]. While piezoresistive accelerometers operate based on the principle that mechanical strain caused by an acceleration force results in a change in the resistivity of a piezoresistive material [28]. These accelerometers function similarly to strain gauges and are characterized by a broad bandwidth and low sensitivity, making them ideal for detecting impulses or impacts. In fact, they are the preferred choice for such applications. Furthermore, piezoresistive accelerometers remain highly popular and widely utilized in the field of MEMS [28]. This is primarily due to their straightforward fabrication and packaging processes, as well as their inherent durability and robustness. Over time, advancements have continuously enhanced the specifications of piezoresistive accelerometers for various applications, including improvements in input range, frequency response, and sensitivity [28,35].

Moving on to optical accelerometers, they employ optical fibers, gratings, and other optical elements as part of their sensing mechanism [25]. The working principle of these accelerometers is based on technologies such as Fabry-Perot cavity, Fiber Bragg grating (FBG), and waveguide coupling [46]. By leveraging optical measurement technology, optical accelerometers achieve exceptional precision and can measure acceleration with resistance to electromagnetic interference. These accelerometers exhibit a high level of sensitivity, enabling them to accurately measure even small accelerations [25]. Additionally, they are designed to be noise-proof, ensuring reliable and accurate measurements in various environments. This makes optical accelerometers particularly well-suited for applications in the medical field, where measuring small accelerations with precision is crucial [25,46].Another type of accelerometer is Field Effect Transistor(FET) based,which operates by utilizing transducing materials in the gate or channel region to regulate electrical current flow. In FET sensors, changes in capacitance within the dielectric layer serve as the primary sensing mechanism. Even a small change in capacitance can yield a relatively high

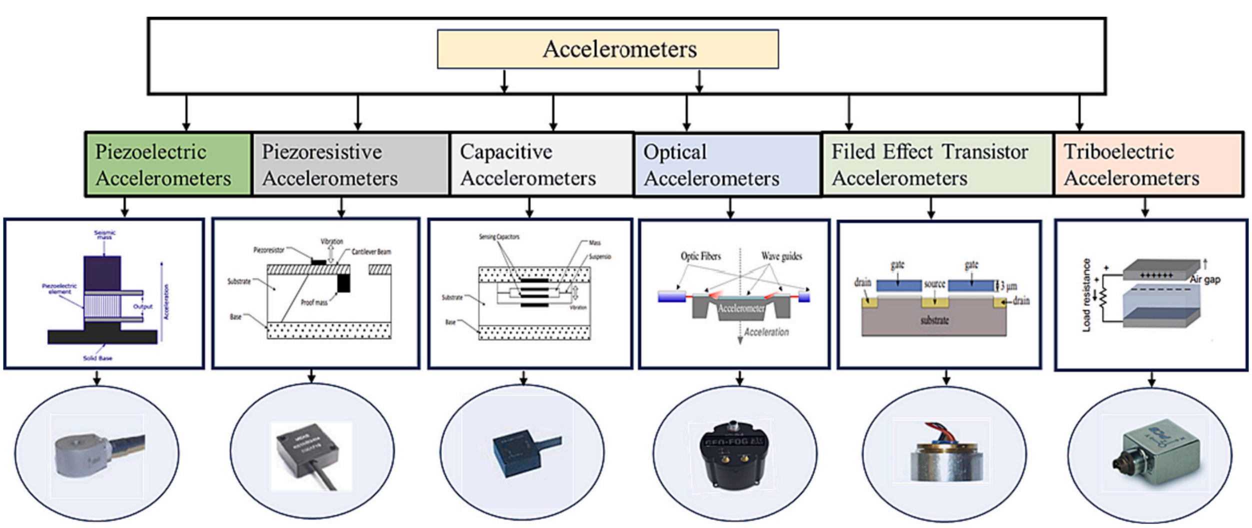

Fig. 1. Types of accelerometers. Piezoelectric accelerometer [36,37],Piezoresistive accelerometer [37,38], Capacitive accelerometer [36,37,39,40], Optical accelerometer [39,41], Field Effect Transistor accelerometer [42,43] and Triboelectric accelerometer [44,45].

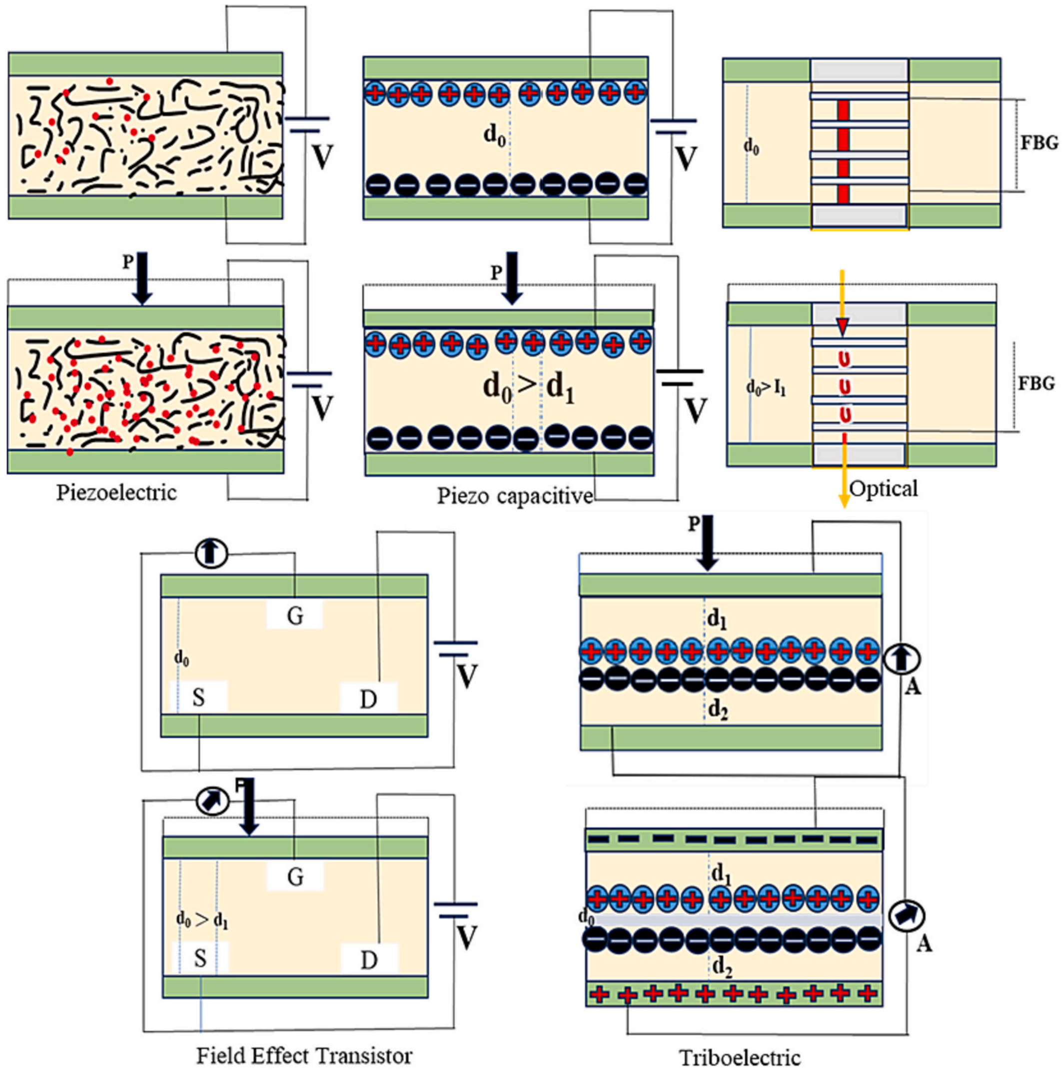

Fig. 2. Sensing mechanism [47] of different types of accelerometer sensors.

current signal output due to the transistor's signal amplification function [47].On the other hand, the triboelectric based accelerometer functions based on contact-induced electrification. When different materials come into physical contact, they become electrically charged, with varying charge strengths depending on the materials involved [48,49]. However, triboelectric-based sensors typically exhibit a relatively low limit of detection. Furthermore, their mechanism does not provide a stable and precise signal output that accurately captures the real-time magnitude, direction, and location of the applied stress [47,49].

1.2. Relevance of accelerometer data in BP prediction

The ability of accelerometer data to predict blood pressure is enhanced when paired with physiological and environmental data. Recent studies have investigated the potential of blood pressure prediction utilizing wearable accelerometer-equipped devices [52]. Comfort and usability are of utmost importance because the accelerometer device will be used for prolonged periods of time. The least amount of discomfort for the subjects is required, and it must be easy to put on. Researchers decided on a single, wrist-mounted, tri axial accelerometer for these reasons in order to develop applications for medical and health monitoring [19]. Every time blood pressure is taken, accelerometers can also help by predicting the location to lessen motion inaccuracy and by evaluating the subject's posture and level of physical activity [20,50–52]. Several perspectives on accelerometer data that can be used to predict blood pressure are explored next and summarized in Table 1.

1.3. Physical activity

The complexity of continuous blood pressure monitoring rises, particularly outside of hospitals, due to changes in each person's physical attributes and the potential for different postures. Accelerometers provide objective measurements of physical activity and body posture without relying on self-reporting or subjective judgements, which may be biased. [20,50–59]. Accelerometers come up with a non-invasive, unbiased way to evaluate a person's level of physical activity and posture, potentially minimizing measurement errors and biases [50–59]. Correlation between self-reported physical activity and a gold standard (such as accelerometry) is frequently low, falling between 0.3 and 0.5 [53]. It demonstrates the significance of an accelerometer-based assessment of physical activity. Wearable accelerometers can give activity measurement that is more accurate and repeatable than self-reported data [54]. The daily physical activity patterns of working adults as recorded by accelerometers were compared to their cardiometabolic health by aviroop et al. [10].

Workers who engaged in fluctuating levels of moderate activity and those with the highest activity levels demonstrated lower systolic blood

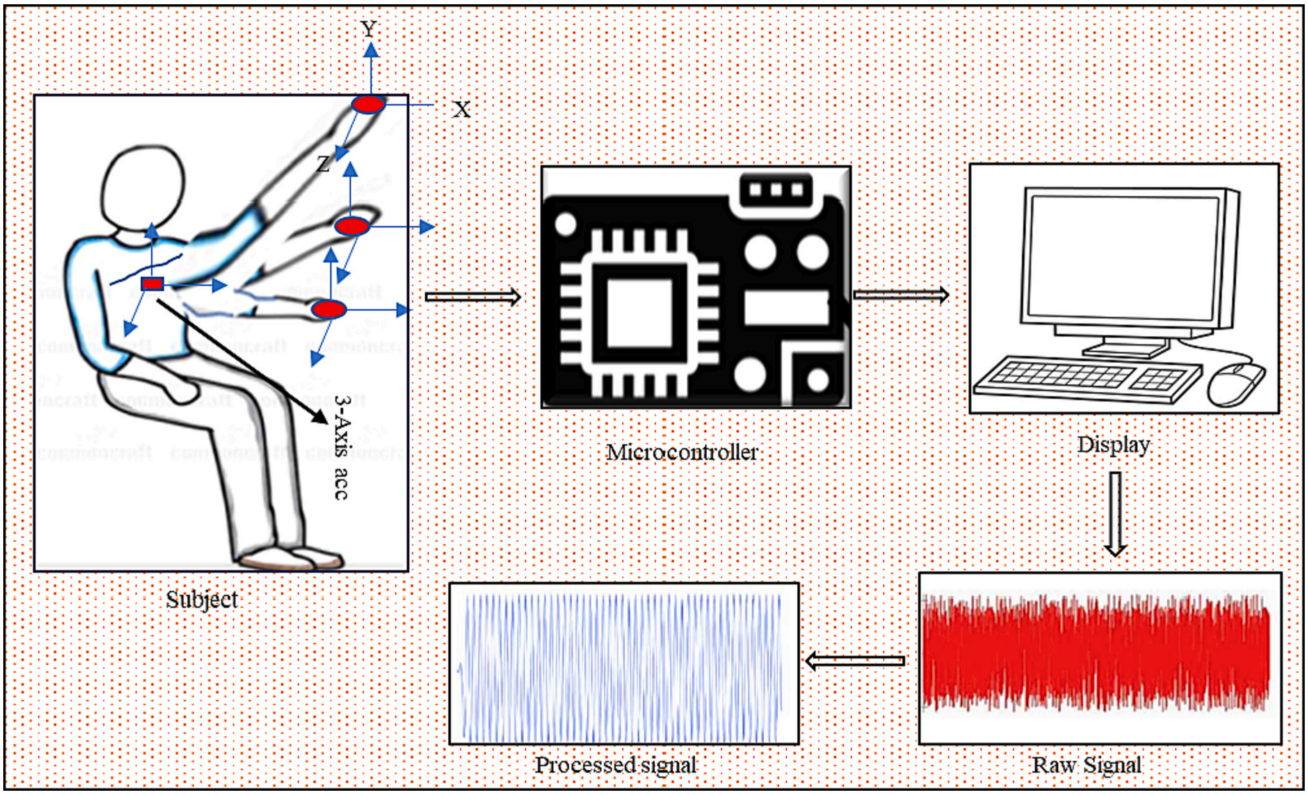

Fig. 3. Demonstration of 3-dimentional accelerations and positioning of the accelerometer for health care monitoring system.

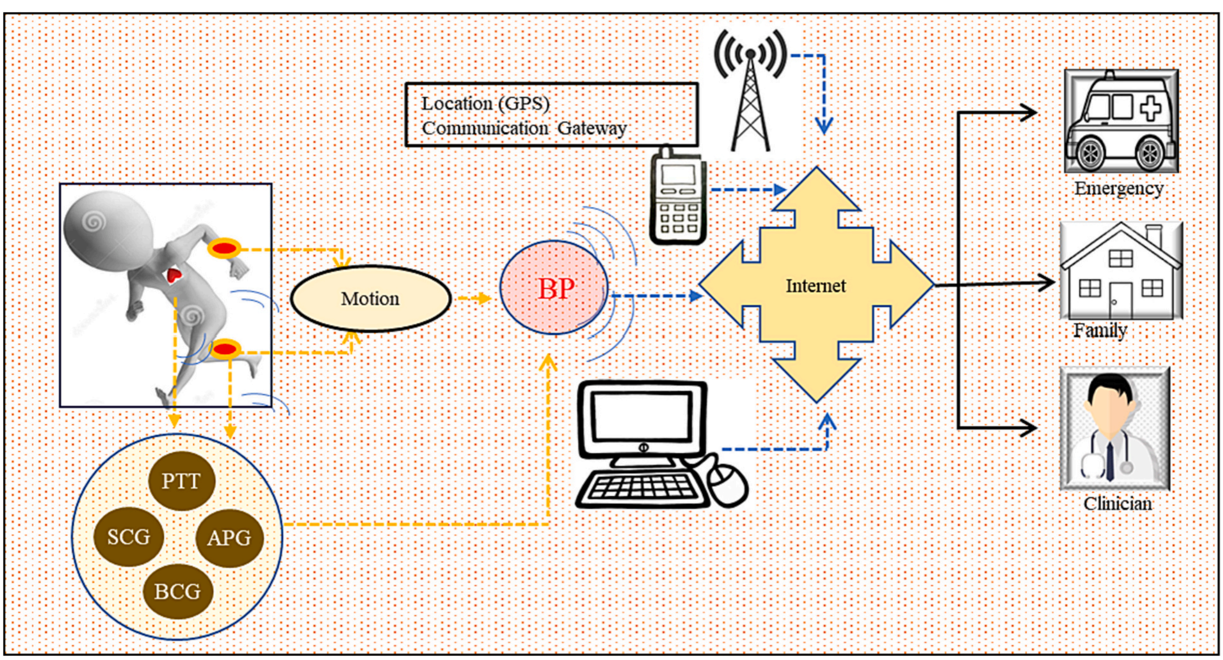

Fig. 4. Graphical representation of 3-axis accelerometer for BP measurement in distinctive ways.

pressure. Conversely, workers who had activity levels that steadily increased to moderate levels until midnight and then steadily decreased in the early morning exhibited lower diastolic blood pressure. Furthermore, among younger employees, engaging in moderate activity was associated with lower diastolic blood pressure [10].

It would be possible to assess the effectiveness of anti-hypertensive medications on patients more effectively if ambulatory systolic blood pressure (ASBP) variability were to be decreased. An evaluation of a potential approach to lessen ASBP variability during 24-h recordings was presented in this work [20] as a feasibility study. An accelerometer and a heart rate recorder were added to the portable blood pressure recorder. The logarithm of the body's acceleration and ASBP were discovered to be in a linear connection. When acceleration was recorded along the anterior-posterior axis, it was discovered that the correlation

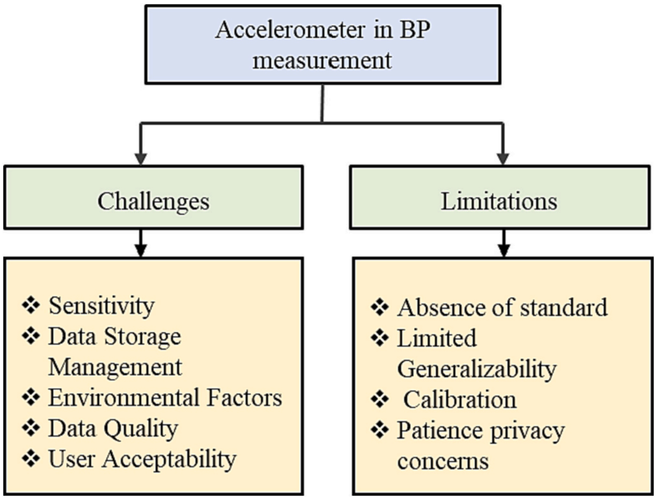

Fig. 5. Challenges and limitations of accelerometer.

Table 1
Different applications of accelerometer in blood pressure measurement.

Applications	Uses
Physical activity	Accurate ambulatory blood pressure monitoring for hypertension patients [20,50] Continuously track postures while taking blood pressure measurements [51,52]
To avoid Motion artifact of physiological signal	To get better physiological signal like PPG by avoiding motion artifact
To measure distance between raising and lowering the subject's arm	Hydrostatic pressure variations-based BP measurement by raising and lowering the subject's arm
Accelerometer to collect SCG signal	SCG signals are used to estimate BP along with other physiological signals like PPG
Accelerometer to collect BCG signal	BCG signals are used to estimate BP along with other physiological signals like PPG
Cuffless BP monitoring from a 3-axis accelerometer	They extract more physiological information from 3-dimensional data to estimate BP [19]
Optics-based accelerometers	Two optics-based accelerometers used to measure PTT. and hence BP
Implantable accelerometer	To directly detect acceleration plethysmogram at an artery. Accurate PTT, RWTT results in better estimation of BP
Accelerometer data as contextual data	Accelerometer can provide useful contextual information that can improve the precision of blood pressure prediction models

between ASBP and acceleration was higher. They limit fluctuations brought on by physical activity by creating a model that can link ASBP variations with body acceleration and heart rate data [20]. Conventional blood pressure readings made in a clinical setting could not accurately reflect a person's blood pressure changes throughout the day. It has been demonstrated that ambulatory blood pressure monitoring (ABPM), which is carrying a portable blood pressure monitor and taking periodic readings over a 24-h period, provides a more accurate assessment of a person's blood pressure profile. Hence, it is considered as a diagnostic test for hypertension, however, blood pressure variability, which is correlated with physical activity, is a major concern in ambulatory monitoring [50,51]. The feasibility of using an accelerometer as a position/activity monitoring system while performing ambulatory ECGecg and blood pressure monitoring was examined by Marie-Laure Wetzlera et al. [50]. Accelerometer was worn on the subject's thigh with a position sensor worn at the subject's waist. The accelerometer enabled precise differentiation between the standing, sitting, and laying positions. The accelerometer correctly identified the walking, whereas the activity score and treadmill speed had a good correlation. With a mean inaccuracy of less than 3 s, changes in position and activity were identified. They concluded that accelerometer based system is a viable option for routine activity/positioning monitoring [50].

Luis and coworkers investigated the association between routine physical activity and the circadian pattern of 24-h ambulatory arterial blood pressure in the general population, as measured scientifically by an accelerometer and by a questionnaire

The dipping pattern and the sleep-to-wake blood pressure (BP) ratio have shown predictive capabilities for cardiovascular diseases in hypertensive patients.According to results, the dipper-pattern patients had greater levels of activity than non-dipper patients. Physical activity measurements are correlated favorably with the percentage decline in systolic blood pressure and negatively with the systolic and diastolic sleep-to-wake ratios and heart rate [51].Simi Susan Thomas and team make an effort to offer a wearable solution and recommend training for a particular posture and person to further increase accuracy of bp measurement [52]. The wristwatch-based device measures ECG and photoplethysmograms (PPG) and uses accelerometers to authenticate readings while the user is in various positions. Additionally, the created device calculates BP using various models after measuring PTT. They demonstrated the value of adjusting the device to each posture and each person and validate measurements on various postures and subjects.They found that roor mean sqaured erro for predicting systolic BP is in the range of 7.83–9.37 mmHg. In an effort to maintain the sensor at the right place, the system can also automatically determine the user's arm position using an accelerometer with an average accuracy of 98%. Likewise, PTT and BP values vary significantly between individuals and postures and it highlights the significance of employing an accelerometer to continuously track postures while taking blood pressure measurements [52].

Variations in physical activity associated with as six-minute walk distance, echocardiographic parameters, or health-related quality of life assessments was investigated by sameep Sehgal et al. [55]. The best indicators of physical activity are steps taken each day and the amount of time spent at different levels of exercise, and a combination of these two indicators gives the greatest overall picture of activity and changes in the severity of PAH (pulmonary arterial hypertension) over time. Activity measurement has enormous potential for long-term PAH monitoring. Subjects with PAH, changes in daily step count and time spent for different activities correlate with changes in six-minute walk distance and health-related quality of life assessments, suggesting that accelerometry may be a useful monitoring tool [55]. The practicality of using the PPG-based heart rate to calculate heart rate variability (HRV) and forecast hypertension was done by Kun-chan Lan et al. [21]. The sensor board had an accelerometer so that data ignored when a user's motions are significant enough to introduce an artifact. It produces more accurate predictions [21]. Han Li et al. used an accelerometer in smartphone to measure displacement of hand while measuring systolic blood pressure (SBP) [56]. Using a smart phone's built-in camera, volume pulse waves were captured, and pulse wave transit time between the progressive and reflected waves of the accelerated pulse waves were measured. While holding the phone, the subject makes hand motions to detect variations in the SBP. The displacement of the hand was calculated using the smartphone's accelerometer. Experimental results indicate that there is no appreciable difference between SBP measured by the proposed method and by an electronic sphygmomanometer with an error of less than 10 mmHg [56].

The relationship between home blood pressure (HBP), sleep, and activity was explored by Akiyo Sasaki-Otomaru et al. utilizing information from a wristwatch-style pulsimeter with an accelerometer [57]. They hired 40 people who were between the ages of 24 and 81 and were not taking anti-hypertensive or sleeping pills, totaling 28 elderly people. Over the course of 5–7 days, HBP, activity, and sleep were all measured in succession. In both a simple and multiple linear regression analysis, there was a significant correlation between age, base heart rate (HR0), and body mass index (BMI) and HBP. In the linear regression analysis, HR0 and log deep sleep duration were positively correlated with HBP. In a simple linear regression, physical and mental activity were negatively correlated with SBP, but intense physical and mental activity tends to shorten the length of deep sleep. There was no connection between HBP and self-reported sleep duration. In conclusion, HBP showed relationships with HR0, BMI, age, deep sleep duration, and activity [57].Paul et al. looked at hypertensive people to see if objectively assessed physical activity was related to all-cause mortality [58]. The presence of hypertension was assessed using measured blood pressure and blood pressure-lowering drugs. The ActiGraph 7164 accelerometer is used to gauge physical activity. Accelerometry data was combined into 1-min time intervals after being restricted to just those with at least 4 days and 10 h/day of observed data using the statistical analysis system. To prevent, treat and control hypertension in individuals with high blood pressure, regulating physical activity is also advised. Controlling physical activity may help hypertensive people manage their blood pressure and prevent premature death through a number of plausible mechanisms, including improved cardiorespiratory fitness, modulation of inflammation, oxidative stress, and endothelial function, loss of body fat, improved baroreflex sensitivity and reversal of left ventricular hypertrophy [58]. Even when hypertensive people are not taking medication to treat their hypertension, physical activity seems to enhance their chances of survival. Every additional 60 min of physical activity decreased the risk of all-cause mortality in hypertensive people by 19% [58]. Additionally, a dose-response relationship was demonstrated, and compared to the lowest tertial, the risk of death from all causes decreased by 31 and 42% in the middle and upper tertials, respectively. The results did not support an interaction effect that was sex-specific [58].

An accurate assessment of the subject's arm height (relative to the heart) is necessary for any unattended blood pressure monitor. The majority of currently available methods either use video motion tracking or fluid-filled tubing, both of which can be difficult and unworkable. Philip A Shaltis et al. used a dual MEMS accelerometer technique to measure height in their PPG-based sensor unit for measuring blood pressure [59]. The key to accurately measuring height with sensors is to consider how gravity's angle affects each sensor's output. The upper arm is equipped with one accelerometer, with the axis of the accelerometer aligned with the upper arm's longitudinal axis. The other accelerometer is housed within the PPG sensor near the base of the finger, where one of its axes either the x-axis or the y-axis—aligns with the forearm's longitudinal direction. It was found that there was great agreement between the estimated arm heights using accelerometers and the actual arm heights measured with a ruler. Accelerometer based height sensor that could gauge the PPG's hydrostatic pressure offset from the heart [59].

Philips et al. described a study by using a modified volume-oscillometric methodology, which makes use of the natural hydrostatic pressure variations brought on by raising and lowering the subject's arm [22]. While in conventional oscillometry the blood vessel is pressurized from the outside, hydrostatic pressure does it from within. The location of the first accelerometer was on the upper arm, and it provided an approximate report of the humerus's orientation with respect to gravity. The second accelerometer, which was integrated with the PPG sensor. At a sampling rate of 200 Hz, continuous data from the PPG, pressure and height sensors were captured. Compared the data of PPG-AC and (pressure from cuff + Hydrostatic pressure) with a Gaussian curve. The mean arterial pressure (PMAP) was taken to be represented by the curve's peak [22]. At an amplitude equivalent to 0.45 times the peak amplitude, the PS(systolic pressure) optimum point was located. PD (Diastolic pressure) values were determined by applying the well-known formula PMAP = PD +1/3(PS PD), given PMAP and PS to solve for PD. This novel approach has the particular advantage of allowing measurements to be made using an absolute gauge pressure without the need for further actuation [22].

1.4. Accelerometer as BCG and SCG sensor for BP measurement

Cardio vibrations are frequently measured using the ballistocardiogram (BCG) and seismocardiogram (SCG) techniques. The BCG depicts the overall body movements in reaction to changes in centre of mass brought on by blood flow through the body [60]. Aortic valve opening can be precisely determined using SCG, which depends on vibration caused by blood circulation and valve activity when the heart beats [61].Researchers are using accelerometers to measure SCG,BCG data [62].

Mohammad and coworkers used the triple axis accelerometer as the major sensor in the system that detects the heart wall motion [63]. Systolic blood pressure was calculated using a SCG that was recorded using a tri-axial accelerometer. The linear regression approach is used to create an equation from the recorded dataset. The equation is verified using the data gathered from the commercially available SBP recording equipment (Portapres) [63]. They have shown that for the patient with high SBP as well as normal SBP, there is very little relative error between the values from the equation and the corresponding data from the Portapres [63]. In another paper by Venu. G.ganti et al. used an accelerometer for collecting SCG signals [64]. The PTT was computed as the difference between the proximal timing reference, which was the aortic valve opening (AO) point of the dorso-ventral SCG (i.e., z-axis acceleration) and the distal timing reference, which was the foot of highest SNR PPG. Using PTT in a home setting, BP has been completely calculated noninvasively. Instead of using the traditional oscillometric cuff, they demonstrated a more practical way to measure ambulatory blood pressure [64].

Accelerometer-derived SCG signals, ECG, and PPG were used by Joonnyong Lee and colleagues to estimate BP [65]. Despite the accelerometer having three outputs, only the anteroposterior axis signal was used as SCG. SCG was used for measuring PTT and PEP by employing PEP monitored constantly and non-invasively, they provided a unique method for estimating BP and PP based on PTT and SV approximations [65].The proposed method in this work may enable better widespread BP monitoring and therapy of hypertension, as evidenced by the enhanced accuracy of PP and SBP estimation. RMSE for predicting PP was 3.46 mmHg, 21.9 mmHg for static exercise and cold pressure test respectively. The RMSE of the suggested approach for estimating DBP is 6.31 mmHg during static activity and 3.87 mmHg during a cold pressor test, respectively [65].

Seismo a smartphone-based BP monitoring app was created and tested by Edward Jay Wang et al. [61]. The method depends on monitoring the amount of time that passes between the aortic valve opening and the pulse eventually reaching a peripheral artery location. The vibration caused by the beating of the heart and the fingertip pulse are both recorded by the smartphone's camera and accelerometer. Using the phone's accelerometer while holding it against the chest, the SCG is recorded. By holding the phone in this manner, the user's finger covers the camera, which then records the PPG at the finger and measures the pulse as it occurs. This method easily records both the proximal (near the heart) and distal (far from the heart) time from a single device, negating the need for any additional gear. SCG from accelerometer is used for PTT measurement and PEP measurement. Total of 9 subject was there in which each one took part in four sessions of stationary cycling at various intensities. The participants' blood pressure estimates have a an RMSE of 3.0–9.2 mmHg [61].

Yang Yao et al. [66] explores the possibility of the limb BCG for unobtrusive assessment of diastolic, pulse, and systolic pressures. An upper-limb BCG is built on an accelerometer that is built into a wristband, and a lower-limb BCG is built on a strain gauge that is incorporated into a weighing scale. A finger PPG was also instrumented at the same time. The device uses an armband accelerometer based BCG signal and PPG signal used extracts data-driven features, such as the pulse transit time, from the data and calibrates the cuff to translate the features into blood pressure readings [67]. They demonstrated the ability to monitor changes in blood pressure during interventions in healthy people using both this system and a BCG-PPG weighing scale method. High correlations with diastolic, pulse, and systolic pressures were found for both methods [66,67].

a wrist worn device along with an accelerometer for continuously tracking the blood pressure R Narasimhan and coworkers [68]. The accelerometer was configured to monitor cardiac accelerations in the appropriate directions as blood begins to spread from the left ventricle. To measure accelerations in one, two, or three directions, for instance, the accelerometer is used to collect collected both SCG and BCG from accelerometer. The wrist-worn device keeps track of acceleration data pertaining to accelerations that have been recorded throughout time. The signal from the accelerometer and the ppg data from the wrist-worn device are processed by a controller to yield the PTT and blood pressure [68].

1.5. Accelerometer as a BP measurement device

Convenient, cuffless BP monitors desired to raise awareness of hypertension, especially for high risk of hypertension related fatal diseases. Eric chang et al. proposed a cuff-less BP monitoring approach based on the data from a 3-axis accelerometer [19]. Demonstration of accelerations of 3-axis accelerometer is shown in Fig. 3. They extract more physiological information from 3-dimensional data as opposed to BCG, which only uses vertical dimension ballistic data. The effectiveness of the suggested strategy was tested on 8 young, healthy volunteers while they engaged in a variety of activities with a 3-axis accelerometer positioned on their upper chest. To choose features for the computation of systolic pressure (SPB) and diastolic pressure (DPB), the 3-dimensional accelerations were utilized.

With the help of the linear combination of the obtained features, DP and SP could be approximated. The linear combination of the mean of the L2 norm of lateral acceleration and the state variation of vertical acceleration might be used to estimate SP most effectively. DP was estimated by linear combinations of the mean of the I-J interval of vertical acceleration and the mean of the L2 norm of lateral acceleration. For both the estimated and measured DP, the correlation coefficient (r) was 0.97; for the measured SP, it was 0.96. The best results for difference errors in leave-one-out cross validations were 0.59 7.46 mmHg for SPB and 0.02 3.82 mmHg for DPB. The proposed acceleration-based method met the AAMI standard. The accelerometer-based method demonstrated the possibility for simple, affordable, and cuffless blood pressure monitoring [19].

Two fiber optics-based accelerometers was BY Aleksandra Zienkiewicz for collecting the data and predicting the BP [69]. These accelerometer act as both a light source and a light detector. A cantilever with fibers attached is pointed toward with light from the free end [63]. Peripheral arteries regularly change in diameter as a result of the forceful flow of blood at each heartbeat. Near the arteries, this correlates to minute skin movements. The cantilever of an accelerometer sensor, which is firmly affixed to the skin, bends because of the acceleration brought on by the heartbeat. Cantilever deformation alters the amount of reflected light by deflecting the beam. Intensity of the reflected light has a direct relationship to output voltage [63]. Accelerometers were placed to the patient's neck and chest; they can determine heart rate and the time between pulse appearances in these two locations since they are sensitive to blood pulsation and the PTT is used for blood pressure estimation. Although the methods presented need to be improved in order to provide accurate blood pressure readings, they can be used to monitor BP oscillations for scientific research [69].

Using single- or multi-element accelerometers or accelerometric sensors, Nabeel et al. created an accelerometer-based system for non-invasive measurement of vascular wall stiffness indices and arterial blood pressure parameters [70]. By twice integrating the accelerometer signal obtained from the measurement site, the developed accelerometric system can continually acquire the artery wall displacement waveform. It is possible to quantify arterial diameter parameters using APG signals acquired using a single accelerometric sensing element, and thus allows for the determination of vascular wall stiffness indices such as arterial compliance, stiffness index, distension, and Young's elastic modulus. One accelerometer is set up to track the first acceleration signal from first measurement site. A different accelerometer is set up to measure a second acceleration signal obtained from a second measurement site. PWV is measured form APG from the two different sites [70]. Change in arterial dimensions based on a time difference between the first acceleration signal and the second acceleration signal is also measured. All these paraters are used for BP predcitons. Local PWV and diameter parameters obtained from accelerometer-derived wall displacement waveforms is appropriate for non-invasive, cuffless and continuous evaluation of arterial blood pressure parameters. APG from the two distinct sites is used to calculate PWV. The time interval between the first and second acceleration signals is used to calculate the change in arterial dimensions. These all serve as parameters for BP predictions. For non-invasive, continuous, and accurate evaluation of arterial blood pressure parameters, local PWV and diameter parameters derived from wall displacement waveforms measured by accelerometer are suitable [70].

An implantable accelerometer that can directly detect acceleration plethysmogram (APG) at an artery was developed by Michael Theodor et al. the APG, which enables more precise PTT detection than the PPG [24]. The sensor also has the ability to measure the transit time of reflected waves, which is related to both PWV and blood pressure. The accelerometer was suitable for PTT and the Reflected Wave Transit Time (RWTT), according to in-vivo measurements. Both metrics exhibit a strong relationship with systolic blood pressure. RWTT and PTT were shown to agree with the theory more closely when the blood pressure was varied. RWTT and systolic blood pressure correlated quite well, with a mean variation of 4.3% and a correlation coefficient of 0.96 for 1800 pulses. In comparison to conventional PPG sensors, this new sensor's current consumption is at least a factor of ten lower. [24,71]. The graphical representation of 3-axis acceleormeter for BP measurment in distinctive ways shown in Fig. 4.

2. Contextual data

Data from accelerometers can provide useful contextual data that can improve the precision of blood pressure prediction models. For instance, blood pressure levels can be impacted by the quantity, quality, and duration of physical activity, with regular exercise being linked to reduced blood pressure. Blood pressure readings can also be impacted by body posture, including sitting, standing, and lying down. Accelerometer data can record these environmental elements, enabling a more thorough evaluation of a person's blood pressure and enhancing the precision of blood pressure prediction models. Cederick Landry et al. presented a modeling method for predicting blood pressure (BP) waveform during daily activities [72]. Artificial neural networks were used to develop and train a nonlinear autoregressive model that predicts BP waveform from the ECG and forehead PPG. Training set inlude wide range of datas from sitting, standing, walking, Valsalva maneuvers, and static handgrip exercise. For continuous BP determination over 4.67 h, the cuffless BP method's efficiency was assessed. A mean absolute error of 6.3 and 5.2 mmHg was attained for systolic and diastolic blood pressure estimation, respectively. Better BP estimation was possible when static hand grips and Valsalva maneuvers were included in the training dataset. The suggested approach showed the capacity to calculate the range of blood pressure encountered during daily activities. The activities were identified with the use of accelerometer data, which further enhanced model prediction [72].

2.1. Additional positive aspects

Real-World Environments: Accelerometers can be worn in everyday activities, at work, or during leisure time, reflecting an individual's average levels of physical activity and body posture. Compared to measures taken in a clinic, which might not accurately reflect a person's blood pressure in their natural environment, this offers a more ecologically accurate portrayal of a person's blood pressure. Accelerometers make it possible to create and test blood pressure prediction models in actual environments, increasing their utility and generalizability [73,74].

Potential for Personalized Treatments: Personalized interventions can potentially be created using accelerometer data. An individual's physical activity levels and body posture patterns can be used to generate individualized interventions, such as exercise regimens that are especially designed for them, changes to their lifestyle, or reminders to adjust their posture, to help them better control their disease condition [75]. The control of blood pressure can be improved, and the risk of cardiovascular illnesses can be decreased, with the help of this individualized method [11].

Early detection and risk assessment: Accelerometers have been used for early detection of various health conditions [76]. Precise blood pressure prediction is essential in identifying people who are at risk of developing hypertension or suffering from consequences connected to high blood pressure. Blood pressures are related to age, sex, body mass index (BMI), and family history thus it has been used in predictive models [77–80]. Further information on a person's level of physical activity, which has been demonstrated to be a significant predictor of blood pressure, can be obtained from accelerometer data [81]. For instance, inactivity has been linked to higher blood pressure levels, whilst increasing physical activity has been demonstrated to lower blood pressure. Accelerometer data can improve blood pressure prediction models' ability to identify those who are most likely to acquire hypertension early on, enabling prompt pharmaceutical or lifestyle changes to effectively avoid or control hypertension [82].

3. Challenges and limitations

1. ***Calibration:*** Accelerometer calibration is necessary to achieve accurate measurement. The goal of calibration is to establish a correlation between accelerometer data and actual blood pressure readings, which can differ from person to person depending on things like body mass index, posture, and movement patterns. Calibration can be difficult and time-consuming, and it might need to be adjusted frequently [83,84].
2. ***Data Quality and Dependability:*** Depending on the type of accelerometer, where the sensor is placed, the data processing methods used, and the data quality control procedures used, the accuracy and dependability of accelerometer data can vary. Unreliable measurements or poor data quality can result in erroneous forecasts of blood pressure. Therefore, it is essential to carefully assess data quality and dependability when using accelerometer data to estimate blood pressure [85,86].
3. ***User Acceptability:*** Wearing accelerometers for long periods of time may demand user compliance, and some people may find them inconvenient or uncomfortable [87]. Individual differences in compliance with wearing accelerometers can result in data being lost or being incomplete. As a result of knowing they are being watched, people may also adjust their behavior or degree of physical activity, which could affect their blood pressure patterns [88].
4. ***Gadget Position:*** How the accelerometer gadget is worn on the body can affect how accurately blood pressure is estimated. For accurate data to be obtained, accelerometers must be consistently and precisely positioned [89]. While performing daily activities that involve body movement, garment obstruction, or changes in device attachment, it may be difficult to ensure consistent and appropriate placement on the body.
5. ***Interference from Other conditions:*** Environmental conditions (including temperature and humidity), motion artifacts, and noise from other devices or sources can all skew accelerometer data [90]. The accuracy of blood pressure calculation using accelerometer data can be impacted by these factors, which can introduce mistakes.
6. ***Variability among Individuals:*** The accuracy of accelerometer data for estimating blood pressure can vary depending on the activity patterns, body positions, and lifestyles of everyone [90–92]. As diverse populations may have varied activity patterns and physiological reactions, individual variation in body habits, age, and health problems may also have an impact on the precision of accelerometer-based blood pressure assessment.
7. ***Absence of Standards:*** Using accelerometer data for blood pressure calculation does not presently have a widely recognized standard. Inconsistent results and difficulties in making comparisons between research may emerge from the use of various accelerometer types, placement protocols, calibration methodologies, and algorithms in investigations [93].
8. ***Ethical and Privacy Issues:*** It is a major concern in most of the wearables [94].Since using accelerometer data to estimate blood pressure includes gathering and analyzing personal health information, it is possible that doing so will give rise to ethical and privacy issues. To ensure data security, privacy, and consent as well as adherence to pertinent laws and policies, the proper procedures must be implemented [95].
9. ***Limited Generalizability:*** Because the accuracy of the estimation can vary across different demographic groups, health conditions, and activity levels, the results from accelerometer-based blood pressure estimation may not be as generalizable to a wide range of populations [96]. Finally, the overall limitations and challenges of the accelerometer are shown in Fig. 5.

4. Conclusion

This article summarizes earlier investigations on blood pressure measurement and advancement using accelerometer data. First, we discussed the importance of accelerometer data in blood pressure prediction, where accelerometers provide non-invasive and unbiased way to evaluate one's physical activity that mitigating the measurement errors and biases. Therefore, controlling physical activity may assist in managing hypertension that leads to avoid premature deaths. In addition, by monitoring PTT and employing vertical dimension ballistic data, accelerometers can also function as blood pressure measurement tools. Furthermore, we discussed that the data from accelerometers can offer convenient contextual information that can improve the robustness of blood pressure prediction models. Also mentioned about an implantable accelerometer that could directly detect plethysmographs and determine blood pressure. The potential major obstacles that, if tackled, could lead to better results were outlined in the final part, along with some research-related constraints. This review emphasizes the importance of comprehending the role of accelerometers in precisely diagnosing and treating hypertension.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

No data was used for the research described in the article.

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