



FuSenseRing: An Open-source Platform for Robust Cuffless Blood Pressure Monitoring via Multimodal Sensor Fusion and Temperature-adaptive Attention

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Reliable, frequent blood pressure (BP) monitoring outside clinical settings is crucial for cardiovascular health management, yet current wearable solutions often fail to deliver clinically accurate measurements in real-world conditions. A key limitation stems from the common reliance, particularly in convenient ring form factors, on photoplethysmography (PPG) sensing alone. PPG signals acquired from the finger are highly susceptible to physiological and environmental noise; notably, finger skin temperature fluctuations induce errors exceeding 10 mmHg due to vascular changes, while sensor-skin contact pressure further distorts the signal. This inherent sensitivity of PPG, when uncompensated, prevents many devices from consistently meeting clinical accuracy standards. We introduce *FuSenseRing*, an open-source smart ring engineered to overcome these issues through synergistic hardware-software co-design. *FuSenseRing* integrates a multimodal sensor suite (PPG, ECG, skin temperature, contact force) on a custom flexible PCB within a low-cost form factor, approximately \$94.9 per unit at retail (batch of 5) and approximately \$28.72 per unit at wholesale (batch of 500), while remaining lightweight (4.6 g) to ensure optimal signal acquisition during BP measurements. Our core algorithmic innovation is a Temperature-Adaptive Attention (TAA) mechanism that dynamically fuses PPG/ECG features and recalibrates their contributions using real-time

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Project Webpage: <https://www.cse.psu.edu/~mkg31/projects/fusenseringBP>

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temperature context to specifically mitigate thermal drift. Efficient personalization via transfer learning requires only 5-10 normal-temperature calibration samples. Through rigorous evaluations involving total 60 participants across diverse laboratory-controlled temperatures (17 °C to 40 °C skin temp) and challenging real-world ambulatory conditions (−10 °C to 24.4 °C ambient temp), we demonstrate *FuSenseRing*'s effectiveness. Our system maintains high accuracy across the full temperature range (Overall SBP/DBP ME±STD: $-0.09 \pm 7.67 / 0.42 \pm 5.74$ mmHg), satisfying the stringent accuracy criteria of the FDA-recognized AAMI/ISO 81060-2 standard. Furthermore, *FuSenseRing* significantly outperformed three popular commercial BP rings in the real-world study.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Applied computing** → **Health informatics**; • **Hardware** → **PCB design and layout**.

Additional Key Words and Phrases: wearable sensors, blood pressure monitoring, sensor fusion, open-source hardware

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1 INTRODUCTION

Cardiovascular diseases, such as heart disease and stroke, which are often aggravated by hypertension, constitute a primary global health burden, causing roughly 17.9 million deaths each year [61]. Hypertension, often termed a “silent killer” [57], typically lacks symptoms until severe stages, making regular blood pressure (BP) monitoring essential for early detection and effective management. Frequent, out-of-clinic BP measurements are particularly vital for identifying conditions like white coat hypertension (affecting 15-30% of hypertensive patients [29]) and masked hypertension (around 16.8% prevalence in the U.S. [59]), which are often missed during sporadic clinical visits [19]. The growing prevalence of hypertension underscores the urgent need for accessible and reliable tools for frequent BP monitoring in daily life.

While cuff-based sphygmomanometers remain the clinical gold standard for accuracy, their bulkiness, operational requirements, and potential discomfort render them impractical for regular use. This limitation has spurred the development of wearable alternatives, including wristbands [4], smartwatches [68, 72], and even ear-based monitors [14]. Among these, the smart ring is a particularly promising form factor due to its comfort and the high-quality physiological signals available at the finger. Yet, this promise remains largely unfulfilled. Our preliminary analysis reveals that leading commercial rings, like the CIRCUL Plus [3] and PulseRive [7], consistently fail to meet clinical-grade accuracy. They exhibit significant instability and errors that exceed FDA-recognized AAMI standards in real-world conditions (see Figs. 11a and 11b) [71].

This accuracy gap stems from three fundamental challenges unique to the finger-based form factor:

- **System Integration:** Creating an open-source multi-sensor ring that can capture signals such as PPG, ECG, and temperature while remaining comfortable and power-efficient presents a significant integration challenge.
- **Contact Pressure Variability:** Unlike the arm or wrist, the finger is highly susceptible to variations in sensor-skin contact pressure. Because fingers have minimal underlying tissue to buffer physiological changes (e.g., hydration levels), subtle shifts in diameter translate directly into significant pressure fluctuations against a rigid ring. This can distort PPG waveform morphology and undermine BP estimation reliability [17].
- **Skin Temperature Fluctuations:** The finger's temperature can change dramatically (>15-20°C). As extremities, fingers have a large surface area for their size, making them key locations for the body to regulate its temperature [18]. In response to environmental or internal changes, the body actively adjusts

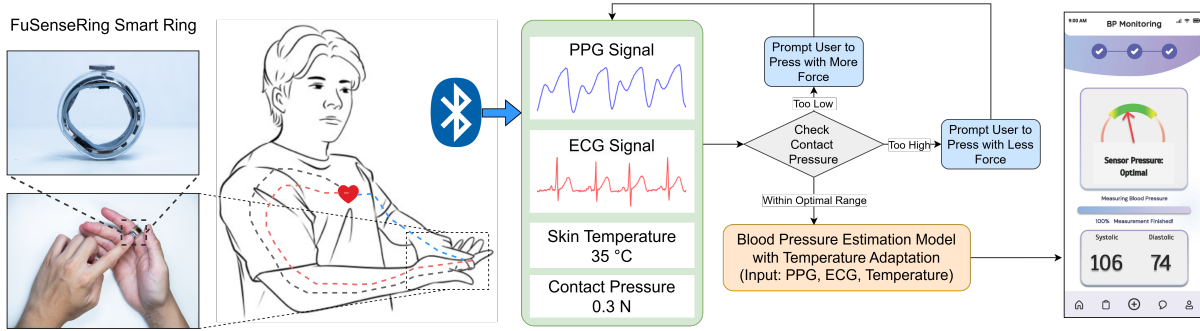


Fig. 1. *FuSenseRing* System Overview: To initiate a BP reading, the user wears the ring and lightly presses the designated sensor area with an index finger from the opposite hand, ensuring optimal PPG sensor contact and completing the ECG circuit. The companion UI provides real-time visual feedback based on the integrated force sensor, guiding the user to achieve ideal contact pressure, thereby minimizing variability due to finger size or application force. The system processes the multimodal data (PPG, ECG, temperature, pressure) using our temperature-adaptive model, displaying the final BP result.

blood flow to the fingers, causing the blood vessels to significantly narrow (vasoconstriction) or widen (vasodilation) [18, 45]. This drastically alters the volume of blood being measured by the PPG sensor. This sensitivity to temperature is a known and significant source of measurement error, posing a major, often-overlooked threat to the consistency and accuracy of cuffless BP estimation [43, 51].

To overcome these challenges, we present *FuSenseRing*, an open-source smart ring platform for robust and reliable BP monitoring. As illustrated in Fig. 1, our system leverages a unique hardware and software co-design to address each challenge with the following opportunities:

- **For System Integration:** We leverage advancements in System-on-Chip (SoC) design and double-sided flexible printed circuit board (FPCB) technology. This allows us to integrate a full suite of sensors (PPG, ECG, temperature, pressure), a microcontroller, and a wireless module into a compact, comfortable, and open-source ring form factor.
- **For Contact Pressure Variability:** We integrate a force-sensitive sensor that measures the contact pressure between the device and the finger. This hardware is coupled with a companion UI that provides real-time visual feedback, guiding the user to apply optimal and repeatable pressure, thereby ensuring high-quality, consistent signal acquisition.
- **For Skin Temperature Fluctuations:** We are the first, to our knowledge, to explicitly mitigate temperature-induced errors in BP estimation. We achieve this by incorporating a temperature sensor and developing a novel Temperature-Adaptive Attention (TAA) mechanism within our multimodal deep learning model. This TAA component uses real-time finger temperature to dynamically recalibrate the fusion of PPG and ECG signals, compensating for thermal artifacts.

Through this integrated approach, *FuSenseRing* demonstrates high reliability in real-world conditions, including diverse environments and wide skin temperature variations (skin temperature: 17°C to 40°C). As detailed in Section 6, our system achieves a mean error of -0.09 mmHg (SBP) and 0.42 mmHg (DBP) with standard deviations of 7.67 mmHg (SBP) and 5.74 mmHg (DBP), satisfying the FDA-recognized AAMI standard across varied participants and conditions.

Table 1. Comparison of Related Blood Pressure Monitoring Systems.

System	Sensors	Device Placement	Comfort Level	Device Weight	Open source	Adaptive Sensor Contact Pressure	Temperature Variation Adaptation	SBP ME $\pm$ STD (Normal Temp)	DBP ME $\pm$ STD (Normal Temp)	SBP ME $\pm$ STD (Varying Temp)	DBP ME $\pm$ STD (Varying Temp)
Seismo [78]	Camera & Accelerometer	Phone	High	Medium	✗	✓	✗	N/A	1.30 ± 6.90	✗	✗
eBP [14]	PPG	Ear	Medium	Moderate	✗	✓	✗	1.8 ± 7.2	-3.1 ± 7.9	✗	✗
CrispBP [15]	PPG	Wrist	Medium	Moderate	✗	✓	✗	1.67 ± 7.31	0.86 ± 6.55	✗	✗
Senbiosys Ring [33]	PPG	Finger	High	Low	✗	✗	✗	-0.28 ± 7.54	-1.30 ± 7.18	✗	✗
Zhou et al [27]	Ultrasonic	Wrist	High	Low	✗	✗	✗	-2.06 ± 4.16	1.56 ± 3.58	✗	✗
Kaan Sel [69]	Bioimpedance	Finger	High	Low	✗	✗	✗	0.11 ± 5.25	0.11 ± 3.87	✗	✗
FuSenseRing (Ours)	PPG & ECG & Temp	Finger	High	Low	✓	✓	✓	-0.54 ± 6.61	-0.83 ± 6.07	-0.09 ± 7.67	0.42 ± 5.74

In summary, *FuSenseRing* makes the following contributions:

- The introduction and open-source release of *FuSenseRing*, the first complete smart ring platform designed explicitly for robust ambulatory cardiovascular health monitoring research. It features fully integrated multimodal sensors (PPG, ECG, Temperature, Contact Force) and includes hardware designs (custom 2-layer FPCB), and firmware, enabling transparent validation, reproducibility, and community innovation in wearable cardiovascular health.
- The design and validation of a novel multimodal deep learning framework featuring a Temperature-Adaptive Attention (TAA) mechanism. This TAA component leverages real-time finger temperature for dynamic feature recalibration (PPG/ECG fusion), demonstrably reduces BP estimation error caused by thermal variation, enabling the system to achieve validated FDA-recognized AAMI-compliant accuracy across a wide temperature range (17 °C to 40 °C) with highly data-efficient personalization (5-10 samples).
- The identification and first mitigation (to our knowledge) of finger temperature-induced errors as a critical factor in wearable, cuffless BP monitoring using integrated temperature sensing and adaptive algorithms.

2 RELATED WORK

Developing convenient and reliable methods for frequent, out-of-clinic blood pressure (BP) monitoring is an active area of research. Existing approaches predominantly fall into cuff-based and cuffless categories, each with distinct advantages and limitations relevant to achieving accurate ambulatory measurements. A summary comparison is provided in Table 1.

2.1 Cuff-based Blood Pressure Monitoring

Traditional auscultatory or oscillometric sphygmomanometers, while providing clinically accepted accuracy [76], rely on arterial occlusion via an inflatable cuff. This process can cause discomfort or even potential tissue injury with repeated use [30], making standard cuffs unsuitable for the frequent monitoring needed for effective hypertension management. Advanced clinical systems like the Finometer employ techniques such as the volume-clamp method for continuous beat-to-beat BP [38], but their size, cost, and complexity restrict them to laboratory or hospital settings. In contrast, *FuSenseRing* is compact and comparable to a ring, making it extremely convenient to carry and wear for extended periods. Efforts have been made to adapt cuff-based principles into more wearable form factors. For example, the eBP system utilized an inflatable balloon and PPG sensor within the ear canal [14]. While innovative in placement, such systems still require active pressure application, potentially causing user discomfort during prolonged or frequent use, hindering adherence. These approaches highlight the persistent challenge of balancing accuracy derived from occlusion/pressure principles with the user comfort and unobtrusiveness required for practical ambulatory monitoring. This motivates the exploration of truly cuffless methods.

2.2 Cuffless Blood Pressure Monitoring

Cuffless methods aim to estimate BP by analyzing physiological signals, typically photoplethysmography (PPG) and/or electrocardiography (ECG), without arterial occlusion. This approach offers significant potential for user comfort and enables the frequent monitoring necessary for effective hypertension management. These methods largely follow two main strategies: (i) extracting handcrafted physiological features and (ii) employing machine learning models to extract features directly from raw signals.

2.2.1 Feature-based Approaches. For methods that extract physiologically relevant features from sensor signals, the most common approach is to use pulse transit time (PTT) – the time taken for the pulse wave to travel between two arterial points (often measured between ECG R-peak and a characteristic PPG point) [31]. Commercial devices [68] and academic research [79] have explored PTT. However, PTT’s utility is fundamentally limited as its relationship with BP is confounded by numerous non-BP factors (e.g., arterial stiffness, heart rate, vascular resistance, sensor placement) [65]. Furthermore, the PTT-BP correlation exhibits significant inter-subject variability, where some individuals show extremely poor or even no correlation [50]. This inconsistency necessitates frequent, inconvenient user calibration and hinders the reliable achievement of clinical-grade accuracy across diverse populations. Other features, like Reflected Wave Transit Time (RWTT) used in CrispBP [15], show potential but introduce usability issues; CrispBP required users to maintain specific, potentially uncomfortable wristband tightness to ensure adequate signal quality.

In contrast, *FuSenseRing* directly addresses the critical issue of variable sensor contact pressure on the finger not through uncomfortable, constant tightness, but via our interactive TapBP mechanism. By integrating a force sensor and providing real-time UI feedback, *FuSenseRing* guides the user to achieve optimal contact pressure specifically during the brief measurement period, ensuring high-quality signal acquisition while maintaining high user comfort.

The second approach involves machine learning models that bypass manual feature extraction, using architectures like CNNs and RNNs to process raw signals. FewshotBP [28] employs a ResNet architecture to map PPG and ECG signals to BP values. Ring-based devices like the Senbiosys Ring [33] and bioimpedance-based systems [69] highlight the potential for improved comfort and usability over traditional sensor placements on the wrist or ear. However, existing ring-based systems often overlook challenges like temperature and finger size variations, which degrade signal quality and BP estimation accuracy. Our system integrates a temperature variation cancellation algorithm to address these issues, ensuring consistent and accurate BP readings across diverse environmental and physiological conditions.

2.2.2 Machine Learning-based Approaches. Recognizing the limitations and calibration burden of handcrafted features, recent research increasingly leverages machine learning (ML), especially deep learning (e.g., CNNs, RNNs), to learn complex mappings directly from physiological signals to BP values. This end-to-end approach holds promise for capturing more nuanced patterns. Examples include ResNet architectures processing PPG and ECG [28], and various ring-based prototypes exploring improved comfort and usability [33, 69].

However, a critical limitation persists in many existing ML-based systems, particularly those using finger-based PPG: the failure to adequately address real-world signal variability. Factors like finger temperature fluctuations (inducing >10 mmHg errors [39]) and contact pressure changes significantly distort PPG waveforms [17]. ML models trained primarily under optimal conditions often learn spurious correlations and consequently fail to generalize reliably when these variations occur during ambulatory use, undermining their practical accuracy.

FuSenseRing’s framework is explicitly designed to overcome this limitation. Our Temperature-Adaptive Attention (TAA) mechanism leverages the integrated real-time temperature sensor input to dynamically re-weight and fuse features from the multimodal inputs (PPG, ECG), actively mitigating the influence of thermal drift (detailed in Sec. 5). This adaptive capability, combined with the pressure consistency ensured by TapBP (detailed in Sec. 4.3), allows *FuSenseRing* to maintain robust performance across diverse environmental and physiological conditions where previous methods falter.

2.3 SmartRing Platforms Sensing

In recent years, we observe an increasing trend of prompting smart rings in daily life due to their compact design and high social acceptance [24, 67]. Commercial platforms like OuraRing [9] and Samsung Galaxy Ring [67] have gained favorable reviews online [22, 36]. A recent comprehensive in-situ usability study using a mock ring demonstrated strong user acceptance for wearing rings continuously [12]. The study highlighted potential of smart ring for various applications, including activity tracking, user interfaces, mobile payments, and healthcare, showing that users are comfortable with rings as wearable technology in everyday contexts. Along with this trend, many researchers have integrated smart rings and advanced sensors for human activity tracking, health and fitness tracking, such as heart rate monitoring and sleep analysis [23, 24, 26, 53].

Various ring-based platforms have been developed, incorporating different modes of sensing such as IMU, temperature, pressure, and ECG, as highlighted in a recent survey [77]. In contrast to prior works, we present the first open-source blood pressure smart ring platform that integrates multiple sensors, including ECG, PPG, force, and temperature sensors, while maintaining a total weight of approximately 4.6g depending on finger size, comparable to the wedding ring [34], which weighs between 3g to 5g.

3 BACKGROUND

3.1 Basic of Physiological Signals (PPG & ECG)

PPG and ECG are widely used for non-invasive physiological monitoring, enabling measurements of heart rate, blood pressure, and oxygen saturation.

- PPG quantifies changes in cutaneous blood volume by analyzing the optical properties of blood flow. Light emitted by an LED is absorbed or reflected according to instantaneous blood concentration and flow, as described by the Beer–Lambert law [13, 16]. The resulting waveform comprises an AC component, which reflects the pulsatile volume changes during each cardiac cycle, and a DC component, which represents steady absorption by static tissue constituents [47, 58].

- ECG captures the heart’s electrical activity via electrodes placed on the skin, producing characteristic waveforms: the P wave (atrial depolarization), the QRS complex (ventricular contraction), and the T wave (ventricular repolarization) [80]. Modern wearables such as the Apple Watch and Samsung Watch leverage the body’s conductivity to obtain a single-lead ECG by forming a circuit between a wrist-mounted sensor and a fingertip electrode.

Together, PPG and ECG provide complementary information—PPG reflecting vascular dynamics and ECG revealing cardiac electrical events. These dual modalities form the basis of our blood pressure monitoring framework.

3.2 Physiological Signals Under Temperature Effects:

A critical challenge in achieving reliable BP estimation from finger-worn devices is the pronounced sensitivity of photoplethysmography (PPG) signals to skin temperature variations [44, 62]. As finger temperature decreases (e.g., due to cold environments or physiological changes in peripheral circulation), vasoconstriction reduces local blood flow. This significantly dampens the pulsatile (AC) component of the PPG signal relative to its static (DC) component, thereby lowering the crucial AC/DC ratio and altering underlying tissue optical properties (such as the reduced scattering coefficient, μ'_s) [44, 62]. Conversely, warmer temperatures tend to improve the AC/DC ratio via vasodilation. These temperature-induced modulations of PPG waveform morphology, illustrated conceptually in Fig. 2c, can introduce substantial errors into derived parameters, severely impacting the accuracy of BP estimation [39]. [83]

In contrast, the electrical nature of electrocardiogram (ECG) signals renders them inherently more robust to typical ambient and physiological temperature fluctuations. ECG signal’s robustness against temperature

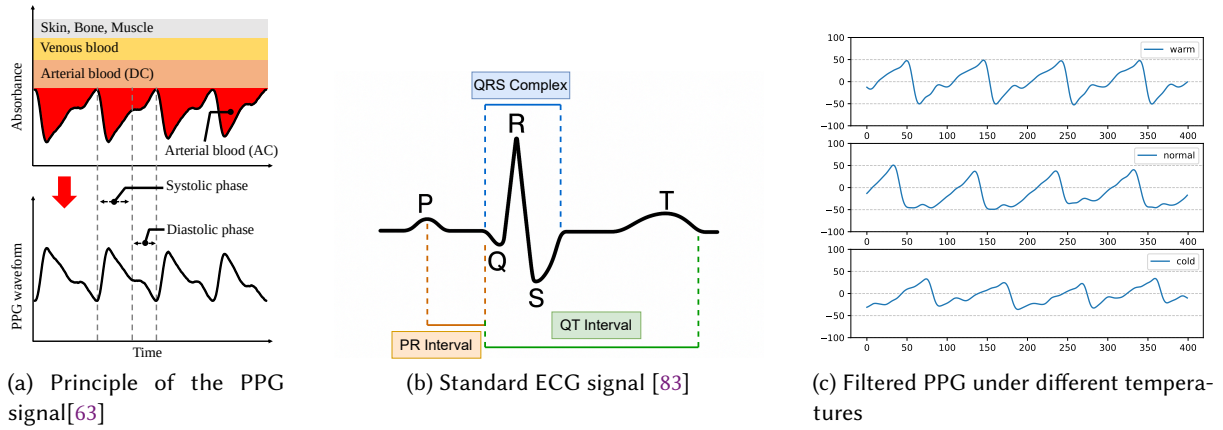


Fig. 2. Illustration of PPG and ECG signals, and the effect of temperature on PPG. (a) PPG principle. (b) Standard ECG waveform. (c) Filtered PPG signal from one subject's finger under various temperature levels.

changes strongly motivates our multimodal fusion strategy. By integrating the relatively stable ECG signal with the temperature-sensitive PPG signal, and crucially, by explicitly incorporating real-time finger temperature measurements from our integrated sensor, our framework aims to actively compensate for these thermal drifts. The specific mechanism, detailed in Section 5, leverages this multimodal input to enhance BP estimation robustness across diverse thermal conditions.

3.3 Blood Pressure Estimation with Physiological Signals

As PPG and ECG signals do not have a direct correlation with BP readings, research efforts over the past decades have focused on developing equations/models to establish a relationship between these physiological signals and blood pressure.

• **Traditional Methods:** The Moens–Korteweg equation relates arterial mechanics to pulse wave velocity (PWV) and pulse transit time (PTT) [74] in (1):

$$PWV = \frac{D}{PTT} = \sqrt{\frac{E_{inc} \cdot h}{2r\rho}} \quad (1), \quad BP = a \cdot \frac{1}{PTT} + b \quad (2)$$

where E_{inc} is the arterial elastic modulus, h artery wall thickness, r artery radius, ρ blood density, and D travel distance. Blood pressure is estimated using PTT, measured as the delay between the ECG R-wave and PPG systolic peak. While effective, PTT-based methods require calibration and are sensitive to individual variability, limiting real-world accuracy.

• **Machine Learning & Deep Learning Methods:** Machine learning techniques have enhanced BP estimation by addressing the limitations of traditional methods, leveraging features like pulse arrival time (PAT), augmentation index [42], and PPG morphological features [49]. Common models include linear regression, random forests, and support vector machines (SVMs).

Deep learning further enhances performance by automatically extracting features and modeling nonlinear dependencies. Su et al. [25] applied recurrent neural networks (RNNs) and bidirectional long short-term memory (BiLSTM) to capture temporal relationships, while Convolutional neural networks (CNNs) have been effective in learning spatial and temporal patterns from raw physiological signals [70]. These approaches demonstrate the potential for improved BP estimation accuracy.

4 THE *FuSenseRing* OPEN-SOURCE PLATFORM

In this section, we describe the platform design of *FuSenseRing*. First, we elaborate on the choice of sensing modalities of *FuSenseRing*. Later, we discuss platform design, including hardware, mechanical design, software framework, and price breakdown in detail. The open-source hardware design files, firmware, and example software for the *FuSenseRing* platform presented in this paper are publicly available. The main repository can be found on GitHub at: https://github.com/FuSenseRing/FuSenseRing_Beta.

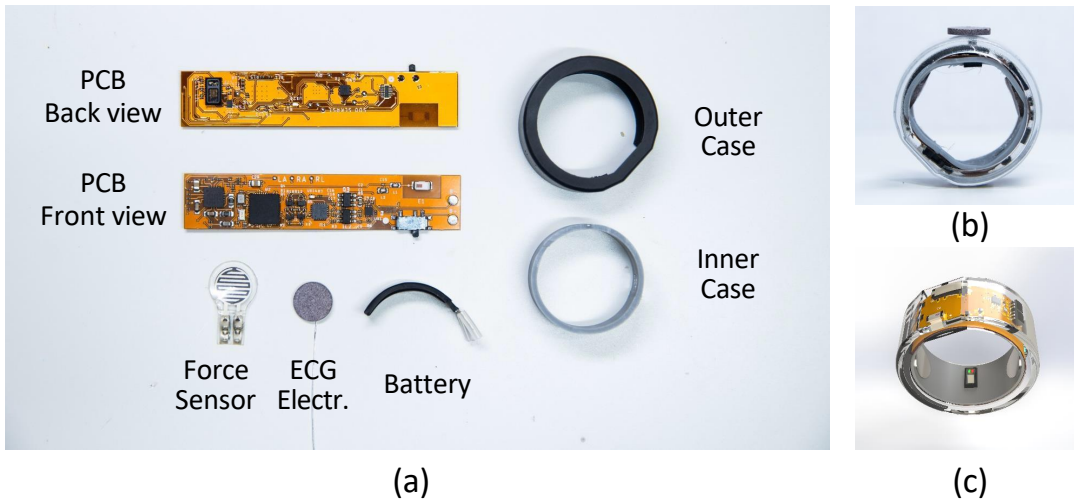


Fig. 3. (a) Disassembled components of the *FuSenseRing* prototype. (b) Final assembled prototype of *FuSenseRing* with electronics enclosed in a case (transparent resin shown for visibility). (c) Illustration of the 3D rendered assembled prototype.

4.1 Choice of Sensing Modalities:

The primary goal was to design a sensor device that is discreet, highly portable, low-cost, and capable of monitoring physiological parameters comfortably and conveniently for everyday use. To achieve this, we selected the following sensing units, whose integration is shown in Fig. 4. For a long time, ECG provides essential information on cardiac electrical function and has been a crucial input for many cuffless blood pressure estimation techniques [35, 40, 46]. PPG-based techniques are becoming increasingly popular due to their affordability, compact size, non-intrusive monitoring features, and user-friendly user experience. To enhance the robustness of *FuSenseRing* against varying environmental temperatures, we integrated a high-precision digital temperature sensor to monitor finger skin temperature. Additionally, a cost-effective force-sensitive resistor was included to measure the applied finger pressure during measurements, aiding signal quality. Therefore, *FuSenseRing* integrates a combination of these sensors (PPG, ECG, temperature, and force) to collect complementary physiological signals, aiming to enhance the accuracy and environmental robustness of cuffless blood pressure monitoring within a smart ring form factor.

4.2 Platform Design

• **Form Factor Design:** After selecting the appropriate sensing modalities for the *FuSenseRing* system, the next step was prototyping *FuSenseRing* within a ring form factor. Our goal was to develop a lightweight, comfortable, and compact smart ring that integrates all sensing units while ensuring the reliable collection of precise data

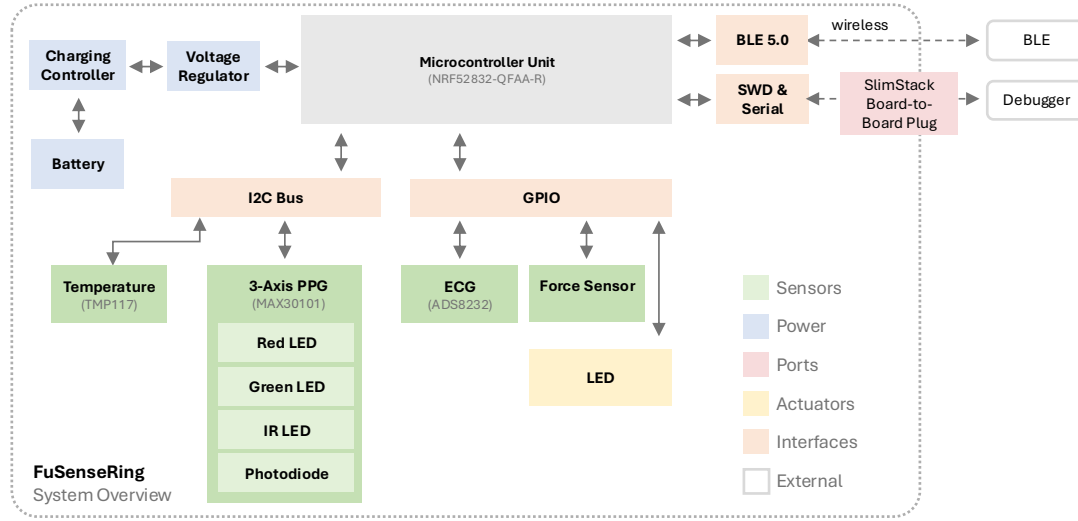


Fig. 4. Hardware architecture overview of *FuSenseRing*. The microcontroller unit is the central hub that communicates with sensors, actuators, and the display.

from these multiple sensors. Designing such a multi-sensor smart ring is highly challenging, requiring careful integration within a compact space while maintaining high system performance and user comfort. We addressed these challenges through the following design strategies: (i) We design the electronics using a 2-layer FPCB which is subsequently formed into the shape of a ring, as illustrated in Fig. 3 and Fig. 5d and c. (ii) We strategically arranged multiple sensors within a compact space while maintaining optimal signal quality, as depicted in Fig. 5b. (iii) We enclosed the hardware assembly within an outer case fabricated from clear resin material using Stereolithography (SLA) 3D printing technology. The inner case, in contact with the skin, is separately printed using Fused Deposition Modeling (FDM) with flexible TPU material for enhanced comfort. The overall form factor is depicted in Fig. 3. The final device weighs between 4.6–5.2g, depending on finger size, which is comparable to the commercially available Oura Ring (4–6g [9]).

• **Hardware and Power Circuitry:** Given the design goals discussed above, the main challenges included the following: (i) *FuSenseRing* needs to embed the microcontroller (MCU), multiple sensors, and a Bluetooth module within the limited space available in a ring form factor. (ii) Each sensor requires distinct sensing methods and placements, all of which must coexist within the ring’s limited space without interfering with one another. For example, PPG requires optical components (LEDs, photodetectors) positioned precisely for optimal light penetration to measure blood volume changes, while ECG relies on conductive electrodes requiring direct skin contact and careful placement relative to the heart’s electrical axis. To address these competing spatial and functional requirements, we meticulously designed the component layout on the FPCB to ensure proper sensor positioning, maintain signal integrity, and meet mechanical constraints. Various hardware components were carefully integrated onto a 2-layer FPCB, as shown in Fig. 5c and d. We have implemented the NRF52832 [5] MCU with the sensing components and wireless data transmission, drawing inspiration from prior work [24, 64]. The MCU features a 2.4 GHz RF transceiver compatible with BLE and is powered by an ARM Cortex-M4 32-bit processor with a 64 MHz clock speed. It supports multiple communication protocols, including Serial Peripheral Interface (SPI), Inter-Integrated Circuit (I2C), Analog-to-Digital Converter (ADC), and Universal Asynchronous Receiver-Transmitter (UART), among other interfaces. *FuSenseRing* incorporated the following sensing electronics: (i) **AD8232 [11]:** Integrated as a low-power analog front end (AFE) for single-lead ECG measurement. The analog

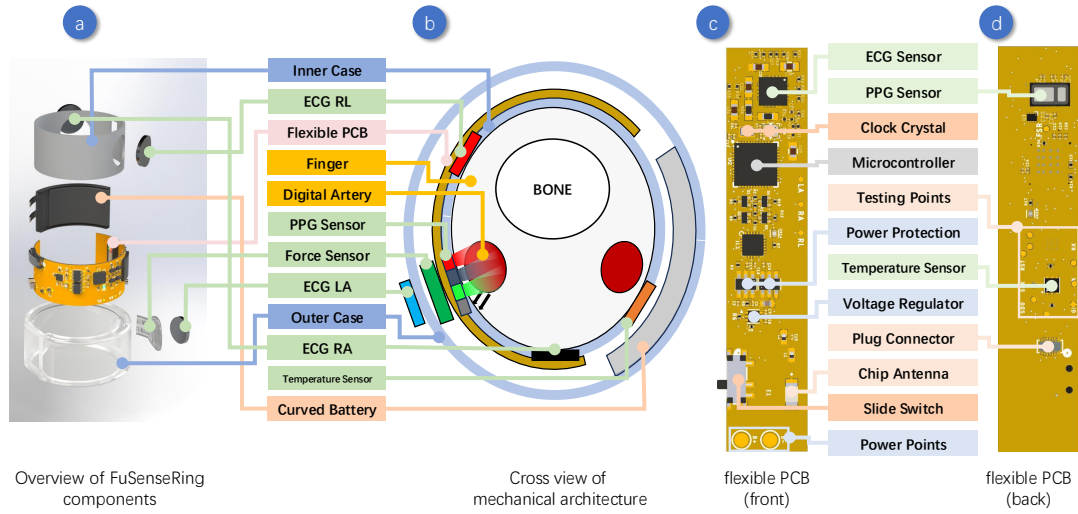


Fig. 5. (a) Explosion rendering of *FuSenseRing* depicting an overview of the individual components. (b) The mechanical structure of *FuSenseRing*, illustrating the position and arrangement of various sensors and the curved battery. (c) The top of the flexible PCB board contains the computing and sensing. (d) The bottom of the PCB board contains the PPG, temperature sensor, and SWD programming interface.

ECG signal is acquired by the MCU's ADC. (ii) **MAX30101** [1]: Implemented as the PPG sensor, providing 3 channels of PPG data (Red, Green, IR LEDs). It interfaces with the MCU via the I2C protocol. (iii) **TMP117** [2]: Implemented as the temperature sensor, providing high-precision digital temperature readings ($\pm 0.1^\circ\text{C}$ accuracy). It interfaces with the MCU via the I2C protocol. (iv) **Force-Sensitive Resistor (FSR)** [82]: A cost-effective FSR is implemented for detecting the contact pressure applied by the user's finger during measurement. The resistance change is measured via the MCU's ADC.

We used a 3.7 V, 15 mAh rechargeable LiPo ring-shaped battery to power the entire PCB. Under continuous data streaming, the system consumes approximately 14.5 mA. To maximize battery life, the power-hungry sensors remain inactive between measurements, placing the ring in a low-power idle state. In this mode, only the MCU remains active to detect user input, dropping the average current to approximately $500\ \mu\text{A}$. Based on usage statistics collected from the daily operation of *FuSenseRing* and clinical guidelines [81], daily consumption is approximately 0.08–0.16 mAh. This low-power design enables a battery life of up to one week under typical usage.

• **Mechanical Design and Sensor Integration:** Fig. 5b depicts the mechanical design of the smart ring, showcasing how different sensors are integrated within its structure. To ensure optimal sensing of blood flow, the PPG sensor is positioned on the inner surface of the ring, intended to align near the digital artery. Two ECG electrodes, Right Leg (RL) and Right Arm (RA), are integrated on the ring's inner surface for direct skin contact with the primary finger. The third electrode, Left Arm (LA), is attached on the ring's external surface. Inspired by Einthoven's triangle principles [8], this configuration requires the user to touch the external LA electrode with a finger from the opposite hand, completing the circuit with the inner RA/RL electrodes for ECG signal acquisition (as depicted in Fig. 1). Because PPG readings are highly sensitive to contact pressure, maintaining an optimal force improves the accuracy and consistency of the measurement. The force sensor is strategically placed between the LA electrode and the PPG sensor to measure the pressure applied by the user's other finger. This arrangement ensures that the pressure measurement coincides with the action that completes the ECG circuit.

Table 2. Manufacturing Cost Breakdown. Prices are presented for both retail (5-unit batches) and wholesale (500-unit batches). “Others (RCL)” collectively refers to other essential passive electronic components such as resistors, capacitors, and inductors.

Electronic Component	Unit Price (Retail) [\$]	Unit Price (Wholesale) [\$]
MCU (NRF52832)	3.47	3.47
ECG Sensor (AD8232)	6.03	2.34
PPG Sensor (MAX30101)	11.90	7.44
TMP Sensor (TMP117)	2.15	1.44
Force Sensor	4.20	4.20
Chip Antenna	0.51	0.25
Voltage Regulator ICs	0.50	0.37
Battery Protection ICs	0.47	0.14
Others (RCL)	9.45	3.28
Case (Filament)	0.01	0.01
Arc Battery	8.00	7.50
FPCB Manufacturing	48.21	2.48
Total	94.90	32.92

(contacting the LA electrode). The measured force readings are visualized in real-time on the companion mobile application (Fig. 1 UI), providing feedback that enables the user to interactively adjust their finger pressure to the optimal range, thereby enhancing PPG signal quality for the measurement.

- **Software Framework:** The *FuSenseRing* companion application allows interaction with the platform. The *FuSenseRing* phone application is created for both iOS and Android platforms utilizing the React Native framework [55], which facilitates the development of cross-platform mobile APPs on iOS and Android systems. The *FuSenseRing* interfaces with the APP through BLE, employing a tailored GATT profile at a 100 Hz sampling rate. More details on data processing are discussed in Sec. 5.

- **Price Breakdown:** Table 2 provides a summary of both retail and wholesale unit prices for key hardware components and the PCB manufacturing service. The retail prices are based on purchases in batches of 5 units, whereas the wholesale prices reflect bulk purchasing in batches of 500 units. All firmware and software developed for *FuSenseRing* will be provided free of charge. The 3D-printed case of *FuSenseRing* is fabricated in-house using lab equipment and is also made available at no additional cost. The 2-layer flexible PCBs were manufactured by JLCPCB [41]. The manufacturing cost is approximately \$48.21 USD per board for a batch of 5 units, and significantly decreases to around \$2.48 USD per board when ordered in a batch of 500 units. The total manufacturing cost for one *FuSenseRing* platform, including PCB fabrication and all hardware components, is approximately \$94.90 at retail and around \$28.72 at wholesale, making it more cost-effective than existing market alternatives such as the Oura Ring[9].

4.3 Interactive Contact Pressure Guidance for Optimal PPG Sensing

A fundamental challenge in ring-based PPG monitoring is ensuring consistent, optimal sensor-skin contact pressure, which significantly impacts signal quality [17]. Unlike cuff-based systems (e.g., Finometer [38]) that use bulky mechanisms or wristbands requiring potentially uncomfortable tightness (e.g., CrispBP [15]), *FuSenseRing* employs a compact, interactive solution to manage contact pressure effectively during each measurement.

We developed an interactive mechanism, termed *TapBP*, that integrates a dedicated force sensor with real-time software feedback. As illustrated in Fig. 1, the user initiates a measurement by gently pressing the ring’s sensor area with an index finger from the opposite hand. This single action achieves three goals simultaneously: (i) it applies controlled pressure to the underlying PPG sensor, (ii) it completes the electrical circuit necessary for ECG

signal acquisition using electrodes on the ring's inner and outer surfaces, and (iii) it achieves this within the minimal form factor of the ring without requiring additional bulky components.

The force-sensitive resistor (FSR) located directly beneath the MAX30101 PPG sensor continuously measures the applied contact pressure. This data is transmitted via Bluetooth to the companion mobile application, which provides intuitive, real-time visual feedback to the user, as shown in Fig. 1". The interface guides the user to adjust their applied force to fall within the optimal contact force range of 0.2 N to 0.4 N. This range was identified by Teng et al. [73] as promoting high-quality PPG signal acquisition across most individuals. This force is applied over the surface area of the MAX30101 PPG sensor, which measures approximately $5.5 \text{ mm} \times 3.3 \text{ mm} \approx 18.15 \text{ mm}^2$. This corresponds to a target contact pressure range ($P = F/A$) of approximately 11.0 kPa to 22.0 kPa. Since our FSR system is calibrated to provide readings corresponding to apparent mass in grams (m_{grams}), we converted the target force range (F_{Newtons}) using the standard relationship between force, mass, and gravitational acceleration ($g \approx 9.81 \text{ m/s}^2$):

$$m_{\text{grams}} = \frac{F_{\text{Newtons}}}{g} \times 1000$$

Applying this conversion (Eq. 4.3), the target force range of 0.2 N to 0.4 N translates to an FSR reading of approximately 20 g to 41 g. The real-time visual feedback then guides the user to maintain an applied pressure yielding an FSR reading within this 20 g to 41 g target window, ensuring the optimal contact pressure (11.0-22.0 kPa) is achieved for the MAX30101 sensor beneath it.

Once the application confirms that the user's applied pressure is stable and within this target range, it provides a notification (e.g., visual cue or vibration) and automatically initiates a 10-second data recording period, capturing synchronized PPG, ECG, and skin temperature signals. Following data acquisition, these signals are processed by the BP estimation model (detailed in Section 5) to generate and display the final SBP and DBP readings in the application.

This interactive *TapBP* mechanism ensures reliable signal quality at the specific time of measurement by actively involving the user with clear guidance, thereby accommodating variations in finger size and user habits without resorting to uncomfortable constant pressure. It represents an efficient hardware-software co-design solution optimized for the constraints and opportunities of the smart ring form factor.

5 ATTENTION-GUIDED MULTIMODAL FUSION FOR CUFFLESS BLOOD PRESSURE ESTIMATION

This section details the machine learning framework developed for *FuSenseRing* to estimate blood pressure. Our approach includes specialized signal preprocessing pipelines and a novel multi-modal deep learning model incorporating a temperature-adaptive attention mechanism designed to mitigate environmental thermal effects.

5.1 Noise-resilient Preprocessing for Finger-based Physiological Sensing

To handle data from diverse sources (public datasets for base model pre-training, *FuSenseRing* data for fine-tuning and evaluation), we developed tailored preprocessing pipelines designed to standardize data formats and enhance signal quality.

For the base BP model training phase, we curated data from VitalDB and MIMIC-III [6, 48]. To ensure consistency, we segmented each patient's record into 10-second intervals, discarding sections with missing or aberrant PPG, ECG, or ABP signals. We adopt a hybrid filtering approach: the PPG signal is processed with a 4th-order Butterworth bandpass filter (0.5–8 Hz) and the ECG signal with a 6th-order Butterworth filter (2–30 Hz). The magnitude response of an n th-order Butterworth bandpass filter can be expressed as:

$$|H(j\omega)| = \frac{1}{\sqrt{1 + \left(\frac{\omega^2 - \omega_0^2}{\omega\Delta\omega}\right)^{2n}}}$$

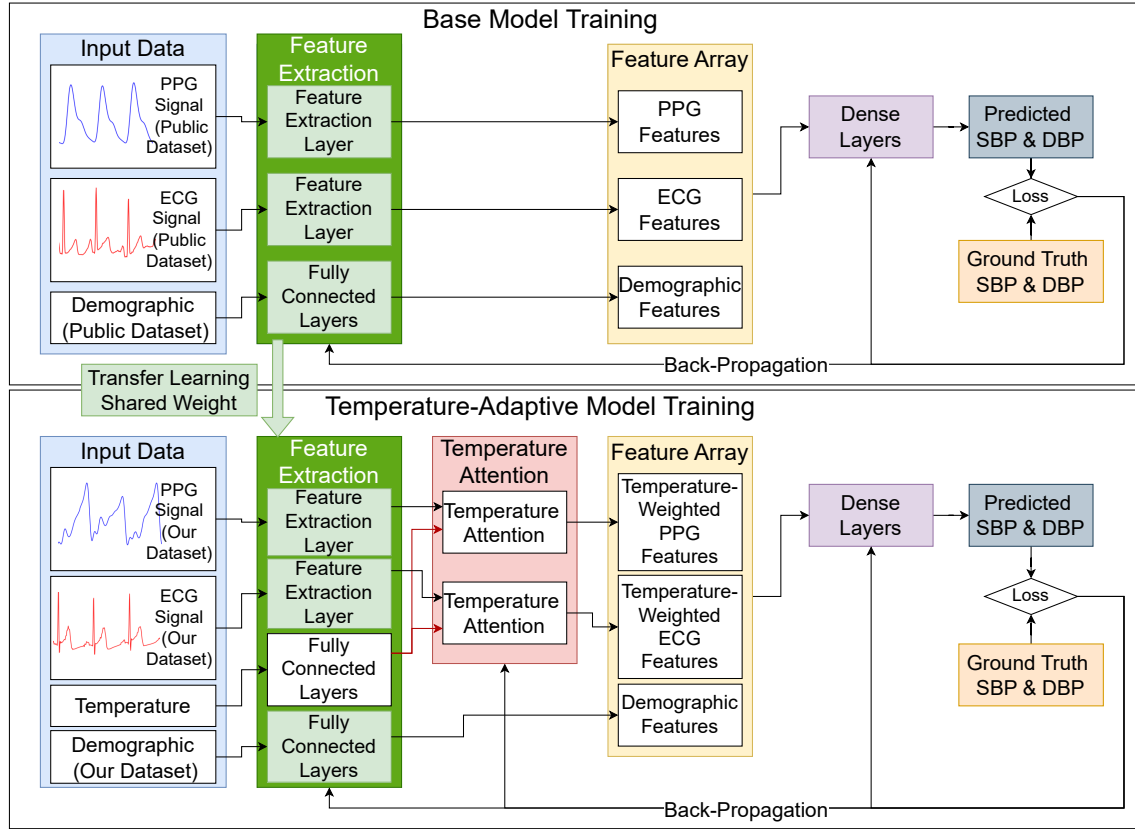


Fig. 6. Machine Learning Overview.

where ω_0 is the center frequency, $\Delta\omega$ is the bandwidth, and n is the filter order. Blood pressure (SBP and DBP) is extracted as the average of the peaks and troughs within each segment. This specialized filtering scheme not only removes noise but also preserves critical physiological patterns, setting the stage for accurate model training. Following filtering, we apply a Quantile-Based Sliding Window Normalization to scale the input data to a range of 0 to 1. This normalization enhances model robustness by mitigating numerical instability and accelerating convergence.

For our in-house data, we preserved the integrity of the public dataset pipeline by down-sampling from 160 Hz to 125 Hz, ensuring compatibility. However, recognizing the unique challenges of acquiring ECG data from the finger—where noise levels are inherently higher—prompted us to augment the standard Butterworth filter with a wavelet transform module. This hybrid technique effectively suppresses noise while capturing subtle signal variations, leading to cleaner inputs and demonstrable improvements in model performance. As with the public datasets, the filtered signals are then normalized using the sliding window method, ensuring consistency across all data sources.

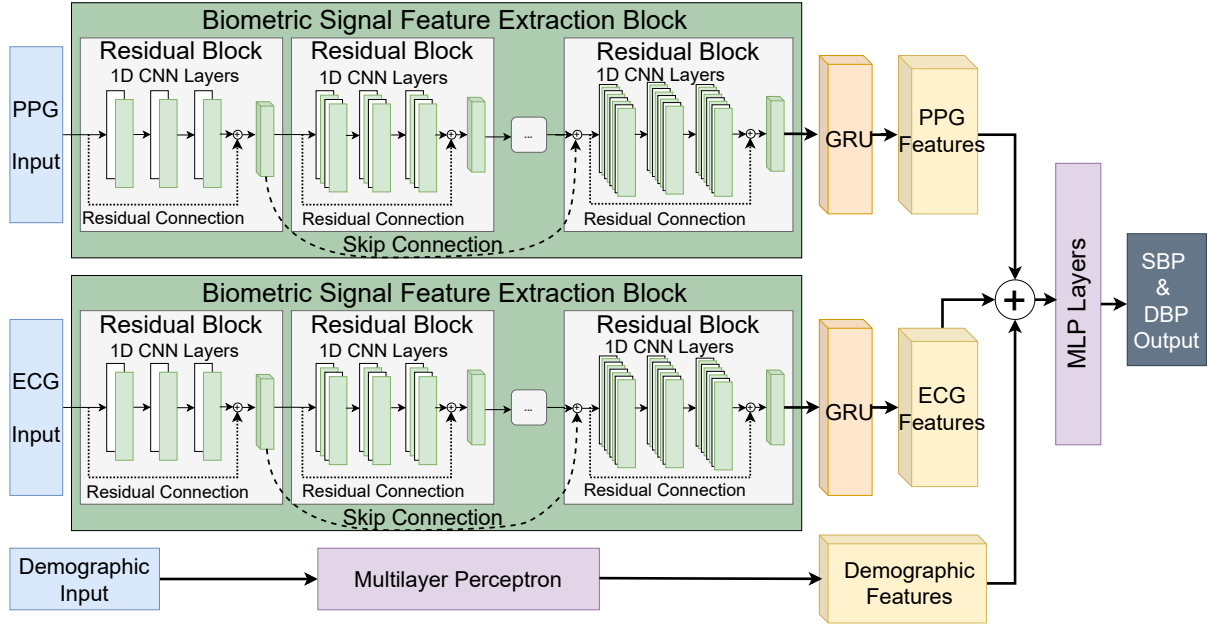


Fig. 7. Foundational Blood Pressure Estimation Model.

5.2 The Temperature-adaptive BP Estimation Architecture

Accurate Blood Pressure (BP) estimation from finger-worn sensors presents unique machine learning challenges due to multimodal time-series data inherently affected by significant variations. These include environmental factors like skin temperature shifts encountered across diverse settings (e.g., AC-controlled rooms vs. locations with seasonal temperature changes), and physiological factors contributing to inter-individual variability (linked to BMI, Age, etc.). Standard deep learning models often prove inadequate, lacking the robustness and specificity needed for reliable performance. Our framework (Fig. 6), therefore, employs a specialized deep network architecture featuring a novel adaptive mechanism, designed explicitly to ensure reliable BP estimation resilient to thermal fluctuations while generalizing across a diverse user population.

5.2.1 Foundational Model: Learning Generalized BP Features. The foundation of our framework is a multi-modal deep network (Fig. 7) pre-trained with public datasets to extract generalized BP-relevant features from PPG and ECG signals. Recognizing that blood pressure is a complex physiological parameter influenced by cardiovascular dynamics reflected across multiple scales within these waveforms, we designed an architecture capable of capturing both fine-grained morphology and broader temporal patterns.

Custom Temporal Residual Block for Hierarchical Feature Extraction: Accurate BP estimation requires understanding intricate waveform characteristics. Standard CNNs can struggle to learn these deep hierarchical features from physiological signals without encountering training difficulties like vanishing gradients. To address this, we employ custom *Temporal Residual Blocks*. Inspired by ResNet [37] and prior work [28], the core residual connection $H(x) = F(x) + x$ explicitly facilitates gradient flow, enabling the stable training of deeper networks needed to capture complex dependencies. Our block design specifically incorporates depthwise 1D convolution ($k = 7$) for parameter-efficient extraction of local temporal patterns, combined with point-wise MLPs (via dimension permutation and Linear layers) for effective feature transformation and channel interaction. This

structure, summarized as:

$$y_{out} = \text{Pool}(\text{ReLU}(\text{BN}(\text{MLP}_{pointwise}(\text{ReLU}(\text{BN}(\text{DWConv}(x)))))) + \text{BN}(\text{Conv}_{1 \times 1}(x)))$$

is tailored to efficiently process 1D physiological sequences, extracting increasingly abstract features related to BP correlates at each stage.

U-Net Skip Connections for Morphological Fidelity: While deep features capture abstract relationships, critical BP information resides in the precise morphology of PPG and ECG waveforms—such as the timing and amplitude of the dicrotic notch, systolic peak characteristics, and specific ECG intervals, which are direct correlates of vascular tone, stiffness, and cardiac function. Standard deep architectures often progressively dilute these fine-grained details. To counteract this information loss, we integrate U-Net style skip connections [66]. Specifically, by concatenating intermediate features from the early block with the deeper features from the final block, we explicitly re-inject crucial morphological details into the later stages of processing. This ensures the network leverages both high-level abstract features and low-level waveform fidelity for accurate BP regression, a critical design choice differentiating our approach from models that lose such detail.

Temporal Cardiovascular Dynamics Modeling: Blood pressure is not solely determined by the morphology of individual beats but also by their temporal evolution and beat-to-beat variability within a measurement window. While the CNN layers excel at extracting spatial (morphological) features within beats, we employ Gated Recurrent Units (GRUs) to explicitly model these temporal dynamics across the 10-second sequence represented by y_{cat} . GRUs, governed by the hidden state update $h_t = f_{GRU}(h_{t-1}, y_{cat,t})$, use gating mechanisms (z_t, r_t) to adaptively learn long-range dependencies and sequential patterns indicative of the underlying cardiovascular state. We selected GRUs over LSTMs for their comparable modeling power in capturing temporal patterns relevant to BP variability, but with greater computational efficiency and fewer parameters, making them well-suited for potentially resource-aware mobile systems. Average pooling over the GRU output sequence yields final embeddings (F_{PPG}, F_{ECG}).

Feature Fusion and Prediction: Our model creates a holistic representation by synergistically fusing the learned physiological embeddings (F_{PPG}, F_{ECG}) with contextual user information ($Demo_{emb}$, a embedding of age, gender, BMI via an MLP). This fusion, $F_{combined} = \text{Concat}(F_{PPG}, F_{ECG}, Demo_{emb})$ (dim 528), allows the model to account for known demographic influences on cardiovascular function, feeding into the final MLP prediction head.

Training and Personalization Strategy: Pre-training on large, diverse public datasets (MIMIC-III, VitalDB [6, 48]) enables the foundational model to learn robust and generalizable representations of cardiovascular signals, capturing common physiological patterns. However, achieving the highest accuracy and clinical reliability necessitates personalization, as individual users exhibit unique physiological characteristics (e.g., variations in arterial stiffness, specific waveform morphology, differing responses to stimuli) that influence BP dynamics. Directly training a complex deep learning model from scratch for each individual would require a prohibitively large amount of personal data. To overcome this, we employ a highly data-efficient pre-training and fine-tuning strategy. Personalization is achieved via parameter-efficient fine-tuning, adapting the generalized knowledge of the pre-trained model to individuals' characteristics. Specifically, only a subset of layers (by default, the final prediction MLP and the last Residual Blocks within both the PPG and ECG feature extraction branches) are made trainable and updated using a small amount of user-specific calibration data collected via the *FuSenseRing* device. Our empirical evaluations (detailed subsequently in Sec. 6.2, Figs. 17-18) rigorously determined the optimal trade-off between calibration effort and performance. We found that fine-tuning on just 5 to 10 calibration samples (10-second recordings) per user is sufficient to achieve personalized accuracy that satisfies the stringent FDA-approved AAMI standard across diverse conditions. This minimal data requirement represents a crucial "sweet spot," maximizing personalization benefits while minimizing the data collection burden on the user, thereby significantly enhancing the practical deployability of *FuSenseRing*.

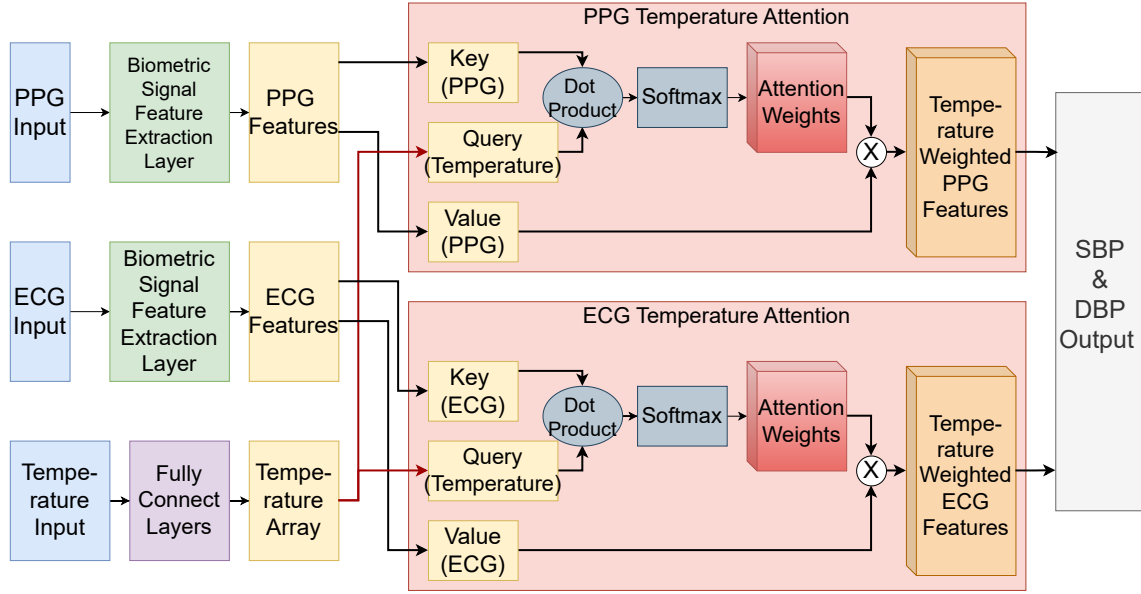


Fig. 8. Temperature Adaptation Attention.

5.2.2 Attention-guided Feature Re-calibration Under Thermal Stress. A critical barrier hindering reliable cuffless BP monitoring, particularly using convenient finger-based PPG sensors, is the significant signal distortion induced by inevitable temperature fluctuations during daily life (e.g., moving between indoors and outdoors, changes in peripheral circulation). Vasoconstriction at lower temperatures, for example, drastically alters PPG morphology [39, 44]. Existing models often fail to account for this dynamic, real-world variability, leading to unreliable predictions. Our key algorithmic innovation directly addresses this challenge: we introduce a Temperature-Adaptive Attention (TAA) mechanism (Fig. 8) that empowers the model to dynamically interpret physiological signals within their real-time thermal context.

Dynamic Feature Recalibration via Attention: The PPG and ECG feature embeddings ($F'_{PPG/ECG}$) serve as the attention keys (K) and values (V). The TAA mechanism computes attention weights $\alpha = \text{softmax}(QK^T / \sqrt{d_k})$ based on the learned compatibility between the temperature context (Q) and the physiological features (K). These weights are then used to compute context vectors $C_{PPG/ECG} = \alpha \cdot V$. This implements a powerful form of dynamic feature recalibration: the model learns, through training, how temperature typically affects PPG vs. ECG reliability. When presented with a specific temperature reading at inference time, it can generate weights that appropriately suppress features likely corrupted by that thermal condition (e.g., down-weighting temperature-sensitive PPG features during predicted vasoconstriction) while preserving or amplifying features deemed robust against thermal changes (e.g., ECG). This adaptive re-weighting based on the temperature query is crucial for maintaining accuracy across diverse real-world thermal environments.

Robust Prediction Through Conditioned Fusion: Applying attention independently to PPG and ECG allows the model to leverage their distinct and well-known differential sensitivities to temperature changes, maximizing robust information extraction. The resulting temperature-aware context vectors (C_{PPG}, C_{ECG}) are fused with demographic embeddings ($Demo_{emb}$), $F_{att_combined} = \text{Concat}(C_{PPG}, C_{ECG}, Demo_{emb})$. This ensures that the final prediction stage operates on physiological features already intelligently filtered and recalibrated based on the thermal context. Processing through shared and task-specific heads yields the final SBP/DBP predictions, demonstrating significantly enhanced resilience to environmental temperature variations compared to non-adaptive models.

6 PERFORMANCE EVALUATION

This section details the rigorous, multi-phase evaluation designed to comprehensively assess the performance, robustness, and usability of the *FuSenseRing* system. Our evaluation strategy encompasses four key components: (1) Controlled laboratory experiments featuring a crucial ablation study to validate and quantify the contribution of our novel Temperature-Adaptive Attention (TAA) mechanism to performance robustness under thermal stress (17 °C to 40 °C); (2) A real-world user study conducted during daily activities to evaluate ecological validity and benchmark *FuSenseRing* against commercial wearable BP devices under challenging ambient conditions; (3) Specific analyses investigating system robustness across demographic factors (gender, skin tone) and the impact of calibration data size on personalization efficiency; and (4) A comparative usability assessment against alternative BP monitoring technologies. Performance throughout these evaluations is quantified using standard metrics (Table 3) against an FDA-cleared clinical reference device (SunTech Tango M2 [52]). Statistical significance for comparisons between groups or conditions was assessed using appropriate inferential tests (e.g., paired/independent t-tests, ANOVA), with a significance level (α) set at 0.05.

Table 3. Evaluation Metrics for Blood Pressure Estimation.

Metric	Equation
Mean Absolute Error (MAE)	$\frac{1}{N} \sum_{i=1}^N y_i - \hat{y}_i $
Mean Error (ME)	$\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)$
Standard Deviation (STD) of Error	$\sqrt{\frac{1}{N} \sum_{i=1}^N (e_i - \text{ME})^2}$, where $e_i = y_i - \hat{y}_i$
Pearson Correlation (r)	$\frac{\sum_{i=1}^N (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^N (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^N (\hat{y}_i - \bar{\hat{y}})^2}}$

6.1 User Study Methodology

The user study protocol was approved by a university-affiliated Institutional Review Board (IRB), and informed consent was obtained from all participants. Our evaluation comprised two main phases with a total of 60 adult volunteers. The first phase involved a controlled laboratory study with all 60 participants to establish baseline performance. Following this, a subset of 15 participants continued to the second phase: a real-world ambulatory study comparing our device against commercial blood pressure rings.

- **Participant Characteristics** Recruitment was targeted to ensure a cohort with broad demographic and physiological diversity. Our final cohort of 60 participants demonstrated a wide distribution in age and Body Mass Index (BMI), as detailed in Table 4. This demographic diversity, in turn, yielded an extensive and clinically significant spectrum of ground-truth blood pressure measurements, as visualized in Figure 9. This range is significant as it includes readings that fall within hypotensive (SBP < 90 or DBP < 60 mmHg), normal (SBP < 120 and DBP < 80 mmHg), Stage 1 hypertension (SBP 130-139 or DBP 80-89 mmHg), and even Stage 2 hypertension (SBP ≥ 140 or DBP ≥ 90 mmHg) categories categories, per American Heart Association guidelines [10, 81]. Validating our system across this wide physiological range provides strong evidence of its robustness.

- **Ground Truth Measurement:** Reference SBP and DBP values were measured using the FDA-cleared SunTech Medical Tango M2 automated sphygmomanometer [52], applied to the participant’s left upper arm according to manufacturer guidelines.

- **Smart Ring Sizing and Fit:** To ensure both high-quality sensor contact and a comfortable fit, our *FuSenseRing* flexible PCB was housed within enclosures of four standard sizes, corresponding to US Ring Sizes 6, 8, 10, and 12 (with inner diameters of approx. 16.5, 18.1, 19.8, and 21.4 mm, respectively). Before the study, each participant

Table 4. Participant demographics (N=60).

Characteristic	Value / Range
Number of Participants	60
Age Range	18–76 years
BMI Range	16–32 kg/m ²
Gender Distribution	34 Male / 26 Female
Skin Tones Represented	Light, Medium (Yellow), Dark

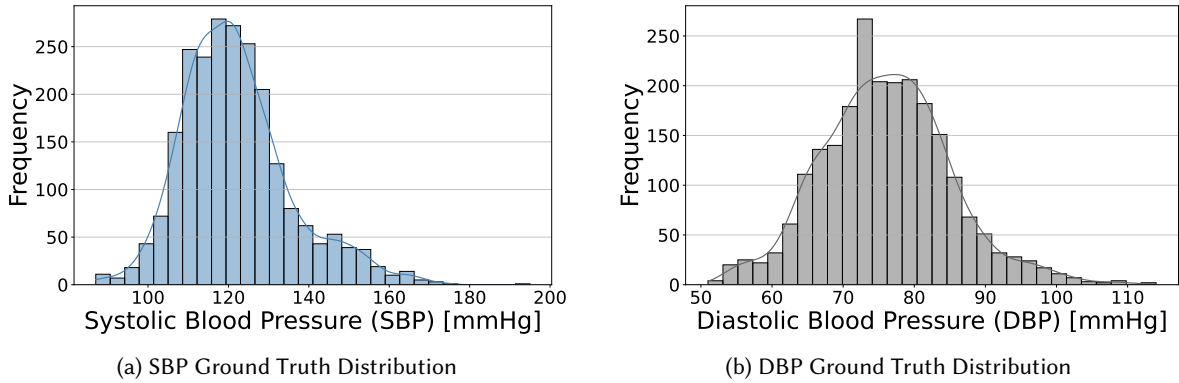


Fig. 9. Distribution of ground-truth SBP and DBP measurements across all 60 participants in the study, demonstrating a wide range covering hypotensive, normal, and hypertensive categories.

was individually fitted to select the size that offered a secure yet comfortable fit, preventing sensor movement without constricting the finger. Similarly, to ensure an appropriate fit for the commercial devices used in our comparison study, we purchased and made available three common sizes (US size 8, 10, and 12) for each of the tested models.

• **Phase 1: Controlled Laboratory Evaluation:** This phase aimed to isolate the effect of finger skin temperature on BP estimation and collect data for training and validating the TAA mechanism across diverse participants and conditions. Participants were seated comfortably with their right hand (wearing *FuSenseRing*) placed inside a custom-built temperature-controlled chamber made of polypropylene material (Setup shown in Fig. 10). To achieve precise air temperature control between 15 °C and 45 °C, simulating real-world thermal shifts, an insulated aluminum tube delivered conditioned air from external Midea air conditioning [56] or Dreco heater [21] units. Each participant completed four separate 30-minute sessions, with sufficient rest between sessions. During each session, the chamber temperature was systematically varied to induce finger skin temperature changes (measured by *FuSenseRing* and verified by TC004 thermal imaging camera [75]) across the target range of 17 °C to 40 °C. Simultaneous measurements were taken from *FuSenseRing* and the Tango M2 reference device at 3-minute intervals. Crucially, to ensure model robustness against variations in placement, the *FuSenseRing* ring was removed and remounted by the participant between each session. This protocol yielded a total of 2200 paired lab-based measurements. To accommodate participant schedules, individual session durations varied, with each of the 60 participants contributing an average of approximately 37 valid BP readings (ranging from 20 to 40). For data alignment, we employed a retrospective protocol: each ground-truth SBP/DBP value, time-stamped

upon completion of the Tango M2's measurement cycle, was aligned with the immediately preceding 10-second window of raw sensor data from our ring. We estimate the precision of this alignment to be within 1-2 seconds, an error margin considered sufficient given the stable, resting state of the participants.

• **Phase 2: Real-World Ambulatory Evaluation:** This phase assessed *FuSenseRing*'s performance and robustness during ecologically valid conditions and provided a benchmark against other ring-form BP devices on the market. Participants wore *FuSenseRing* alongside three commercial smart rings (Pulserive [7], Circul Plus [3], CNBRO [20]) on their non-dominant hand for an 8-hour period during a typical weekday. They engaged in their normal routines, including sedentary office work, commuting (e.g., walking, driving), light household activities, and spending time outdoors. Approximately every hour, when convenient and after being seated and resting for at least 2 minutes, participants took simultaneous measurements using *FuSenseRing*, each commercial ring, and the Tango M2 reference device. The environmental temperatures encountered during this phase spanned a wide range from approximately -10°C (outdoor in wintertime) to 24.4°C . In this phase, 15 participants conducted a real-world comparison of *FuSenseRing* against three commercial smart rings. Over an 10-hour period, each participant took approximately eight measurement sets. To accommodate the multiple devices, readings within each set were performed sequentially; participants measured their BP with each of the four rings in a counter-balanced order, separated by a 20-second rest period. Critically, each individual ring measurement was immediately paired with a ground-truth reading. The finish time of data acquisition on the ring and the finish time of the reference device's cycle were manually synchronized by a researcher using a timestamp, ensuring a temporal alignment with an estimated maximum error of less than 2 seconds. This protocol yielded a total of 150 measurement sets, resulting in approximately 600 individual, time-aligned device-and-cuff paired readings for analysis.

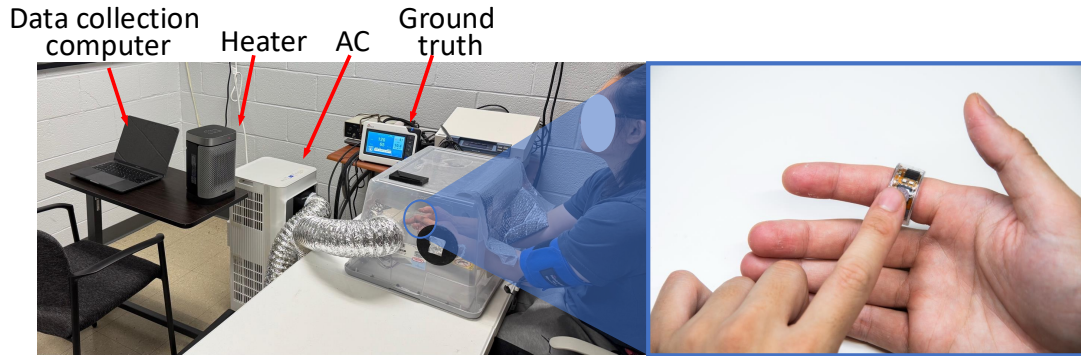


Fig. 10. (Left) Experimental setup for the user study. (Right) Illustration of a participant placing their finger on the sensing ring for data collection.

6.2 EVALUATION RESULTS AND ANALYSIS

We now present the evaluation results, analyzing *FuSenseRing*'s accuracy against the clinical reference, its robustness under real-world conditions and temperature variations, its performance relative to commercial devices, and its usability.

6.2.1 Real-world Performance against Commercial Devices. To evaluate *FuSenseRing*'s accuracy and reliability during daily life compared to existing commercial BP-monitoring smart rings, we analyzed data from the Phase 2 ambulatory study, comparing hourly measurements from *FuSenseRing*, Pulserive (claims to have FDA-Approval), Circul Plus, and CNBRO Ring against the ground truth reference. Absolute errors were computed for each device over the study duration.

Figures 11a and 11b provide a striking visual comparison of the mean absolute estimation errors (MAE) throughout the day, with changing finger skin temperature. The plots clearly show that *FuSenseRing* (blue bars) consistently maintained low absolute errors, typically remaining close to or below the 5 mmHg (red dashed line). In stark contrast, all three commercial rings frequently exhibited large error spikes, often exceeding 10 mmHg to 20 mmHg, visually correlating with fluctuations in skin temperature.

Quantitative analysis across all participants and measurements during this real-world phase confirms *FuSenseRing*'s markedly better performance and robustness. *FuSenseRing* achieved a Mean Error (ME) $\pm$ Standard Deviation (STD) of 0.36 ± 3.88 mmHg for SBP and 0.27 ± 4.69 mmHg for DBP. These results comfortably satisfy both stringent FDA-recognized AAMI accuracy criteria (ME $\leq \pm 5$ mmHg and STD ≤ 8 mmHg) [71], demonstrating accuracy maintained during daily life.

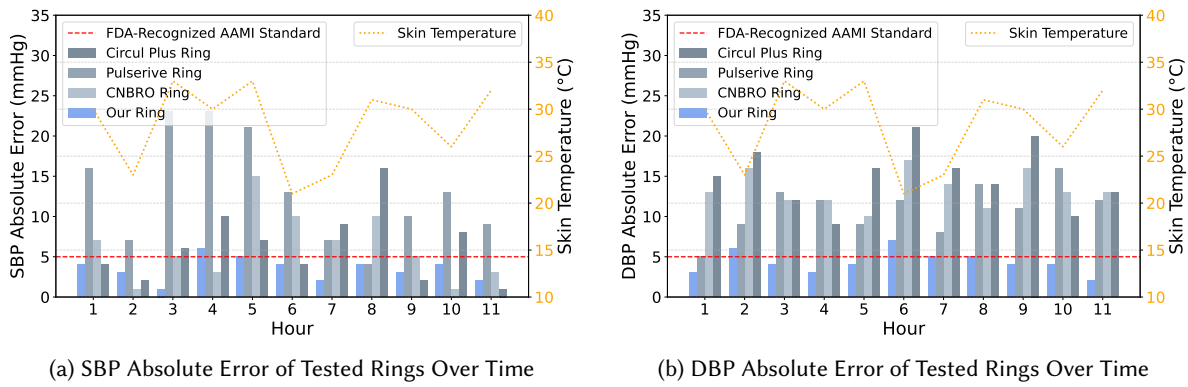


Fig. 11. Comparison of systolic and diastolic blood pressure absolute errors across tested ring devices over time.

Table 5. BP Estimation Accuracy Comparison and AAMI Criteria Compliance in Real-World Conditions.

Device/Standard	SBP Accuracy (mmHg) ME $\pm$ STD	DBP Accuracy (mmHg) ME $\pm$ STD	Meets Standard? (ME & STD)
<i>FuSenseRing</i> (Ours)	0.36 ± 3.88	0.27 ± 4.69	✓
Circul Plus [3]	6.27 ± 4.41	14.91 ± 3.83	✗
Pulserive [7]	13.27 ± 6.71	11.00 ± 3.07	✗
CNBRO Ring [20]	6.09 ± 4.30	13.36 ± 2.20	✗
FDA-Recognized AAMI Standard [71]	ME: $\leq \pm 5$ / STD: ≤ 8	ME: $\leq \pm 5$ / STD: ≤ 8	(Reference Limit)

Conversely, the evaluated commercial devices failed to meet these clinical benchmarks under the same real-world conditions. Their performance statistics were listed in Table 5. These results, particularly the large positive mean errors (indicating systematic bias) far exceeding the ± 5 mmHg limit, highlight the significant challenges faced by current commercial offerings in providing reliable ambulatory BP estimates.

This head-to-head comparison under uncontrolled, real-world conditions provides compelling evidence for the efficacy and robustness of the *FuSenseRing* system. Its ability to maintain accuracy, satisfying clinical standards

in daily environmental and physiological variability—conditions where contemporary commercial ring solutions demonstrably falter, underscores the critical contribution of our integrated design. We attribute this improved performance directly to the synergy between our robust multimodal feature extraction (using PPG and ECG), stabilized sensor contact pressure during each measurements and, crucially, the Temperature-Adaptive Attention mechanism that appears to significantly compromise the accuracy of the other tested devices (as suggested by Fig. 11a and 11b). This represents a substantial advancement towards achieving reliable, truly ambulatory cuffless blood pressure monitoring.

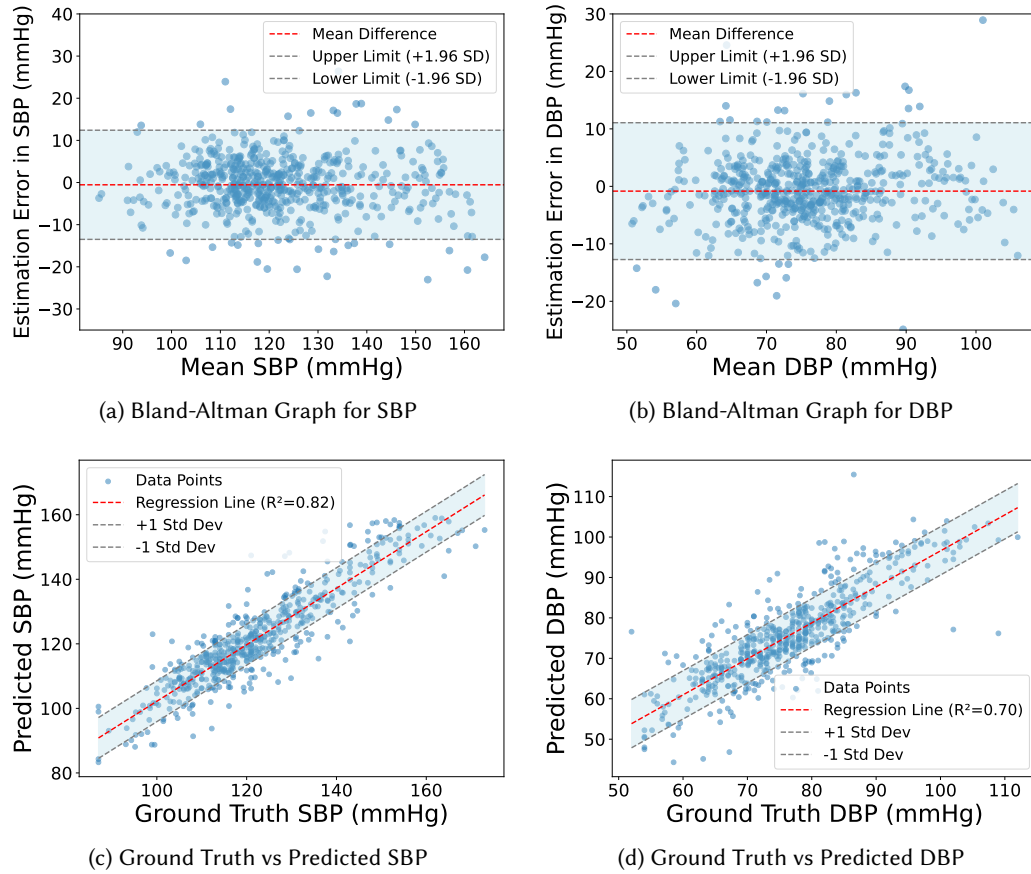


Fig. 12. Validation of *FuSenseRing* BP Accuracy vs. Reference Device under Optimal Conditions (Normal Temperature: 30 °C to 36 °C). (a, b) Bland-Altman plots demonstrate low overall bias and standard deviations meeting FDA-recognized AAMI criteria. (c, d) Correlation plots show the relationship between predicted and ground truth SBP/DBP values.

6.2.2 Accuracy under Optimal Conditions. To establish *FuSenseRing*'s intrinsic accuracy and validate the core system performance under favorable sensing conditions, specifically optimal contact pressure and normal physiological skin temperature, we analyzed measurements collected during Phase 1 where participants maintained optimal sensor contact pressure (guided by TapBP feedback) and experienced finger skin temperatures within

the normal range (30 °C to 36 °C). Agreement between *FuSenseRing*'s estimates and the Tango M2 reference was evaluated using Bland-Altman analysis and Pearson correlation.

Figure 12 presents the analysis under these optimal conditions. The Bland-Altman plots (Fig. 12a for SBP, Fig. 12b for DBP) demonstrate excellent agreement with minimal bias. Quantitatively, the Mean Error (ME) $\pm$ Standard Deviation (STD) was -0.54 ± 6.61 mmHg for SBP and -0.83 ± 6.07 mmHg for DBP, with MAE of 5.01 mmHg and 4.52 mmHg, respectively. These results comfortably satisfy the accuracy criteria specified by the FDA-recognized AAMI standard (ME $\leq \pm 5$ mmHg, STD ≤ 8 mmHg) [71]. The corresponding 95% limits of agreement show no significant systematic trend in error across the pressure range. Furthermore, the correlation analysis (Fig. 12c for SBP, Fig. 12d for DBP) confirmed a strong linear relationship between *FuSenseRing*'s estimates and the ground truth. The Pearson correlation coefficient (r) was 0.90 for SBP (corresponding $R^2 = 0.82$) and 0.84 for DBP (corresponding $R^2 = 0.70$).

This evaluation confirms that the personalized *FuSenseRing* system—integrating its sensor suite, signal processing, contact pressure guidance, and foundational ML model—achieves clinical-grade accuracy under optimal operating conditions. It establishes a crucial baseline performance level before assessing the system's robustness against real-world challenges, particularly temperature variations.

6.2.3 Ablation Study: Analyzing Impact of Sensor Modalities. To analyze the sources of performance in our system and validate our core architectural choice, we first isolated the contribution of the sensor fusion itself. By evaluating performance under optimal, normal temperature conditions (30 °C to 36 °C), we can establish the foundational accuracy of our multimodal approach before examining its robustness to environmental stressors. We compared three model configurations using a rigorous leave-one-participant-out cross-validation protocol:

- **Our Fused Model (PPG+ECG):** The base model architecture that leverages features from both sensor streams.
- **PPG-Only Model:** An ablated version relying exclusively on features derived from the PPG sensor.
- **ECG-Only Model:** An ablated version relying exclusively on features derived from the ECG sensor.

Table 6. Performance comparison of sensor modalities under optimal temperature conditions (30 °C to 36 °C). We highlight values in red that fail to meet the FDA-recognized AAMI standard (Mean Error [ME] $\leq \pm 5$ mmHg and Standard Deviation [STD] ≤ 8 mmHg).

Model Configuration	SBP (ME / STD / MAE)	DBP (ME / STD / MAE)	Meets AAMI?
PPG-Only	-0.48 / 10.25 / 7.71	-5.28 / 7.58 / 8.41	✗
ECG-Only	0.20 / 8.87 / 6.57	-6.43 / 7.25 / 7.87	✗
<i>FuSenseRing</i> (Ours)	-0.54 / 6.61 / 5.01	-0.83 / 6.07 / 4.52	✓

The results in 6 indicate the necessity of a multimodal sensing approach. Even under these favorable conditions, neither single-modality model achieves clinical-grade accuracy. The PPG-only model, while rich in morphological detail, proves susceptible to noise, evidenced by an SBP standard deviation (10.25 mmHg) that substantially exceeds the AAMI limit. Conversely, the ECG-only model, while providing stable timing references, lacks sufficient information to constrain the DBP mean error, resulting in a significant bias of -6.43 mmHg. Both configurations fail the AAMI standard.

In contrast, by fusing these complementary data streams, the model achieves the low bias and low variance required. Our proposed model comfortably satisfies all AAMI criteria and, critically, reduces the MAE by 24% for SBP and 43% for DBP compared to the best-performing single-modality ablated model. This confirms the value

of synergistic fusion, as the model leverages the ECG's clean timing reference to correct for noise and reliably interpret the rich, blood-flow-related morphological features of the PPG waveform.

6.2.4 Ablation Study: Validating the Temperature-adaptive Attention Mechanism. The core algorithmic innovation of *FuSenseRing* is the Temperature-adaptive Attention (TAA) mechanism, specifically designed to mitigate temperature-induced errors in finger-based BP estimation. To rigorously quantify its effectiveness, we conducted an ablation study comparing our full TAA-enabled model against two key baselines: an identical architecture that ignores temperature completely (Base Model), and another that incorporates temperature as a simple input feature without a dynamic attention mechanism (Temperature Concatenation Model) inspired by Temp-Resnet from WildPPG [54].

We evaluated two configurations:

- **TAA-Enabled Model:** The complete architecture described in Sec. 5, incorporating the TAA mechanism which utilizes real-time finger temperature input to modulate PPG/ECG feature fusion.
- **Temperature Concatenation Model (Baseline):** A model identical to our architecture, but instead of the TAA module, it simply concatenates the scalar temperature value with the PPG/ECG features before the final prediction MLP. This represents a standard approach for including environmental context, similar to methods used in works like WildPPG [54].
- **Base Model (No TAA):** An ablated version identical to the TAA-Enabled model in all aspects (feature extractors, GRUs, demographic fusion, prediction heads) except that the TAA module is bypassed. Temperature input is ignored, and the PPG/ECG features are directly concatenated with demographic features before the final prediction MLP.

We employed a leave-one-participant-out cross-validation protocol using the Phase 1 laboratory dataset, which spans the full range of induced finger skin temperatures (17 °C to 40 °C). For each held-out participant i :

- (1) *General Temperature-aware Model Pre-training:* To ensure a fair comparison, the temperature-aware components of both relevant models were pre-trained on the general dataset from the other $N - 1$ participants.
 - For the **TAA-Enabled Model**, its TAA-specific layers were pre-trained to learn how to dynamically modulate features based on temperature.
 - For the **Temperature Concatenation Model**, its MLP layers were pre-trained to learn the general predictive relationship of temperature when used as a direct input feature.
 The Base Model, being temperature-agnostic, does not undergo this pre-training step.
- (2) *Personalized Calibration:* All three models—the TAA-Enabled, the Temperature Concatenation, and the Base Model—were personalized to participant i . This crucial step involved fine-tuning designated layers (as defined in Sec. 5.2) using only 10 measurement samples collected from participant i exclusively within the *normal* temperature range (30 °C to 36 °C). This protocol deliberately mimics a practical deployment scenario where calibration occurs under convenient, standard conditions.
- (3) *Evaluation:* The three personalized models were then evaluated on the remaining, unseen test data from participant i . Performance was assessed across the full temperature spectrum, with a specific focus on the Mean Absolute Error (MAE) metric to robustly quantify average error magnitude under conditions where temperature deviates significantly from the norm.

• **Impact of Temperature on Base Model:** Figure 13 illustrates the temperature challenge addressed by our innovation. While both base model and TAA-enabled model perform comparably well within the normal temperature range (30 °C to 36 °C, shaded green), the BP estimation MAE of the Base Model (gray line) increases sharply as finger temperature shifts to colder (<30 °C) or hotter (>36 °C) ranges. This confirms the significant negative impact of temperature variations on standard BP estimation models without temperature adaptation mechanisms.

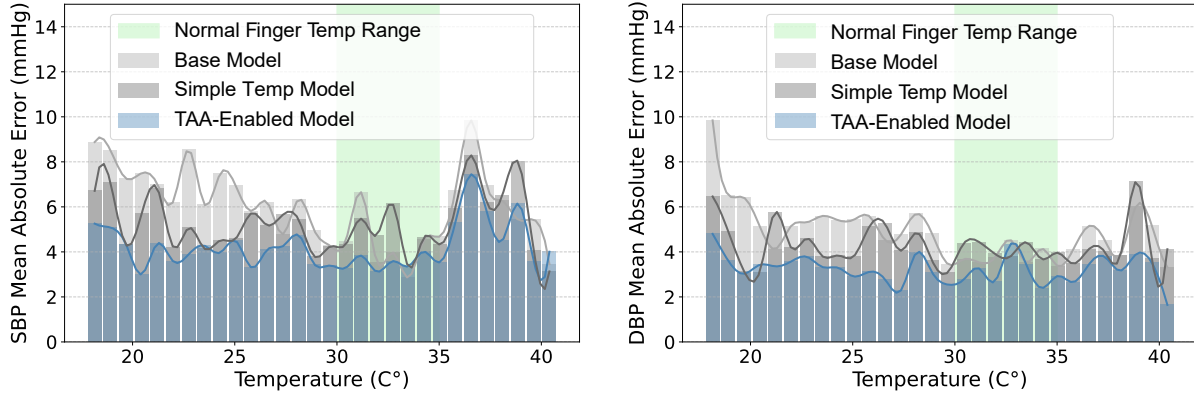


Fig. 13. Mean Absolute Error (MAE) vs. Finger Temperature for BP estimation comparing the Base Model (grey), Temperature Concatenation Model (dark grey) and the TAA-Enabled *FuSenseRing* model (blue). Left: SBP. Right: DBP.

Table 7. Per-participant comparison of MAE in mmHg for the Base model versus TAA-enabled model. The table details the Systolic (S) and Diastolic (D) MAE for each of the 60 participants. The final column shows the percentage change (% Change) in error after applying our Temperature-Adaptive Attention (TAA) mechanism.

Participants 1-20				Participants 21-40				Participants 41-60			
ID	Base (S/D)	TAA (S/D)	% Change (S/D)	ID	Base (S/D)	TAA (S/D)	% Change (S/D)	ID	Base (S/D)	TAA (S/D)	% Change (S/D)
1	5.8/4.5	3.4/3.5	↓41% / ↓22%	21	5.0/3.9	4.0/3.5	↓20% / ↓10%	41	7.3/7.1	4.8/6.0	↓35% / ↓16%
2	12.5/7.6	3.8/4.2	↓70% / ↓45%	22	9.2/4.0	7.7/2.7	↓16% / ↓32%	42	7.0/8.6	5.9/5.6	↓15% / ↓35%
3	7.3/6.9	4.4/3.8	↓40% / ↓45%	23	5.5/4.4	4.1/3.8	↓25% / ↓12%	43	6.7/4.8	5.4/4.4	↓19% / ↓8%
4	5.8/7.3	3.5/2.7	↓40% / ↓63%	24	5.6/6.3	3.7/3.9	↓34% / ↓38%	44	6.3/3.4	5.4/2.7	↓14% / ↓20%
5	20.0/6.5	10.0/5.9	↓50% / ↓9%	25	6.5/5.3	7.0/3.9	↑8% / ↓27%	45	6.1/3.6	5.6/2.7	↓9% / ↓25%
6	7.1/2.9	3.2/2.8	↓55% / ↓3%	26	8.2/5.4	6.5/4.1	↓20% / ↓24%	46	8.0/4.6	5.0/3.6	↓38% / ↓21%
7	5.8/5.1	5.0/5.2	↓14% / ↑2%	27	4.5/7.7	3.9/9.1	↓14% / ↑18%	47	6.2/6.2	5.7/4.9	↓8% / ↓22%
8	6.8/8.5	6.3/5.8	↓8% / ↓32%	28	6.0/3.8	4.6/3.5	↓24% / ↓9%	48	6.4/6.0	5.3/5.2	↓17% / ↓14%
9	12.9/6.4	7.0/4.7	↓46% / ↓26%	29	7.9/5.6	5.9/6.7	↓25% / ↑20%	49	8.3/5.0	9.8/4.2	↑18% / ↓17%
10	8.9/6.7	5.3/4.0	↓41% / ↓39%	30	7.1/4.1	5.6/3.5	↓21% / ↓14%	50	8.9/6.6	8.1/4.2	↓9% / ↓36%
11	7.3/6.9	6.4/4.3	↓12% / ↓38%	31	7.4/5.4	5.0/4.9	↓32% / ↓9%	51	7.7/6.1	5.6/5.3	↓27% / ↓13%
12	7.8/3.6	4.9/2.9	↓38% / ↓19%	32	5.6/4.2	6.7/3.6	↑20% / ↓14%	52	5.8/5.8	5.4/4.1	↓7% / ↓29%
13	6.6/4.3	11.0/7.0	↑67% / ↑63%	33	4.8/3.7	3.3/3.0	↓30% / ↓21%	53	4.7/6.8	4.0/4.5	↓14% / ↓34%
14	7.4/4.7	6.6/2.8	↓11% / ↓39%	34	5.5/7.4	3.8/6.3	↓32% / ↓15%	54	9.9/5.9	8.7/4.3	↓12% / ↓27%
15	8.0/6.2	5.9/4.2	↓25% / ↓33%	35	6.5/8.5	5.9/5.7	↓9% / ↓33%	55	6.2/4.7	4.4/5.2	↓29% / ↑10%
16	7.0/8.0	6.9/3.7	↓2% / ↓54%	36	8.9/5.5	5.5/3.9	↓38% / ↓29%	56	6.4/3.4	5.0/2.4	↓22% / ↓30%
17	5.2/3.2	4.8/2.3	↓8% / ↓27%	37	8.9/5.0	5.7/3.4	↓36% / ↓32%	57	7.5/3.7	5.5/2.7	↓27% / ↓27%
18	6.9/5.5	5.4/5.4	↓21% / ↓2%	38	9.7/6.7	7.6/5.0	↓21% / ↓25%	58	11.2/6.8	7.0/5.5	↓38% / ↓19%
19	8.1/6.0	7.1/4.4	↓12% / ↓26%	39	8.1/5.8	5.9/5.4	↓27% / ↓7%	59	6.4/3.2	4.3/2.8	↓33% / ↓12%
20	8.9/4.1	7.0/3.7	↓21% / ↓10%	40	5.3/4.7	4.7/3.0	↓12% / ↓38%	60	6.3/3.8	4.5/2.4	↓29% / ↓38%

• **Effectiveness of TAA Mechanism:** In contrast, the model incorporating the TAA mechanism (blue line in Fig. 13) maintains a significantly lower and more stable MAE across the entire temperature range. This demonstrates its ability to dynamically compensate for temperature-induced signal distortions. Focusing on the performance specifically under abnormal temperature conditions (17°C to $30^{\circ}\text{C} \cup 36^{\circ}\text{C}$ to 40°C), the TAA mechanism yielded substantial and consistent improvements across 87% of participants (Table 7). The average MAE under these challenging conditions was reduced from 7.75 mmHg to 5.68 mmHg for SBP (a 27% reduction; paired t-test, $p = 0.002$) and from 5.45 mmHg to 4.23 mmHg for DBP (a 22% reduction; paired t-test, $p = 0.001$). These statistically significant reductions highlight the effectiveness of the TAA approach.

Table 8. Performance Comparison Across the Full Temperature Range (17 °C to 40 °C), Demonstrating the Effectiveness of the TAA Mechanism. Values that fail the AAMI standard are in red.

Model Configuration	SBP Accuracy (ME / STD / MAE)	DBP Accuracy (ME / STD / MAE)	Meets AAMI?
PPG-Only	-3.62 / 12.72 / 9.96	-9.09 / 8.01 / 9.79	✗
ECG-Only	-2.29 / 11.72 / 7.89	-8.60 / 7.70 / 8.71	✗
<i>FuSenseRing</i> (No TAA)	-1.76 / 9.87 / 7.45	-3.14 / 7.67 / 6.38	✗ (SBP Std)
Temperature Concatenation [54]	-2.48 / 9.12 / 5.89	-0.69 / 6.97 / 4.83	✗ (SBP Std)
<i>FuSenseRing</i> (with TAA)	-0.09 / 7.67 / 5.60	0.42 / 5.74 / 4.43	✓

• **TAA vs. Temperature Concatenation:** While simply concatenating temperature as an input provides a notable improvement over the temperature-agnostic Base Model, this baseline still fails to meet the AAMI standard for SBP (Table 8). This highlights a key limitation: treating temperature as a static feature can learn a corrective bias but struggles to adapt to dynamic, non-linear signal distortions. In contrast, our TAA mechanism uses temperature as a dynamic context to actively modulate how PPG and ECG features are fused. This architectural advantage allows it to more effectively suppress noise, resulting in a superior error profile (Figure 13).

• **Overall Accuracy with TAA:** Crucially, the enhanced robustness provided by the TAA mechanism allows *FuSenseRing* to maintain high BP prediction accuracy even when evaluated across the entire range of tested temperatures. As shown by the Bland-Altman and correlation analyses in Fig. 14 (which include all data from 17 °C to 40 °C), the overall ME $\pm$ STD was -0.09 ± 7.67 mmHg for SBP and 0.42 ± 5.74 mmHg for DBP. This performance meets the FDA-recognized AAMI accuracy criteria [71], validating the system’s reliability under thermal stress.

This ablation study provides strong evidence validating our core algorithmic contribution. The novel TAA mechanism overcomes the critical limitation of temperature sensitivity in finger-based BP estimation. It is confirmed by the statistically significant error reduction (t-test result: $p \leq 0.002$ for both SBP and DBP) under thermal stress. Critically, the system’s design enables practical deployment: the TAA component learns robust temperature adaptation strategies during its pre-training on wide-ranging temperature data (17 °C to 40 °C), while the subsequent user-specific calibration requires only a small number of samples collected under normal temperatures (30 °C to 36 °C). This effective decoupling of general temperature-compensation learning from convenient user-specific calibration strongly supports *FuSenseRing*’s potential for reliable, real-world BP monitoring across diverse climates.

6.2.5 Ablation Study: Impact of Contact Pressure Guidance (TapBP). To quantify how our real-time contact pressure feedback system, TapBP (detailed in Section 4.3), improves measurement reliability, we conducted an ablation study comparing performance with and without its guidance.

The evaluation involved two distinct conditions. First, with the TapBP guidance disabled, participants were instructed to place their finger on the sensor without any specific guidance on how much force to apply. Data collected under these unguided, variable-pressure conditions was used to estimate BP. Second, the TapBP guidance was enabled, providing participants with real-time visual feedback to help them maintain contact pressure within the pre-defined optimal range while BP readings were taken.

The results in Table 9 unequivocally demonstrate the critical role of TapBP in improving measurement precision. Without guidance, inconsistent contact pressure introduced significant random error, causing the SBP Standard Deviation to exceed the AAMI limit at 9.52 mmHg. While the DBP STD of 7.96 mmHg was compliant, it remained on the edge of the acceptable 8 mmHg threshold. In stark contrast, enabling TapBP guidance dramatically

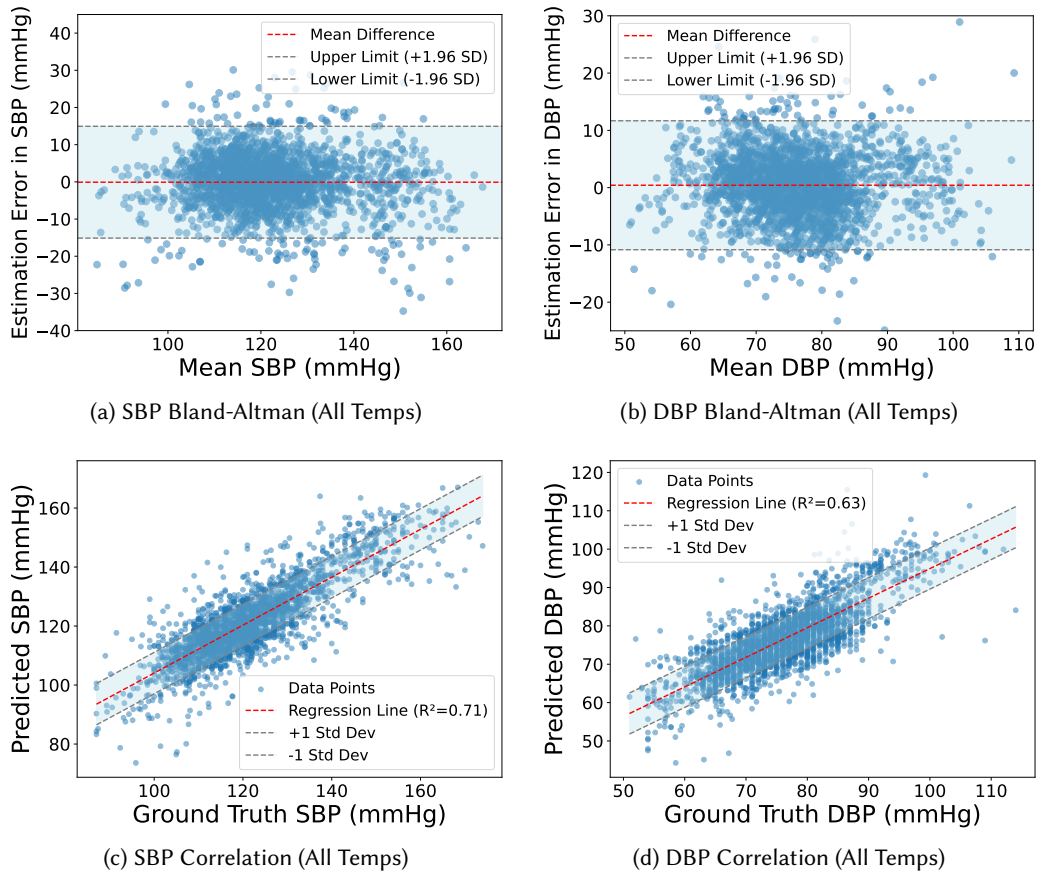


Fig. 14. Overall performance validation of the TAA-Enabled *FuSenseRing* model against the Tango M2 reference across the full tested finger temperature range (17 °C to 40 °C). (a, b) Bland-Altman plots demonstrate low overall bias and standard deviations meeting FDA-recognized AAMI criteria. (c, d) Correlation plots show the relationship between predicted and ground truth SBP/DBP values.

Table 9. Impact of TapBP Contact Pressure Guidance on BP Estimation Accuracy. Performance is shown as Mean Error (ME), Standard Deviation (STD), and Mean Absolute Error (MAE) in mmHg.

Guidance Condition	SBP Accuracy (ME / STD / MAE)	DBP Accuracy (ME / STD / MAE)	Meets AAMI?
Without TapBP Guidance	1.12 / 9.52 / 7.65	-0.79 / 7.96 / 6.47	✗
With TapBP Guidance	-0.31 / 6.31 / 4.78	-0.26 / 5.89 / 4.09	✓

improved reliability, reducing the STD for SBP by 34% and for DBP by 26%, to 6.31 mmHg and 5.89 mmHg respectively. This brought both metrics comfortably within clinical standards, validating the TapBP feature as essential for ensuring the fidelity and reliability of our system.

6.2.6 Benchmarking Against Traditional Baseline Models. To situate the performance of *FuSenseRing* within the context of established methodologies, we benchmarked our final, TAA-enabled system against two categories of traditional algorithms: the classic physiological model based on Pulse Transit Time (PTT), and standard machine learning models. We performed this comparative analysis under both optimal and full-range temperature conditions to rigorously assess not only best-case accuracy but also robustness against thermal stress.

Performance under Optimal Conditions: We first established a best-case performance baseline by evaluating all models on data collected exclusively within the optimal temperature range (30 °C to 36 °C). As shown in Table 10, even under these ideal conditions, none of the traditional baselines could achieve the accuracy required by the AAMI standard. This failure stems from their core design: PTT-based models oversimplify the cardiovascular system into a single time interval, while traditional ML models have limited capability to extract robust features from PPG and ECG, which prevents them from learning the true non-linear dynamics of blood pressure. This highlights a fundamental limitation in these approaches for this complex BP regression task. In contrast, our proposed *FuSenseRing* system demonstrates high accuracy and precision, comfortably satisfying all AAMI criteria.

Table 10. Performance Benchmark against Traditional Algorithms under **Optimal Temperature Conditions**. Values in red fail the AAMI standard.

Model	SBP Accuracy (ME / STD / MAE)	DBP Accuracy (ME / STD / MAE)	Meets AAMI?
PTT-Based Model	-3.71 / 8.23 / 6.95	-3.55 / 7.51 / 5.88	✗
SVR Model	-1.03 / 11.91 / 8.22	-4.21 / 9.87 / 7.87	✗
XGBoost Model	1.87 / 10.67 / 7.88	5.94 / 7.23 / 6.15	✗
<i>FuSenseRing</i> (Ours)	-0.54 / 6.61 / 5.01	-0.83 / 6.07 / 4.52	✓

Performance under Temperature Influence: The baseline models' limitations are most evident under thermal variation. As shown in Table 11, the accuracy of these models degrades significantly across the full temperature range (17°C to 40°C), confirming their unsuitability for reliable ambulatory monitoring. In contrast, *FuSenseRing* demonstrates exceptional robustness by maintaining high precision and satisfying the AAMI standard across these same conditions. This result directly validates the efficacy of our Temperature-Adaptive Attention (TAA) mechanism in successfully compensating for temperature-induced artifacts.

This benchmarking confirms the value of our proposed approach. *FuSenseRing* is not only more precise than traditional methods under ideal conditions, but more importantly, it is more robust to maintain high accuracy when subjected to temperature variations.

Table 11. Performance Benchmark against Traditional Algorithms across the **Full Temperature Range**. All traditional baselines fail to meet the AAMI standard.

Model	SBP Accuracy (ME / STD / MAE)	DBP Accuracy (ME / STD / MAE)	Meets AAMI?
PTT-Based Model	-4.81 / 11.05 / 9.88	-3.92 / 9.15 / 8.05	✗
SVR Model	3.15 / 12.32 / 9.41	3.88 / 9.56 / 8.21	✗
XGBoost Model	-2.98 / 11.32 / 8.51	-4.51 / 8.95 / 8.94	✗
<i>FuSenseRing</i> (Ours)	-0.09 / 7.67 / 5.60	0.42 / 5.74 / 4.43	✓

6.2.7 Robustness Across Demographics. To assess the fairness and consistency of *FuSenseRing*'s BP estimation performance across key demographic subgroups, we analyzed the overall Mean Error (ME) and Standard Deviation (STD) of the error, stratifying the results by participant gender and self-reported skin tone.

Gender: As visualized in Figure 15, *FuSenseRing* demonstrated consistent accuracy for both male (N=34) and female (N=26) participants in our expanded cohort. For males, the ME $\pm$ STD was 0.14 ± 7.35 mmHg (SBP) and 1.21 ± 5.74 mmHg (DBP). For females, it was -1.08 ± 6.97 mmHg (SBP) and 1.45 ± 5.65 mmHg (DBP). Both subgroups comfortably satisfy the FDA-recognized AAMI accuracy criteria (ME $\leq \pm 5$, STD ≤ 8 mmHg) [71]. An independent samples t-test for DBP revealed no statistically significant difference in Mean Error between genders ($p=0.780$). For SBP, the absolute difference between the groups is small (1.22 mmHg) and both mean errors are very close to zero. This suggests the practical impact of this gender-based bias is minimal and that the system demonstrates strong, clinically compliant performance for both genders.

Skin Tone: Similarly, performance remained robust and consistent across different self-reported skin tones (Figure 16). All subgroups comfortably met the FDA-recognized AAMI accuracy criteria, as detailed in the updated Table 12. Crucially, a One-way ANOVA test indicated no statistically significant differences in Mean Error across the three skin tone groups for either SBP ($p = 0.284$) or DBP ($p = 0.291$). This lack of significant difference provides solid evidence of the system's equitable performance.

This demographic analysis demonstrates *FuSenseRing*'s equitable performance, achieving clinically acceptable accuracy across genders and representative skin tones within our participant cohort, with no statistically significant differences found in average error between groups. This consistency suggests that our model generalizes effectively. This generalization across gender and skin tone is potentially aided by the inclusion of demographic features (gender) and robust feature extraction learned during pre-training on diverse public datasets. Such demographic robustness is crucial for ensuring fair performance and supporting the broader clinical applicability of *FuSenseRing* in diverse populations.

Table 12. BP Estimation Accuracy (ME $\pm$ STD) Stratified by Skin Tone for the Full Participant Cohort.

Skin Tone Group	N	SBP Accuracy (mmHg)	DBP Accuracy (mmHg)
		ME $\pm$ STD	ME $\pm$ STD
Light Tones	14	-0.88 ± 6.82	1.06 ± 5.65
Medium/Yellow Tones	22	-0.07 ± 7.15	1.19 ± 6.11
Dark Tones	24	-0.25 ± 7.45	1.53 ± 5.42

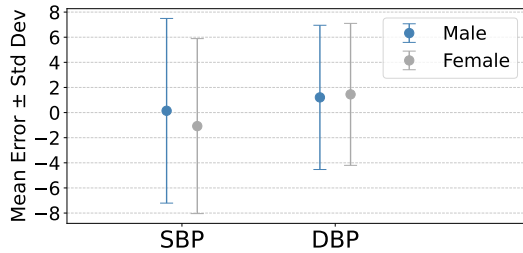


Fig. 15. *FuSenseRing* BP accuracy (Mean Error $\pm$ Std Dev) stratified by participant gender (N=34 Male, N=26 Female). Both groups meet FDA-recognized AAMI criteria.

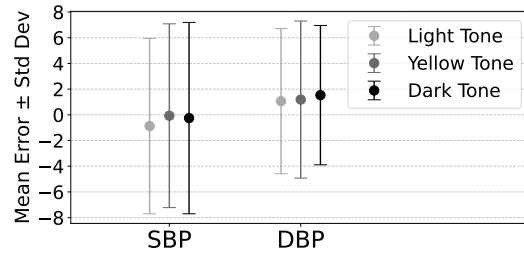


Fig. 16. *FuSenseRing* BP accuracy (Mean Error $\pm$ Std Dev) stratified by skin tone (N=14 Light, N=22 Medium/Yellow, N=24 Dark). All groups meet FDA-recognized AAMI criteria.

6.2.8 Impact of Calibration Data Size. Achieving clinically acceptable cuffless BP accuracy requires personalization due to significant inter-individual variability (e.g., body mass index, skin tone, age, vascular properties, waveform morphology). While a non-personalized base model pre-trained on large datasets captures general patterns, it often generalizes poorly to specific users. Conversely, training fully individual models demands impractically large datasets per person. We therefore employ transfer learning: the robust base model is efficiently fine-tuned using a small amount of user-specific data. This strategy balances generalization with personalization, but the optimal amount of calibration data requires investigation in order to find the balance between accuracy gains and user burden. Therefore, this evaluation aims to determine the minimum amount of user-specific calibration data—finding a balance between accuracy and convenience—that is sufficient to personalize the *FuSenseRing* BP model and achieve reliable performance across varying temperatures when collected under convenient conditions.

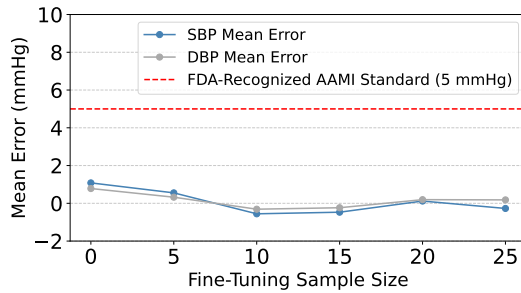


Fig. 17. Mean Error of *FuSenseRing* BP estimation vs. number of calibration samples used for fine-tuning.

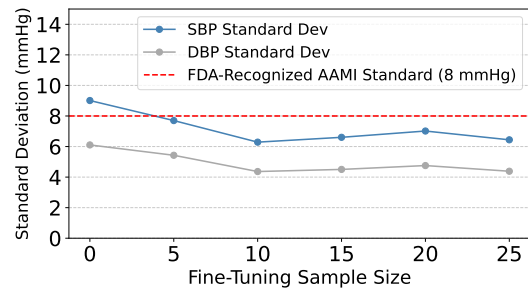


Fig. 18. Standard Deviation of *FuSenseRing* BP estimation vs. number of calibration samples used for fine-tuning.

We employed a leave-one-participant-out cross-validation approach. For each held-out participant, the pre-trained base model was fine-tuned using varying numbers of calibration samples ($N=0, 5, 10, 15, 20, 25$) collected exclusively under optimal temperature conditions (30°C to 36°C). $N=0$ represents the performance of the non-personalized base model. The resulting personalized models were then evaluated on unseen test data covering the full temperature spectrum (17°C to 40°C), assessing Mean Error (ME) and Standard Deviation (STD) of the error against the reference.

Figures 17 and 18 illustrate the relationship between the number of calibration samples and estimation accuracy. As shown in Fig. 17, personalization yields improvements in bias reduction; the ME for both SBP and DBP drops from initial offsets (with 0 samples) and stabilizes very close to zero mmHg after only 5 to 10 calibration samples, remaining well within the ± 5 mmHg FDA-recognized AAMI limit. Figure 18 shows the impact on error variability. The SBP STD for the non-personalized model (0 samples) slightly exceeds the FDA-recognized AAMI limit (≤ 8 mmHg). The calibration process significantly reduces variability, particularly for SBP, with most of the improvement occurring within the first 10 samples, bringing the STD for both SBP and DBP within the FDA-recognized AAMI limit. Specifically, using 10 calibration samples results in performance where ME is consistently near zero and STD is stable around approximately 6.5 mmHg for SBP and 4.5 mmHg for DBP. Adding more than 10 samples provides diminishing returns.

This evaluation highlights the data efficiency of our pre-training and transfer learning strategy. The results empirically demonstrate that only 5 to 10 brief calibration measurements, collected under convenient normal temperature conditions, are sufficient to personalize *FuSenseRing* effectively and achieve performance satisfying the stringent FDA-recognized AAMI accuracy criteria, even when the device is subsequently used across a wide range of temperatures. This minimal calibration requirement significantly enhances the practicality and scalability of deploying *FuSenseRing* for reliable, personalized BP monitoring in real-world healthcare scenarios.

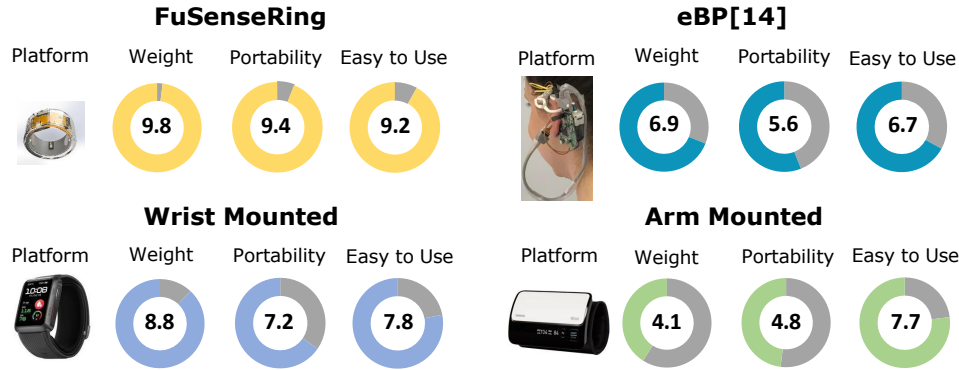


Fig. 19. User experience survey on *FuSenseRing* compared with three alternative sensing platforms.

6.2.9 Comparative Usability Assessment. To evaluate the usability of *FuSenseRing* compared to alternative BP monitoring approaches, we did a survey asking participants to subjectively rate *FuSenseRing*, an ear sensing system (eBP [14]), a commercial cuff-based smartwatch (Huawei Watch D [32]), and a standard upper-arm cuff monitor [60]. Ratings were provided on a 10-point Likert scale (0=Worst, 10=Best) for criteria including *Weight*, *Portability*, and *Ease of Use* during measurement. As summarized in Fig. 19, *FuSenseRing* received significantly higher average ratings across all criteria compared to the other devices. Participants qualitatively commented on *FuSenseRing*'s comfort, discretion, and the simplicity of the TapBP measurement process compared to the perceived cumbersome or discomfort of the cuff-based and ear-based alternatives. This suggests that *FuSenseRing*'s ring form factor and interaction design offer usability advantages, potentially leading to better user adherence for frequent, long-term BP monitoring compared to existing alternatives.

7 DISCUSSION AND FUTURE WORK

In this work, we presented *FuSenseRing*, an open-source smart ring platform designed for reliable, frequent blood pressure monitoring, with a core focus on mitigating temperature-induced signal variations. Our evaluations demonstrate that *FuSenseRing*, leveraging multimodal sensing (PPG, ECG, Temperature, Contact Pressure) and a novel Temperature-Adaptive Attention (TAA) mechanism, achieves clinical-grade accuracy satisfying FDA-recognized AAMI ME/STD criteria, significantly outperforms contemporary commercial smart rings in real-world conditions, and requires minimal user calibration. Here, we discuss our findings, acknowledge the limitations of our work, and outline promising directions for future research.

- **ECG Electrodes Sensing:** We currently use off-the-shelf Ag/Cl ECG electrodes to capture ECG signals for data collection. In the future, we plan to integrate sensing electrodes along the edges of the ring's outer case to optimize the form factor, enhancing wearability and comfort. This approach simplifies the hardware architecture while enabling a more seamless and user-friendly design, making the device better suited for real-world healthcare monitoring applications.

- **Early Detection of Cardiovascular Diseases:** This paper focuses on blood pressure estimation, but we believe *FuSenseRing* can also support the early detection of cardiovascular diseases (CVDs). By analyzing cardiac activity and blood flow data from ECG and PPG sensors, *FuSenseRing* can detect irregularities such as arrhythmias, abnormal heart rates, and blood pressure variations.

- **Temperature Range Selection:** We chose a temperature range that balances real-world applicability and participant safety. We excluded extreme cold conditions (below 0°C) due to ethical and safety concerns, as prolonged exposure can cause vasoconstriction. Additionally, participants reported discomfort and numbness when their finger temperature dropped below 15°C. Thus, 15°C was set as the lower bound. Our study covers a

wider temperature range (17°C–40°C) than prior work [39]’s range (24.5°C–38.5°C). The optimal temperature range (30°C–36°C) was determined as all participants’ resting finger temperatures naturally fell within this range.

- **Motion Artifacts Consideration:** Our system is designed to optimize sensor stability and minimize motion artifacts during blood pressure measurement. During each measurement, users are prompted to gently press the ring with a finger from the opposite hand, ensuring consistent PPG sensor contact and reliable ECG signal acquisition. This deliberate, controlled interaction naturally stabilizes hand posture and reduces motion distortions, resulting in robust, high-quality signal capture.

- **Full-Scale Clinical User Evaluation:** Our initial user study focuses on validating *FuSenseRing* across a broad and clinically significant BP range, establishing its robustness. However, additional studies with a larger and more diverse user base are essential to further assess its clinical-grade performance in real-world settings. As part of our future work, we plan to conduct expanded studies leading up to a full-scale clinical trial. Specifically, we aim to recruit a larger population that includes individuals with diagnosed hypotension and hypertension, following a dedicated clinical protocol to ensure participant safety. In the long term, our vision is to conduct a large-scale study providing comprehensive validation of *FuSenseRing* for both personal health monitoring and clinical applications.

8 CONCLUSION

Reliable and frequent blood pressure monitoring in real-world, ambulatory settings remains a critical yet largely unmet need for effective cardiovascular health management. Current wearable technologies, particularly convenient finger-worn devices relying heavily on PPG sensing, often fail to deliver clinically acceptable accuracy due to their sensitivity to environmental factors like temperature fluctuations and physiological variations like inconsistent sensor contact pressure.

In this paper, we introduced and comprehensively evaluated *FuSenseRing*, an open-source smart ring platform designed to address these challenges. By synergistically integrating a multimodal sensor suite (PPG, ECG, temperature, force) on a custom flexible PCB with innovative hardware-software co-design features—including an interactive pressure guidance mechanism (TapBP), *FuSenseRing* ensures high-fidelity signal acquisition. Crucially, we developed and validated a novel Temperature-Adaptive Attention (TAA) mechanism within our deep learning framework, which is designed to uniquely leverage real-time temperature measurements to dynamically recalibrate fused physiological features and specifically mitigate thermal drift. Our rigorous multi-phase evaluations demonstrated the success of this approach. Ablation studies confirmed the significant impact of the TAA mechanism in reducing temperature-induced errors. The complete *FuSenseRing* system was shown to achieve BP estimation accuracy satisfying the stringent criteria of the FDA-recognized AAMI/ISO 81060-2 standard, notably maintaining this performance across a wide range of experimentally controlled skin temperatures (17 °C to 40 °C). Furthermore, *FuSenseRing* significantly outperformed popular commercial smart rings in a challenging real-world ambulatory study and proved robust across different demographic groups.

By directly tackling the critical barriers of temperature sensitivity and signal quality that have hampered previous finger-based BP monitors, *FuSenseRing* represents a remarkable advancement towards truly reliable ring-based cardiovascular monitoring. The release of this validated system as an open-source platform provides a valuable, reproducible tool for the research community, intended to accelerate further innovation in ubiquitous health sensing.

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