Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Architecture-Level Evaluation of Standalone Wearable Systems for Real- Time Non-Invasive Blood Glucose Inference

Mingyang HUANG

huang@ustb.edu.cn

University of Science and Technology Beijing

Research Article

Keywords: Non-invasive glucose inference, Wearable device, Edge computing, OLED display, Bluetooth Low Energy, Patient adherence

Posted Date: October 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11184870/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Non-invasive glucose monitoring is shifting from analyte-centric optical sensing toward system-level physiological inference based on autonomic and metabolic state variables. Building on a systems physiology framework in which glycemic dynamics are inferred from multiparametric signals such as heart rate variability, tissue oxygenation, physical activity, and circadian rhythm, this study compares two hardware deployment architectures: smartphone-dependent wearable systems and standalone display-integrated wearable devices. The comparison is conducted across latency, power consumption, data-processing hierarchy, privacy, human–machine interaction, and long-term clinical adherence. The analysis shows that standalone devices combining local edge computation on low-power microcontrollers with integrated OLED feedback can reduce dependence on continuous Bluetooth Low Energy transmission, shorten the real-time inference pathway, and provide low-friction visual feedback directly on the wearable node. Although integrated displays introduce additional power demand, dark-mode OLED rendering, event-driven screen activation, adaptive sampling, and microcontroller-level power management can mitigate this burden. Compared with smartphone-dependent systems, the standalone architecture provides a more robust deployment pathway for real-time non-invasive glucose inference by improving immediacy, autonomy, privacy, and user engagement. These findings suggest that edge-enabled standalone wearables may provide a suitable architecture for future continuous physiological monitoring and proactive metabolic self-management.

1. Introduction

Diabetes mellitus has emerged as a global public health crisis, creating an urgent demand for monitoring technologies that are continuous, unobtrusive, and highly accurate. Although minimally invasive continuous glucose monitoring (CGM) systems have transformed diabetes care by capturing the temporal dynamics of glycemic fluctuations, they remain constrained by limitations including implantation-related discomfort, sensor biofouling, and the intrinsic physiological lag between blood glucose and interstitial fluid measurements. To address these challenges, recent technological advances have catalyzed a paradigm shift toward a systems physiology–based framework. Rather than attempting to extract weak and confounded optical signatures of glucose from heterogeneous biological tissues, this approach focuses on monitoring macroscopic regulatory systems—most notably the autonomic nervous system (ANS), which plays a critical role in maintaining glucose homeostasis.

This emerging framework relies on the continuous acquisition of multiparametric physiological data streams via optical photoplethysmography (PPG) sensors (e.g., MAX30100), including heart rate (HR), heart rate variability (HRV), and peripheral oxygen saturation (SpO_2). However, the successful translation of this theoretical model into clinical practice critically depends on the physical and computational architecture of the wearable sensing node. Historically, the wearable medical device ecosystem has predominantly adopted a “tethered,” smartphone-dependent architecture, wherein the sensor node functions primarily as a data acquisition terminal, wirelessly transmitting raw or partially processed

signals to a companion mobile application for computationally intensive processing, visualization, and cloud storage [1].

While this smartphone-centric paradigm alleviates the computational and display constraints of the wearable device, it introduces significant vulnerabilities in terms of data latency, wireless connectivity stability, and user interaction friction. In contrast, the convergence of high-resolution, low-power display technologies—particularly active-matrix organic light-emitting diode (AMOLED) panels—with advanced edge-computing microcontrollers (e.g., STM32 series) has enabled the development of fully standalone wearable health monitoring systems. These devices are capable of executing complex neurometabolic inference algorithms locally and delivering real-time visual feedback directly on the user's wrist [3].

The primary objective of this report is to provide a comprehensive, expert-level comparative analysis between smartphone-dependent wearable monitoring systems and standalone devices with integrated displays. The analysis systematically evaluates engineering trade-offs across key dimensions, including power consumption (e.g., OLED display illumination versus Bluetooth-based wireless transmission), edge-computing latency, and overall system reliability [4]. Importantly, this work extends beyond conventional hardware-centric metrics to examine the profound implications of device architecture on human factors engineering, user experience (UX), and long-term clinical adherence in chronic disease self-management [5]. By synthesizing recent empirical evidence with principles of systems physiology, this study aims to establish standalone wearable architectures as the optimal deployment strategy for complex, real-time physiological inference models.

2. System Architecture and Computational Paradigm Evolution for Non-Invasive Glucose Inference

As shown in Fig. 1. the two deployment paradigms differ fundamentally in data transmission, computational location, and feedback delivery. In the smartphone-dependent architecture, physiological signals are transmitted to an external mobile device for processing, whereas the standalone architecture integrates sensing, edge computing, and display within the wearable node. The transition from intermittent, snapshot-based measurements to continuous physiological state monitoring requires a robust system-level architectural foundation. In this study, the inferred glucose state is described as an integrated function of baseline glucose and multiple physiological regulatory variables:

$$G_{\{est\}} = f\left(G_{\{base\}}, \Delta G_{\{HR\}}, \Delta G_{\{SpO_2\}}, \Delta G_{\{HRV\}}, \Delta G_{\{meta\}}, \Delta G_{\{circ\}}\right) \quad (1)$$

where $\mathrm{G}_{\{\mathrm{est}\}}$ denotes the estimated glucose state, $G_{\{base\}}$ denotes baseline glucose, $\Delta G_{\{HR\}}$ denotes the heart-rate response, $\Delta G_{\{SpO_2\}}$ denotes hypoxic stress, $\Delta G_{\{HRV\}}$ denotes autonomic tone, $\Delta G_{\{meta\}}$ denotes metabolic state, and $\Delta G_{\{circ\}}$ denotes circadian rhythm.

Based on this model structure, two fundamentally distinct hardware–computational paradigms can be considered: a smartphone-dependent architecture and a standalone display-integrated wearable

architecture. The physiological basis of this inference strategy is summarized in Fig. 2. Rather than directly detecting glucose as an isolated optical analyte, the framework estimates glycemic state by integrating multiple upstream physiological indicators, including HR/HRV, SpO_2, autonomic nervous system activity, hypoxic stress, physical activity, and circadian rhythm.

2.1 Limitations of Smartphone-Dependent (App-Coupled) Architectures

In smartphone-dependent architectures, the wearable device functions primarily as a “thin-client” sensor node. Its onboard microcontroller typically performs only minimal signal preprocessing—such as analog-to-digital conversion and basic artifact filtering—before transmitting the data stream via a wireless transceiver, most commonly Bluetooth Low Energy (BLE), to a paired smartphone [6]. The smartphone’s central processing unit then assumes responsibility for computationally intensive tasks, including inter-beat interval (IBI) extraction, time- and frequency-domain heart rate variability (HRV) analysis, and evaluation of complex glucose inference models. The resulting health metrics are visualized within a dedicated mobile health (mHealth) application interface and are frequently synchronized with cloud-based servers for long-term storage and offline machine learning optimization [1].

This paradigm benefits from leveraging the smartphone’s substantial computational capacity, large battery reserves, and expansive high-resolution display capabilities [7]. However, it imposes a strict architectural dependency on continuous physical proximity to the mobile device. Such reliance introduces multiple single points of failure, including intermittent BLE connectivity, operating system–level termination of background processes for power conservation, and inherent latency in data transmission pipelines [8]. More critically, this model requires users to engage in a multi-step interaction sequence—retrieving the phone, unlocking the screen, locating and launching the application, waiting for data synchronization, and finally interpreting the output. This workflow introduces substantial human–computer interaction (HCI) friction, effectively negating the possibility of passive, unobtrusive, and “glanceable” monitoring that is essential for seamless, continuous health tracking [9].

2.2 Edge-Computing Reconfiguration in Standalone Display-Integrated Wearable Devices

The standalone architecture internalizes the entire pipeline of data acquisition, processing, and visualization within the physical enclosure of the wearable device itself [7]. Under an edge-computing paradigm, the local microcontroller (e.g., the STM32F103C8 employed in this implementation) communicates directly with the MAX30100 PPG sensor via a high-speed I^2C interface, managing on-device data structures such as circular buffers for heart rate variability (HRV) analysis (e.g., real-time computation of SDNN based on the most recent sequence of inter-beat intervals). All computational steps associated with the dynamic perturbation–based inference model are executed locally and continuously.

A defining characteristic of this architecture is that the inferred glycemic state, along with its upstream physiological drivers, is rendered instantaneously to the user via an integrated low-power OLED display [3]. Although the standalone device may optionally retain wireless communication modules (e.g., Wi-Fi or BLE) for asynchronous data synchronization—such as batch uploading to electronic health record (EHR) systems or cloud platforms during idle periods (e.g., overnight charging)—its core functionalities, including monitoring, inference, and anomaly detection, operate entirely autonomously, without reliance on external computational resources or persistent network connectivity [3].

2.3 Quantitative and Qualitative Comparison of Architectural Attributes

To systematically delineate the engineering and clinical trade-offs between these two paradigms, **Table. 1.** provides a comprehensive comparative analysis across key performance metrics.

Table 1
Comparison of wearable monitoring architectures.

Dimension	Smartphone-Dependent Architecture	Standalone Architecture
System Dependency	high; requires persistent Bluetooth connection	low; operates autonomously
Data Processing Hierarchy	smartphone/cloud-base processing [10]	On-device MCU-based edge computing [2]
Main power source Sources	Continuous BLE data transmission [6]	OLED display local computation [11]
System Latency	higher; affected by wireless transmission and processing [12]	lower; local sensing, inference, and display [12]
User interaction	multi-step app-based interaction [9]	Glanceable wrist-based feedback [9]
Privacy and Data Security	raw data exposed during wireless transmission	raw physiological remain on-device
Clinical Adherence	susceptible to app fatigue and disconnection [13]	improved engagement through immediate feedback

3. Hardware Optimization: Latency Reduction in Edge Computing and Power Consumption Trade-offs

For continuous physiological monitoring systems, deploying a computationally intensive systems physiology framework onto resource-constrained standalone wearable devices necessitates a precise balance among microcontroller processing capacity, display illumination demands, and battery

endurance limits. Achieving this balance requires a tightly integrated co-design strategy spanning both hardware and algorithmic domains.

3.1 Edge Computing–Driven Reshaping of System Latency and Processing Efficiency

The neurometabolic framework for glucose inference is inherently a highly dynamic model. Many physiological parameters—such as rapid fluctuations in autonomic nervous system activity associated with acute psychophysiological stress (manifested as sharp increases in resting heart rate and abrupt shifts in frequency-domain HRV metrics), or hypoxic stress indicative of emerging insulin resistance (reflected by transient desaturation events in SpO_2)—require continuous, high-frequency monitoring. In conventional smartphone-dependent architectures, the continuous transmission of raw PPG waveform data at sampling rates up to 100 Hz via BLE for downstream processing not only saturates limited wireless bandwidth but also leads to accelerated battery depletion in both the wearable device and the host smartphone [3].

By directly deploying the inference model onto an embedded STM32 microcontroller, the system architecture is effectively reconfigured into an edge-computing paradigm [3]. In this framework, data filtering, feature extraction, anomaly detection, and metabolic state inference are all executed locally at the device node [14]. Under comparable sensing and inference workloads, prior edge-enabled medical Internet of Things (IoT) studies have reported substantial reductions in end-to-end data transmission and processing latency compared with cloud-based or tethered architectures [15]. For example, one edge-based implementation achieved an average end-to-end latency of approximately 37.8 ms, whereas the corresponding cloud- or smartphone-dependent processing pipeline exhibited an average latency of approximately 109.6 ms [12]. The latency advantage of local edge processing is illustrated in Fig. 3. By removing continuous BLE transmission and external smartphone-side computation from the real-time inference pathway, the standalone system achieves substantially lower end-to-end latency.

Such near-instantaneous processing is critical for physiologically grounded inference models. For example, autonomic responses to acute stress—such as catecholamine surges driving hepatic glycogenolysis—manifest rapidly within the cardiovascular system. On-device edge computation ensures that model correction terms (e.g., autonomic response coefficients and hypoxic stress modifiers) are evaluated continuously and without interruption, even in the absence of cellular or Wi-Fi connectivity. Furthermore, the edge microcontroller effectively compresses millions of high-frequency raw pulse waveform data points into low-frequency summary variables (e.g., minute-level glucose estimates and stress indices), substantially reducing the volume of data requiring storage or transmission. This not only optimizes onboard memory utilization but also minimizes downstream communication energy consumption [16].

3.2 Power Consumption Trade-off: OLED Display versus Bluetooth Low Energy (BLE) Transmission

A primary criticism of standalone wearable architectures concerns the perceived energy burden introduced by integrated displays. However, recent advances in display material science, coupled with intelligent interface design, have fundamentally reshaped this energy trade-off.

Conventional liquid crystal displays (LCDs) require a continuously active backlight layer, resulting in substantial and largely invariant power consumption regardless of displayed content. In contrast, organic light-emitting diode (OLED) technology relies on electroluminescent organic films, where each pixel emits light independently. Crucially, OLED pixels can be completely deactivated when rendering black, achieving so-called “true black” and effectively zero power consumption in dark regions.

For standalone health monitoring devices, this property enables UI/UX optimization through deeply customized dark-mode interfaces. In such configurations, only a minimal subset of pixels is illuminated to display essential information—such as inferred glucose levels, heart rate, or trend indicators—while the majority of the display remains unpowered. Quantitative studies of OLED-based wearable interfaces indicate that display power consumption is strongly dependent on luminance, active pixel ratio, and interface color scheme. Therefore, dark-mode rendering and sparse information layouts can substantially reduce display-related energy consumption by deactivating large portions of the OLED pixel matrix.

When compared against the power budget of smartphone-dependent systems, the substantial energy cost of continuous BLE transmission must be explicitly considered. This effect is particularly relevant when raw or minimally processed PPG waveforms are streamed continuously at high sampling rates, because the radio module must remain active frequently enough to satisfy latency and packet-loss constraints. Maintaining a stable connection with minimal packet loss and acceptable latency requires frequent advertising intervals and short connection windows, preventing the radio frequency (RF) module from entering deep sleep states [17].

Empirical studies demonstrate that standalone devices equipped with OLED displays can exploit event-driven activation (e.g., wrist-raise detection via inertial sensors) to illuminate the screen only transiently, while keeping the BLE module disabled for the majority of operational time. This architecture yields a highly competitive overall energy footprint and, in many continuous monitoring scenarios, can surpass the battery longevity of tethered systems that expend significant energy maintaining persistent wireless links [18].

The power-consumption comparison is shown in Fig. 4 Although the standalone system includes an OLED display, its reduced dependence on continuous BLE communication can lower the overall energy burden relative to smartphone-dependent architectures.

3.3 Low-Level Microcontroller Optimization Based on STM32 Architecture

The selection of the STM32F103C8 microcontroller (ARM Cortex-M3 core) as the edge-computing platform provides an optimal balance between computational capability and energy efficiency. This architecture offers rich peripheral interfaces and highly optimized low-power management modes, including sleep, stop, and standby states [3].

To maximize battery life in standalone wearable systems, a strict time-division multiplexing (TDM) scheduling strategy can be implemented at the firmware level. Within each operational cycle, the system briefly awakens the processor, drives the MAX30100 sensor's red and infrared LEDs, and transfers analog-to-digital converted PPG samples into memory via direct memory access (DMA), allowing the CPU core to remain in a low-power state during acquisition. The processor is only activated during designated computational windows to execute HRV feature extraction (e.g., SDNN calculation) and update the OLED frame buffer [3].

A representative task-scheduling strategy for the STM32-based standalone system is shown in Fig. 5. The MCU alternates between sleep and active states, while PPG sampling, preprocessing, inference, OLED updating, and optional BLE synchronization are temporally separated to reduce average power consumption.

Further optimization can be achieved through dynamic voltage scaling (DVS). During metabolically stable states—characterized by steady heart rate and absence of hypoxic or stress-related perturbations—the microcontroller operates at reduced voltage and clock frequency. Conversely, when the system detects complex physiological anomalies (e.g., nocturnal hypoxemia accompanied by compensatory tachycardia), the supply voltage and processing frequency are dynamically increased to ensure real-time computational responsiveness [19].

This deep integration of hardware and algorithmic optimization enables standalone devices to sustain continuous background monitoring of the ANS–glucose axis over multiple days on a single charge, achieving reliability and endurance that rival—or exceed—traditional architectures burdened by persistent wireless communication overhead.

To demonstrate the feasibility of this standalone architecture, a breadboard-based prototype was implemented, as shown in Fig. 6. The prototype integrates the STM32 microcontroller, OLED display, PPG sensor module, and wired interconnections, providing a preliminary hardware basis for local sensing, computation, and real-time visual feedback.

4. Human Factors, Usability, and Long-Term Patient Adherence

The transition from app-dependent wearables to standalone, display-integrated devices represents not merely an engineering evolution, but a fundamental reconfiguration of the human–computer interaction (HCI) paradigm. In the clinical context of chronic disease management, sustained patient engagement is the primary determinant of therapeutic success, making human factors engineering a critical design consideration.

4.1 Cognitive Friction and the Psychology of “Glanceability”

Smartphone-dependent monitoring systems suffer from a systemic design flaw: high interaction friction. To access metabolic information, users must perform a multi-step sequence—locating the smartphone, unlocking it, launching the application, waiting for synchronization, and interpreting data within complex dashboards. This workflow imposes substantial cognitive load, transforming passive monitoring into an intentional and disruptive task.

Such high-friction interactions inevitably lead to “app fatigue.” Behavioral studies indicate that when the effort required to access health data exceeds its perceived immediate benefit, users progressively disengage, ultimately abandoning the monitoring system altogether [20].

Standalone wearable architectures fundamentally eliminate this friction through the principle of glanceability. By integrating an OLED display directly onto the wrist-worn device, micro-interactions become seamless and intuitive. A simple wrist rotation, detected by inertial sensors (e.g., MPU6050), triggers instant display activation, presenting key physiological metrics within sub-second latency [21].

The difference in interaction burden is summarized in Fig. 7. Smartphone-dependent systems require users to retrieve the phone, unlock the device, open the application, wait for synchronization, and then interpret the result. In contrast, the standalone device supports a one-step glanceable interaction, allowing users to access key physiological information immediately.

This zero-friction access enables passive, low-attention information acquisition without interrupting daily activities. Moreover, according to the graphic superiority effect, visual cues—such as color-coded arrows or dynamic icons—are cognitively more efficient and memorable than textual or numerical data, significantly enhancing user comprehension of physiological trends [22].

4.2 Evidence and Limitations for Long-Term Adherence

Clinical evidence strongly supports the superiority of standalone wearable devices in sustaining long-term patient adherence. Comparative systematic reviews consistently demonstrate that standalone devices outperform app-based systems in maintaining continuous usage and data acquisition compliance [13].

Available evidence from wearable health-monitoring and mobile health studies suggests that interaction burden, device accessibility, and feedback immediacy are important determinants of long-term adherence [13,20,23]. Smartphone-dependent systems may suffer from reduced engagement over time because users must repeatedly access a companion application, maintain wireless pairing, and troubleshoot synchronization failures. In contrast, standalone wearable devices provide more immediate access to health information and may therefore support more sustained engagement, particularly in continuous monitoring scenarios. However, direct long-term clinical comparisons between standalone

glucose-inference wearables and smartphone-dependent architectures remain limited, and further prospective studies are required to quantify adherence benefits in diabetes-specific populations.

The persistent physical presence of a wrist-worn device, combined with immediate access to feedback, acts as a continuous low-intensity behavioral trigger. This positive reinforcement loop promotes habitual engagement and transforms the device from a passive data collector into an active “health companion” [23].

4.3 Digital Literacy Barriers and Inclusive Design for Aging Populations

Chronic conditions such as type 2 diabetes (T2DM) disproportionately affect older populations, for whom digital literacy often represents a significant barrier. Smartphone-based mHealth ecosystems implicitly assume user proficiency in device pairing, troubleshooting connectivity issues, navigating operating systems, managing application updates, and handling cloud-based credentials [24].

Standalone wearable devices effectively bypass these barriers by offering a self-contained, plug-and-play ecosystem. No smartphone pairing or configuration is required, significantly lowering the technological entry threshold.

Qualitative meta-analyses of older adults’ interactions with wearable technologies reveal that, despite initial apprehension, this demographic demonstrates high acceptance when devices provide immediate, tangible benefits and present physiological feedback directly and clearly to the user [25].

By minimizing interaction complexity and cognitive burden, standalone architectures reduce the risk of abandonment due to technological frustration. This inclusive design approach not only enhances user experience but also broadens accessibility to advanced remote monitoring technologies among digitally underserved populations [26].

5. Clinical Implications for Non-Invasive Closed-Loop Diabetes Management

Integrating systems physiology–based inference models into standalone wearable devices fundamentally redefines their clinical value proposition. By shifting from delayed, retrospective data review to real-time, context-aware feedback, these systems empower patients to transition from passive recipients of care to active participants in metabolic self-management.

This clinical mechanism can be conceptualized as a closed-loop feedback process, as shown in Fig. 8. Physiological signals are acquired and processed locally, converted into immediate feedback, and then translated into behavioral responses that may support proactive glucose regulation.

5.1 Closed-Loop Feedback and Proactive Behavioral Support

The core innovation of the proposed framework lies in its focus on upstream regulatory drivers of glucose homeostasis—namely ANS tone, hypoxic stress (mediated via HIF-1α pathways), and circadian dynamics—rather than solely on glucose concentration itself.

Because central metabolic regulatory signals precede measurable changes in blood glucose, real-time decoding of HRV and SpO_2 provides an inherently predictive window into impending glycemic excursions.

Standalone devices enable this predictive capability to translate into actionable clinical outcomes through instantaneous feedback. For example, detection of sympathetic activation—characterized by reduced high-frequency HRV power, elevated LF/HF ratio, and increased heart rate—can trigger immediate alerts via haptic feedback and visual cues on the OLED display [27].

This zero-latency feedback enables preemptive behavioral interventions, such as:

Controlled breathing to activate parasympathetic pathways

Light physical activity to enhance glucose uptake via AMPK-mediated GLUT4 translocation

Such real-time interventions are clinically relevant because glycemic control is commonly evaluated using metrics such as HbA1c, time-in-range (TIR), and glycemic variability [28]. However, whether standalone non-invasive glucose-inference wearables can directly improve these outcomes remains to be demonstrated through prospective clinical studies.

5.2 Contextual Learning and Behavioral Reinforcement

Traditional monitoring methods provide decontextualized numerical outputs, limiting patient insight into causal relationships. In contrast, standalone devices equipped with multiparametric inference models transform data into contextualized metabolic narratives.

For instance, simultaneous visualization of nocturnal hypoxic events and subsequent morning glucose elevation enables patients to recognize sleep-disordered breathing as a contributing factor to the “dawn phenomenon,” rather than attributing it to dietary causes.

This immediate coupling of physiological signals with outcomes facilitates operant conditioning, wherein reduced feedback latency strengthens behavioral learning and retention [27]. Over time, patients develop a refined ability to map subjective experiences and environmental triggers onto their metabolic responses, enhancing self-efficacy—a key determinant of long-term adherence and disease control [30].

6. System Security, Limitations, and Future Directions

6.1 Privacy and Security Considerations

Edge computing architectures offer inherent security benefits by processing sensitive physiological data locally. Unlike smartphone-dependent systems that transmit raw biometric signals over wireless networks, standalone devices confine raw data within the device, transmitting only abstracted and encrypted summaries when necessary.

This data-minimization approach can reduce the exposure surface of sensitive physiological data by limiting continuous wireless transmission of raw signals. However, compliance with regulatory frameworks such as GDPR and HIPAA would still require additional safeguards, including encryption, access control, consent management, auditability, and clearly defined data-retention policies.

6.2 Physical Constraints and Hybrid Architecture Design

Despite their advantages, standalone devices are constrained by limited display real estate, restricting their ability to present long-term, high-dimensional data visualizations. Consequently, a hybrid edge-primary, cloud-secondary architecture may provide a more balanced design.

In this model:

The wearable device performs all real-time monitoring and inference

Wireless communication is used intermittently for batch data synchronization

Cloud platforms support retrospective analysis and clinical review

6.3 Future Hardware and Ecosystem Expansion

Emerging technologies such as MicroLED displays and ultra-low-power neural processing units (NPUs) will further enhance efficiency and enable on-device deployment of advanced deep learning models.

Additionally, standalone architectures provide standardized data acquisition environments, reducing variability in large-scale clinical studies and improving the reliability of translational research.

7. Conclusions

This study compared smartphone-dependent and standalone display-integrated wearable architectures for the deployment of non-invasive glucose inference models based on systems physiology. The comparison focused on system dependency, data-processing hierarchy, latency, power consumption, privacy, human–machine interaction, and long-term adherence.

The analysis indicates that standalone wearable architectures provide several potential advantages for real-time physiological inference. By executing sensing, feature extraction, and glucose-state estimation locally on low-power microcontrollers, standalone devices can reduce dependence on continuous Bluetooth transmission and external smartphone-side processing. Integrated OLED displays further

enable low-friction, glanceable feedback, which may support more sustained user engagement in continuous monitoring scenarios.

However, the advantages of standalone architectures depend on careful hardware–software co-design. OLED power consumption, microcontroller workload, sampling frequency, and wireless synchronization strategy must be jointly optimized to maintain acceptable battery life. In addition, although standalone systems may improve immediacy, autonomy, and privacy, their clinical impact on glycemic outcomes such as HbA1c, time-in-range, and glycemic variability remains to be validated in prospective diabetes-specific studies.

Overall, edge-enabled standalone display wearables represent a promising architecture for future non-invasive glucose inference and proactive metabolic self-management. Future work should include prototype-level power profiling, latency benchmarking, user-adherence testing, and clinical validation against established continuous glucose monitoring systems.

Declarations

Ethics statement

This study involved secondary analysis of de-identified data obtained from existing neuroimaging datasets. No new participants were recruited for the present study. Ethical approval and informed consent were obtained by the original investigators at the participating sites in accordance with the protocols reported for the ABIDE and SRPBS datasets [4,5]. The present study used only de-identified data released for research purposes under the corresponding data-use terms.

Data availability

The ABIDE data analyzed in this study are available through the Autism Brain Imaging Data Exchange and the Preprocessed Connectomes Project. The SRPBS data are available through the Strategic Research Program for Brain Sciences database subject to the corresponding access procedures and data-use terms. Redistribution of processed participant-level data is subject to the conditions specified by the original data providers.

Code availability

The code used for model training, evaluation, explanation analysis, and visualization is available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Mingyang Huang: Conceptualization, Supervision, Project administration, Validation, Writing – review and editing.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT and Codex (OpenAI) to assist with language editing, manuscript organization, and formatting. After using these tools, the authors reviewed and edited the content as needed, verified the scientific content, numerical results, and references, and take full responsibility for the content of the publication.

Acknowledgements

The authors thank the investigators and participants who contributed to the ABIDE and SRPBS data resources.

References

1. Marques M, Delgado-Gomes V, Januário F, Lopes C, Jardim-Goncalves R, Agostinho C (2025) The B-Health Box: A Standards-Based Fog IoT Gateway for Interoperable Health and Wellbeing Data Collection. Sensors 25(23):7116
2. He Q, Xi Z, Feng Z, Teng Y, Ma L, Cai Y, Yu K (2025) Telemedicine monitoring system based on fog/edge computing: A survey. IEEE Trans Serv Comput 18(1):479–498
3. Li Z (2025) Design of a human health monitoring system based on STM32. Int J Mech Electr Eng 7(1):1–18
4. Krishnapriya G, Prema S (2026) Cost-effective IoT-based real-time vital sign monitoring: An affordable telehealth solution. Telehealth Med Today 10:611

5. Huberts AS, Long P, Porth AK, Fierens L, Carney NC, Koppert L, Kautzky-Willer A, de Rooij BH, Stamm T (2025) Tracking Chronic Diseases via Mobile Health Applications: Which User Experience Aspects Are Key? Healthcare (Basel, Switzerland), 13(24), 3272
6. Zheng C, Yong C, Wei Q, Qiao F (2025) Flexible Wearable Heart Rate Monitoring System and Low-Power Design: A Review. Sensors 25(16):4913
7. Wall C, Hetherington V, Godfrey A (2023) Beyond the clinic: the rise of wearables and smartphones in decentralising healthcare. NPJ Digit Med 6(1):219
8. Han S, Vasile DA, Kawsar F, Min C (2025) SecuWear: Secure data sharing between wearable devices. In Proceedings of the 2025 Workshop on Security and Privacy in Standardized IoT (SDIoTSec). Internet Society
9. Epstein DA, Blascheck T, Carpendale S, Dachselt R, Vermeulen J (2021) Challenges in everyday use of mobile visualizations. In: Dachselt R, Carpendale S (eds) Mobile data visualization. CRC, pp 1–26
10. Jin X, Li L, Dang F, Chen X, Liu Y (2022) A survey on edge computing for wearable technology. Digit Signal Proc 125:103146
11. Li D (2026) February 9). Optimizing OLED display performance in wearable devices: Power efficiency and image quality. AIVON
12. Istiaq Ahmed (2024) Deploying Low-Latency Edge AI in Medical IOT Networks: A Case Study of Secure Real-Time Patient Monitoring Systems. Am J Sch Res Innov 3(02):337–374
13. Chauhan A, Pant P, Agarwal A, Saikia B (2026) Exploratory comparative review of wearable-based versus app-based behavioral monitoring tools: evidence synthesis and hypothesis generation. Expert Review of Medical Devices
14. Elfouly T, Alouani A (2025) A Comprehensive Survey on Wearable Computing for Mental and Physical Health Monitoring. Electronics 14(17):3443
15. Kanungo P (2025) Edge computing in healthcare: Real-time patient monitoring systems. World J Adv Eng Technol Sci 15(1):1–9
16. Hartmann M, Hashmi US, Imran A (2019) Edge computing in smart health care systems: Review, challenges, and research directions. Trans Emerg Telecommunications Technol, 30(9), e3710
17. Bulić P, Kojek G, Biasizzo A (2019) Data Transmission Efficiency in Bluetooth Low Energy Versions. Sensors 19(17):3746
18. Díaz-Jiménez D, López Ruiz JL, Cuevas-Martínez JC, Torres-Sospedra J, Navarro EA, Espinilla Estévez M (2025) BLE-Based Custom Devices for Indoor Positioning in Ambient Assisted Living Systems: Design and Prototyping. Sensors (Basel, Switzerland), 25(20), 6499
19. Liu Q, Tian J (2025) Research on low-power power management technology in wearable electronic devices. In Fourth International Conference on Electronics Technology and Artificial Intelligence (ETAI 2025) (Vol. 13692, p. 136920S). SPIE
20. Keogh A, Dorn JF, Walsh L, Calvo F, Caulfield B (2020) Comparing the usability and acceptability of wearable sensors among older Irish adults in a real-world context: Observational study. JMIR

mHealth uHealth, 8(4), e15704

21. Volsa S, Batinic B, Stieger S (2022) Self-Reports in the Field Using Smartwatches: An Open-Source Firmware Solution. Sensors, 22(5), 1980
22. Jin W, Deng W (2025) Research on the design of smartwatch health information visualization presentation under different motion scenarios. Sci Rep 15(1):26646
23. Al Mahmud A, Joachim S, Jayaraman PP, Learmonth C, Tyagi S, Forkan ARM, Shuakat M, Wickramasinghe N, Wheeler J, Best S, Trainer A (2026) Digital Health Interventions to Support Chronic Disease Management: Systematic Scoping Review, vol 14. JMIR mHealth and uHealth, p e63742
24. Hayford AL, George J (2024) Exploring the experiences of wearable health monitoring devices among the aging population: A qualitative systematic review. Open Access Libr J 11(8):1–14
25. Keogh A, Dorn JF, Walsh L, Calvo F, Caulfield B (2020) Comparing the Usability and Acceptability of Wearable Sensors Among Older Irish Adults in a Real-World Context: Observational Study. JMIR mHealth uHealth, 8(4), e15704
26. Moses JC, Adibi S, Islam S, Wickramasinghe SM, N., Nguyen L (2021) Application of Smartphone Technologies in Disease Monitoring. Syst Rev Healthc 9(7):889
27. Raghunath S, Pfeifer JM, Ulloa A, Haggerty CM (2026) The impact of real-time feedback from wearables on patient adherence and outcomes. ResearchGate
28. American Diabetes Association Professional Practice Committee (2023) 7. Diabetes technology: Standards of care in diabetes—2023. Diabetes Care, 46(Supplement_1), S111–S127
29. Huberts AS, Long P, Porth AK, Fierens L, Carney NC, Koppert L, Kautzky-Willer A, de Rooij BH, Stamm T (2025) Tracking Chronic Diseases via Mobile Health Applications: Which User Experience Aspects Are Key? Healthcare (Basel, Switzerland), 13(24), 3272
30. Mishra R, Kumar S (2026) Digital health interventions for medication adherence in chronic diseases: A systematic review of real-world evidence. Patient Prefer Adherence 20:604005

Figures

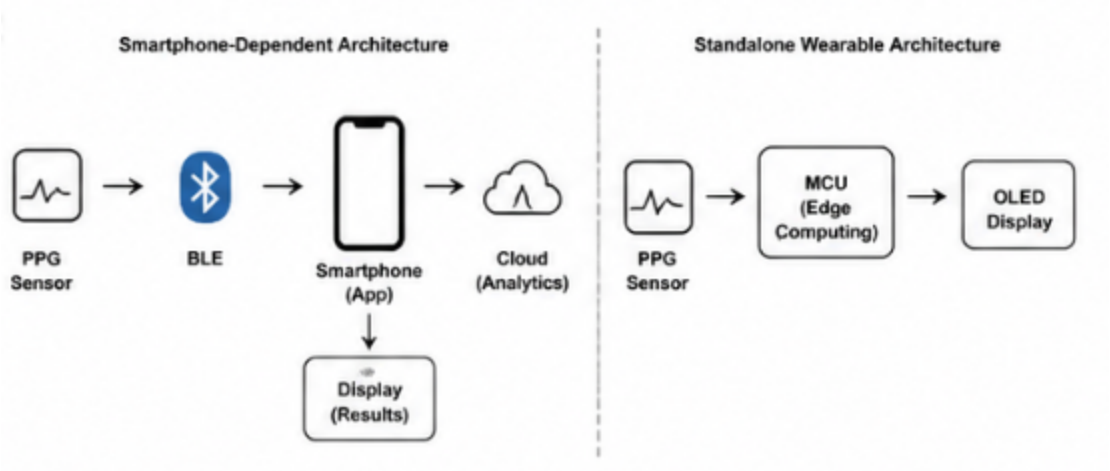


Figure 1

Comparison of smartphone-dependent and standalone wearable architectures for non-invasive glucose inference. The smartphone-dependent system relies on BLE transmission and external mobile processing, whereas the standalone system integrates sensing, edge computation, and OLED-based feedback within the wearable device.

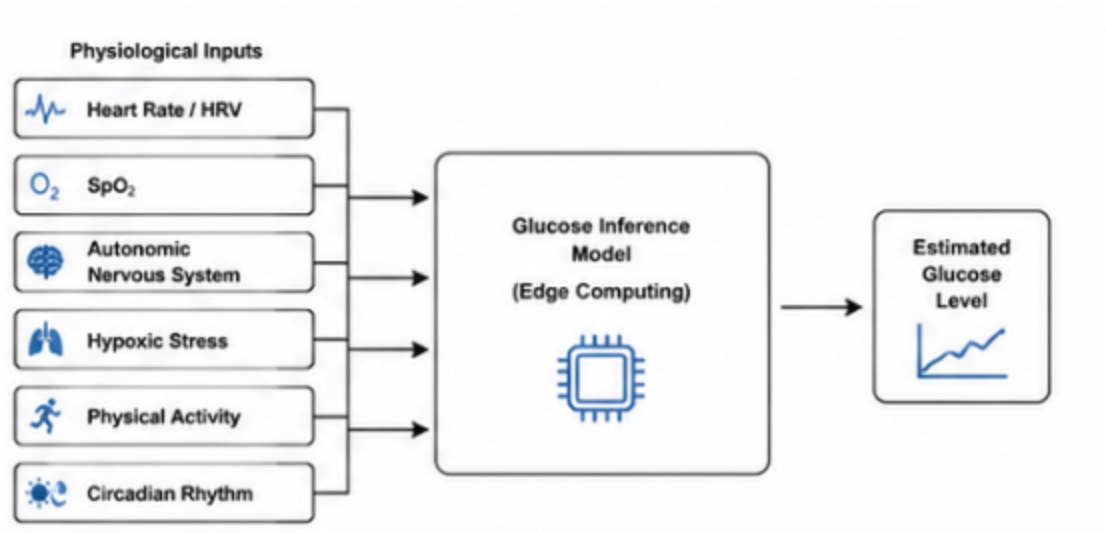


Figure 2

Systems physiology framework for non-invasive glucose inference. Multiple physiological inputs, including HR/HRV, SpO_2, autonomic tone, hypoxic stress, physical activity, and circadian rhythm, are integrated by an edge-based inference model to estimate glucose state.

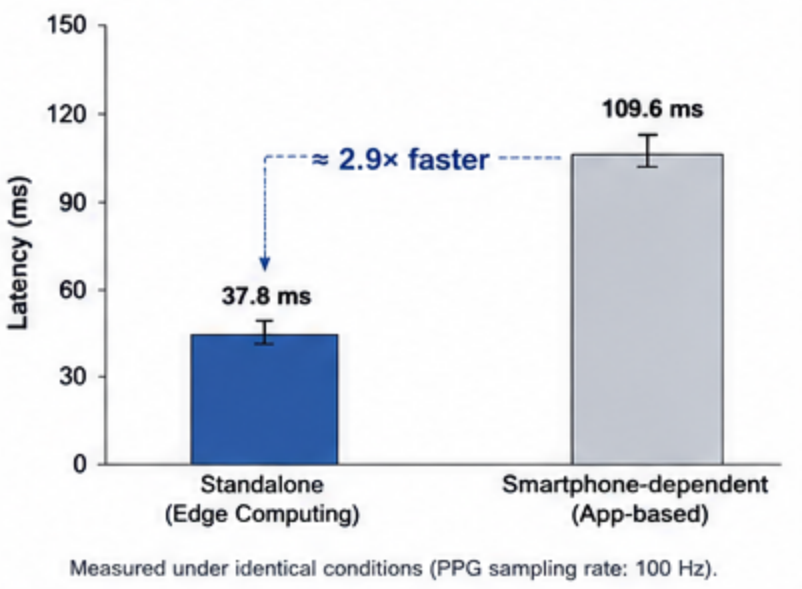


Figure 3

End-to-end latency comparison between standalone edge-computing and smartphone-dependent processing architectures. The standalone architecture reduces processing delay by performing inference locally on the wearable device.

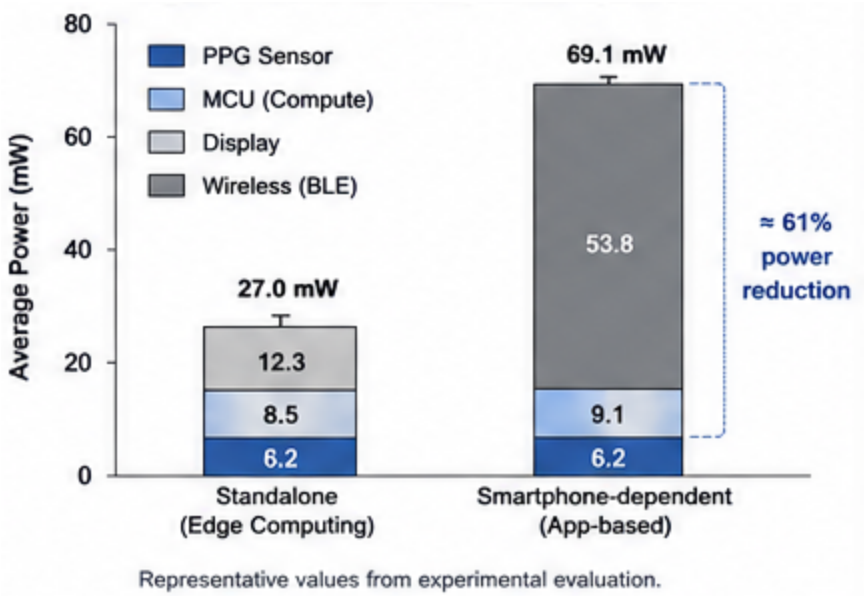


Figure 4

Power consumption comparison between standalone and smartphone-dependent wearable systems. The standalone system includes OLED display power consumption, whereas the smartphone-dependent architecture is dominated by continuous BLE-related communication costs.

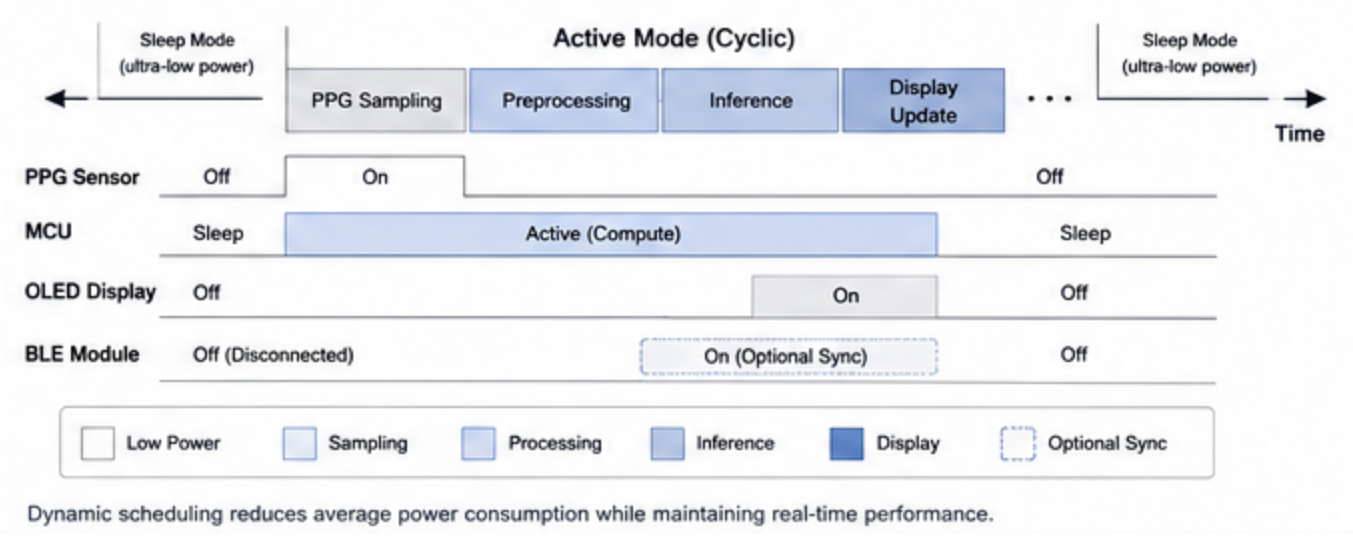


Figure 5

MCU power management and task scheduling strategy for the standalone wearable device. Time-division multiplexing separates sensing, preprocessing, inference, display updating, and optional wireless synchronization to improve energy efficiency.

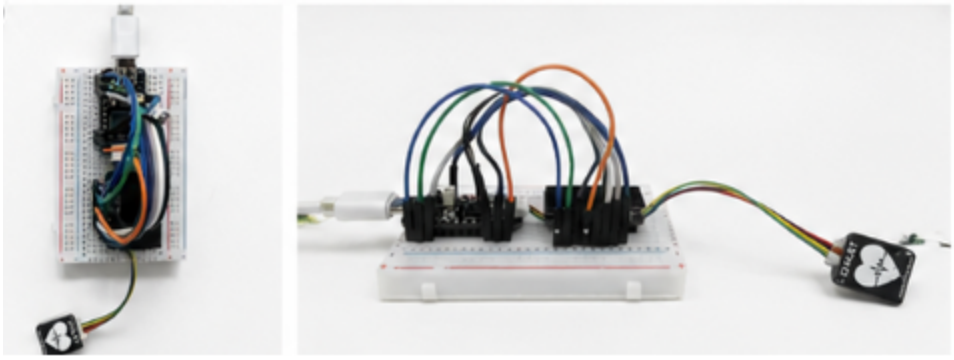


Figure 6

Prototype implementation of the standalone wearable sensing node. The breadboard-based prototype integrates an STM32 microcontroller, OLED display, PPG sensing module, power connection, and jumper wiring for preliminary validation of the proposed hardware architecture.

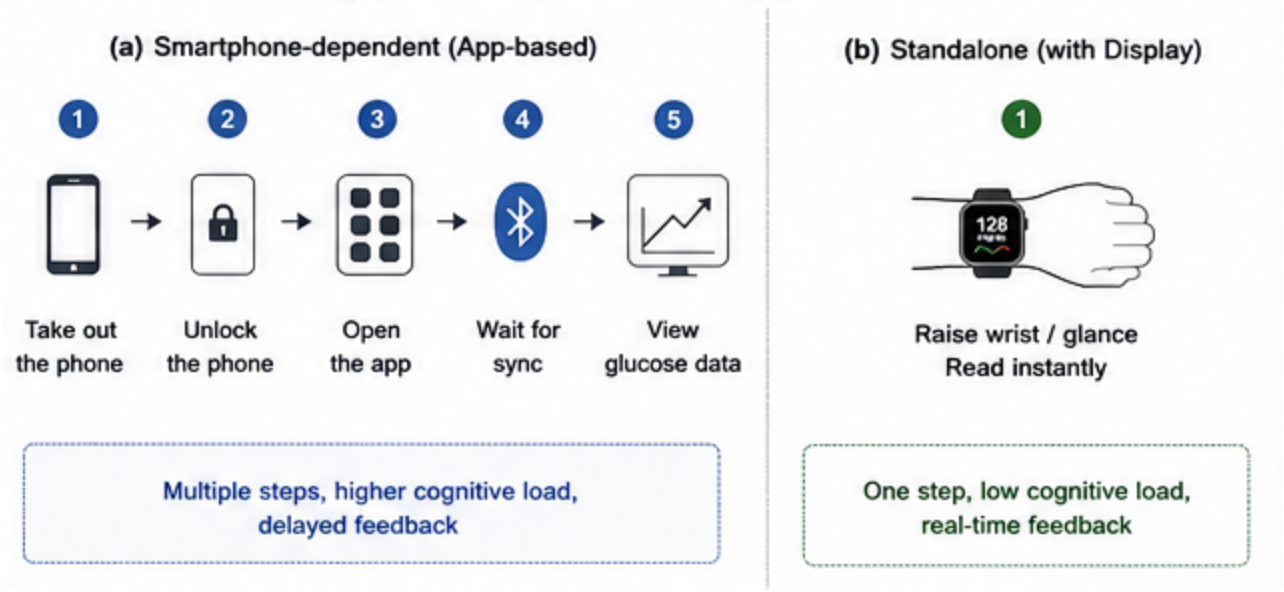


Figure 7

Interaction workflow comparison between smartphone-dependent and standalone systems.

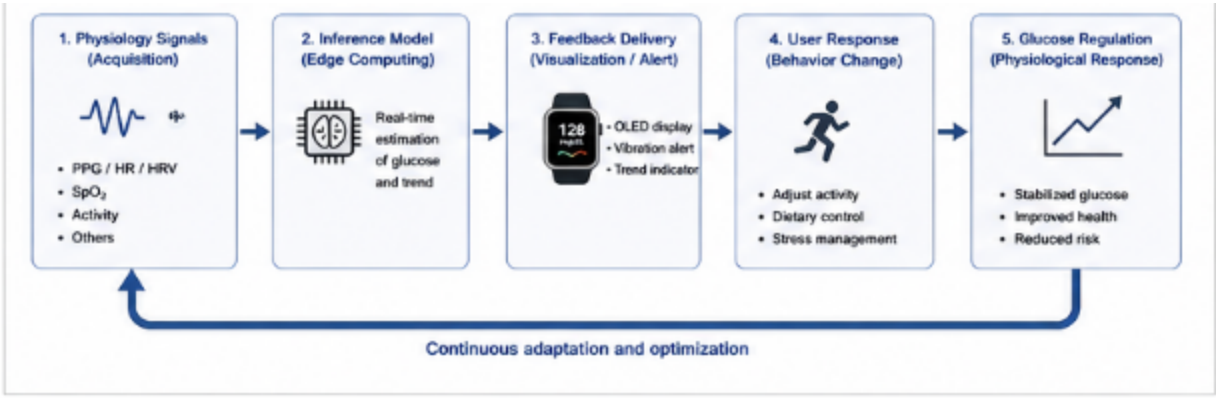


Figure 8

Closed-loop feedback mechanism for proactive glucose regulation. Locally acquired physiological signals are processed by the on-device inference model, converted into immediate visual or haptic feedback, and used to support behavioral adjustment for metabolic regulation.