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CONTACTLESS AND CONTACT-BASED SMARTPHONE PHOTOPLETHYSMOGRAPHY AS A MULTI-PARAMETER CARDIOMETABOLIC HOME SCREEN: BEYOND ATRIAL FIBRILLATION TOWARD BLOOD PRESSURE AND DYSGLYCEMIA ESTIMATION

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ABSTRACT

Smartphone photoplethysmography (PPG) demonstrates a stark maturity gradient across cardiometabolic parameters. For atrial fibrillation (AF) detection, meta-analytic evidence from 14 studies (n = 5,090) shows pooled sensitivity of 96% (95% CI 93 to 97%) and specificity of 97% (95% CI 95 to 98%), with individual validation studies reporting sensitivity up to 99.7% and specificity up to 99.7% using machine learning algorithms in ambulatory settings. AF detection performance is consistent across multiple smartphone devices, robust in unsupervised home use, and clinically impactful: population screening increased oral anticoagulation uptake from 56% to 74%, and digital post-ablation monitoring detected arrhythmia recurrence at more than double the rate of conventional ECG follow-up (38.5% versus 17.7%, OR 3.4). Signal quality rates for PPG (89 to 97%) were comparable to or exceeded those for single-lead ECG. Blood pressure (BP) estimation, by contrast, remains unreliable for population-level screening. Of 18 studies evaluated, only two clearly passed established AAMI/ESH/ISO validation protocols, both relying on per-individual calibration against a reference measurement. The two largest prospective trials (n = 965 and n = 62) explicitly failed validation standards, and contactless remote PPG showed critically low sensitivity for hypertension detection (systolic BP sensitivity 0.04) in a diverse-skinned field population. Diastolic BP was consistently estimated more accurately than systolic BP across approaches. Dysglycemia detection rests on a single large study demonstrating moderate screening discrimination (AUC 0.74 to 0.77) using a deep neural network applied to PPG waveforms, with the score independently associated with HbA1c. The evidence supports smartphone PPG as a clinically ready tool for AF detection and monitoring, particularly in populations aged over 65, but BP estimation requires individual calibration and cannot yet substitute for cuff-based measurement, and dysglycemia screening remains investigational.

KEYWORDS

Photoplethysmography, Smartphone Health, Atrial Fibrillation Screening, Cuffless Blood Pressure, Digital Biomarkers, Remote Monitoring

CITATION

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1. Introduction

Cardiometabolic disease, encompassing cardiac arrhythmia, hypertension, and dysglycemia, accounts for a substantial share of the global burden of morbidity and mortality, and much of that burden is attributable to conditions that remain undiagnosed until a clinical event occurs. Atrial fibrillation is frequently asymptomatic yet markedly elevates stroke risk; hypertension is common and often poorly controlled; and type 2 diabetes is regularly preceded by a prolonged, undetected prediabetic phase. Early, low-cost, and scalable screening for these conditions therefore represents a major public-health opportunity.

Photoplethysmography is an optical technique that detects pulsatile changes in blood volume in the microvasculature, and modern smartphones contain the camera, light source, and computational capacity required to acquire and analyze a PPG signal without dedicated medical hardware. This has prompted intense interest in the smartphone as a universal, already-distributed screening platform capable of estimating several cardiometabolic parameters from a single brief recording, either through contact-based methods in which a fingertip covers the camera, or through contactless remote PPG that extracts the pulse signal from facial video.

The appeal of a single multi-parameter home screen is considerable, but the underlying physiological signals differ greatly in how directly they are encoded in the PPG waveform, and the regulatory and validation requirements differ accordingly. This review synthesizes the evidence for smartphone PPG across three cardiometabolic targets, atrial fibrillation detection, blood pressure estimation, and dysglycemia screening, with three objectives: to characterize diagnostic and screening performance for each parameter against reference standards; to explain the sources of heterogeneity in reported accuracy; and to assess the clinical

feasibility of, and barriers to, multi-parameter cardiometabolic home screening. The central thesis is that smartphone PPG exhibits a steep maturity gradient, being clinically ready for AF detection while remaining unreliable for generalized BP estimation and investigational for dysglycemia, so that a single-device multi-parameter home screen is not yet achievable beyond rhythm assessment.

2. Methodology

A structured literature search was performed across the MEDLINE/PubMed, Scopus, and Web of Science databases, supplemented by manual searching of the reference lists of relevant articles and reviews to identify additional studies not captured by the database queries. Search terms combined controlled vocabulary and free-text keywords relating to the technology, parameters, and validation of interest, including variants of "photoplethysmography," "smartphone," "mobile health," "atrial fibrillation," "blood pressure," "glucose," "diabetes," and "validation," linked with the Boolean operators AND and OR. No language restriction was applied at the search stage, and the search covered publications up to 2026.

All retrieved records were screened manually against a common set of eligibility criteria, and a holistic judgment was made for each paper rather than applying the criteria mechanically. The inclusion criteria were:

- Smartphone PPG technology: the study investigates smartphone-based photoplethysmography for measuring cardiometabolic parameters.
- Cardiometabolic outcomes: the study measures at least one of atrial fibrillation detection, blood pressure estimation, or dysglycemia/glucose estimation.
- Reference standard validation: the study validates the smartphone PPG measurements against reference standard measurements.
- Human participants: the study was conducted in human participants rather than animals or in vitro.
- Study design: the study is original research, including randomized controlled trials, observational, cross-sectional, cohort, case-control, or validation studies.
- Smartphone integration: the study uses smartphone-integrated PPG technology rather than only traditional PPG devices without smartphone integration.

Records were excluded when they fell outside the scope of the review on closer reading. After screening, 63 sources were retained for data extraction. Data were extracted manually by the author using a predefined extraction form covering PPG technology type, cardiometabolic parameters, reference standards, diagnostic performance, study population, setting and protocol, technical limitations, and clinical feasibility. Several sources represented duplicate or companion publications of the same trial and are noted as such where relevant. Owing to substantial heterogeneity in study designs, devices, target parameters, and validation protocols, a narrative synthesis was undertaken rather than a single pooled meta-analysis.

3. Results

3.1. Characteristics of Included Studies

A total of 63 sources were included, spanning 2012 to 2026. The included studies were predominantly primary diagnostic accuracy or validation studies, supplemented by two systematic reviews with meta-analysis, one narrative review, one editorial, and several randomized controlled trials. Full texts were available for 22 of the 63 sources. Among the primary studies, 44 addressed AF or arrhythmia detection, 18 addressed blood pressure estimation, and one addressed dysglycemia detection. A small number of studies measured multiple parameters including heart rate, respiratory rate, and oxygen saturation. The majority of AF studies used a contact-based finger-on-camera approach, while BP and multi-parameter studies were split between contact-based and contactless remote PPG (rPPG) methods. Sample sizes ranged from 3 participants in an early-stage BP usability study to 187,912 in the HUAWEI Heart Study and over 60,000 in the Belgian FibriCheck population screening. Table 1 summarizes the principal characteristics of the larger and full-text studies.

Table 1. Selected characteristics of included studies (illustrative sample of the 63 sources).

Study	Study type	Parameter	PPG approach	Technology	Sample
Guo et al., 2019	Screening cohort	AF detection	Contact (wrist)	Huawei app	187,912
Gruwez et al., 2023	Population screening	AF screening	Contact (finger)	FibriCheck	60,629
Proesmans et al., 2020	Population screening	AF screening	Smartphone PPG	Not specified	62,821
Chan et al., 2016	Diagnostic accuracy	AF detection	Camera-based	Cardiio Rhythm	1,013
Fernstad et al., 2024	Diagnostic validation	AF/AFL detection	Smartphone (iPhone 7)	CORAI Heart Monitor	280
Fernstad et al., 2025	ML algorithm validation	AF/AFL detection	Smartphone (iPhone 7)	CORAI Heart Monitor	460
Gruwez et al., 2024	Diagnostic validation	AF, heart rate	Contact (finger)	FibriCheck	50
Brasier et al., 2018	Two-centre validation	AF detection	Contact (iPhone 4S)	Preventicus	592
Sollee et al., 2025	Multicentre validation	AF detection	Smartphone (10 devices)	FibriCheck	236
Reichl et al., 2025	Multicentre RCT	AF screening	Camera-based	Not specified	1,021
Gruwez et al., 2025	Pragmatic RCT	AF/AFL (post-surgery)	Smartphone PPG	Not specified	450
Avram et al., 2020	DNN development	Diabetes detection	Contact (finger, iOS)	Azumio Instant HR	53,870+
Dörr et al., 2020	Validation (iPARR)	Systolic BP	Contact (finger)	Not specified	965
Eckstein et al., 2017	Prospective validation	Systolic BP	Contact (finger)	Not specified	1,000
Degott et al., 2021	AAMI/ESH/ISO validation	BP (SBP/DBP)	Contact (finger)	OptiBP	91
Sagirova et al., 2021	Cross-sectional validation	BP, AF	Contact (ECG+PPG case)	CardioQVARK	500
Holyoke et al., 2021	Validation (ESH-IP2)	BP (SBP/DBP)	Oximeter + smartphone	MediBeat	62
van Putten et al., 2024	Algorithm validation	BP, pulse rate	Contactless rPPG	Lifelight	Up to 2,000
Dasa & Davies, 2025	Multi-site field study	BP (hypertension)	Contactless rPPG (iPad)	Lifelight	306
Barbosa et al., 2025	Systematic review/MA	AF detection	Smartphone PPG	Multiple	5,090 (14 studies)
Gill et al., 2020	Systematic review/MA	AF detection	Smartphone PPG	Multiple	5,469 (17 studies)

3.2. Atrial Fibrillation Detection

AF detection represents the most mature application of smartphone PPG. Across the individual validation studies, sensitivity for AF detection ranged from 86.4% to 99.8%, and specificity ranged from 90.9% to 100%. Two meta-analyses reported pooled sensitivity of 93% (95% CI 90 to 96%) and 96% (95% CI 93 to 97%), and pooled specificity of 97%. Negative predictive values were consistently very high (generally above 99%), indicating that a negative PPG result reliably excludes AF. Positive predictive values were more variable (53 to 99.6%), largely driven by AF prevalence in the study populations. The machine learning algorithm validated by Fernstad et al. (2025) achieved the highest reported per-recording accuracy at 99.7% sensitivity and 99.7% specificity in the external validation cohort, though this was in a selected post-cardioversion population. Table 2 summarizes diagnostic accuracy across representative studies.

Table 2. Diagnostic accuracy for AF detection across representative studies.

Study	n	Sensitivity	Specificity	NPV	Setting
Guo et al., 2019	187,912	~100%	~99%	Not reported	Home
Chan et al., 2016	1,013	92.9%	97.7%	99.8%	Primary care
Fernstad et al., 2024 (AF only)	280	99.0%	99.7%	Not reported	Home
Fernstad et al., 2025 (AF only)	280	99.7%	99.7%	Not reported	Home
Gruwez et al., 2024	50	98.3%	99.9%	99.6%	Home
Proesmans et al., 2019	223	96%	97%	99.7%	Primary care
Brasier et al., 2018 (1 min)	592	89.9%	99.1%	Not reported	Hospital
Maitas et al., 2012a	81	99.8%	98.6%	Not reported	Hospital
Rozen et al., 2018	98	93.1%	90.9%	92.0%	Hospital
Fan et al., 2019	108	95.4%	99.7%	96.2%	Hospital
Szonyi et al., 2026 (FibriCheck)	206	89.0%	100.0%	Not reported	Hospital/outpatient
Sollee et al., 2025	236	96.3%	99.3%	99.8%	Hospital
Barbosa et al., 2025 (pooled)	5,090	96%	97%	99.7% (>65 y)	Mixed
Gill et al., 2020 (pooled)	2,714	93%	97%	77 to 100%	Mixed

Signal quality rates for PPG were comparable to or higher than those for single-lead ECG: 96.9% versus 95.1% in one ambulatory study, and 89.5% improving to 96.6% with repeated measurements in real-world AF monitoring. Studies across multiple smartphone devices confirmed that AF detection performance was device-independent, with no significant differences in sensitivity or specificity across 7 to 10 different iOS and Android models. The presence of atrial flutter consistently reduced sensitivity: one study reported a drop from 90.1% to 81.2% when atrial flutter was included, and another noted a decline from 99.0% (AF only) to 97.7% (AF plus flutter). Sensitivity was also reduced by darker skin tone and higher BMI in one multicenter validation, although this was mitigated by technician verification of recordings.

3.3. Clinical Effectiveness of AF Screening and Monitoring

Beyond diagnostic accuracy, several studies evaluated the clinical impact of PPG-based AF monitoring. In a population-based screening of 60,629 subjects in Belgium, AF was detected in 1.3%, with clinical confirmation leading to initiation of oral anticoagulation in 45% of newly diagnosed patients and adjustment of rate or rhythm control in 62%; oral anticoagulation uptake among those with a clinical indication increased from 56% to 74% with screening. In post-ablation monitoring, PPG-based digital follow-up detected atrial arrhythmia recurrence in 38.5% of patients versus 17.7 to 17.9% with conventional ECG follow-up (OR 3.4; 95% CI 1.7 to 7.1; p for superiority = 0.001), and a separate study found freedom from AF or flutter in only 58.6% with mobile monitoring versus 82.8% with conventional follow-up (HR 3.14; p = 0.001), demonstrating that conventional monitoring substantially underestimates recurrence. In post-cardiac surgery patients, PPG monitoring detected AF or flutter in 18.5% of monitored patients versus 1.9% in usual care (OR 11.8; p < 0.001), leading to AF management interventions in 10.1% versus 2.4% (OR 5.1; p = 0.002). Notably, the only sham-controlled RCT did not demonstrate a statistically significant increase in overall AF detection rates (1.9% versus 0.5%, p = 0.094), though asymptomatic AF detection was numerically higher in the intervention group.

3.4. Blood Pressure Estimation

BP estimation by smartphone PPG represents a substantially less mature application than AF detection. The studies used heterogeneous methods, including contact-based fingertip PPG, finger-pressing oscillometry, combined ECG and PPG, and contactless remote PPG, with widely varying validation protocols. Of the 18 studies addressing BP estimation, only two clearly passed established validation protocols, and both relied on per-individual calibration against a reference measurement. Table 3 summarizes BP estimation accuracy and validation outcomes.

Table 3. Blood pressure estimation accuracy and validation outcomes.

Study	n	SBP mean error (SD)	DBP mean error (SD)	Validation met?
Dörr et al., 2020	965	−0.41 (±16.52) mmHg	Not tested	No (ESH-IP2010 failed)
Eckstein et al., 2017	1,000	MAD 14 mmHg	Not tested	Not reported
Degott et al., 2021	91	0.5 (±7.7) mmHg	0.4 (±4.6) mmHg	Yes (AAMI/ESH/ISO)
Delmotte et al., 2023	53	−1.4 (±10.1) mmHg	0.2 (±6.5) mmHg	ISO met for DAP/MAP, not SAP
Vischer et al., 2022	50	0.7 (±9.4) mmHg	1.0 (±4.5) mmHg	Not formally assessed
Sagirova et al., 2021	500	Bias 0.32 (SD 3.63)	Bias 0.61 (SD 2.95)	Yes (meets 5±8 criteria)
Holyoke et al., 2021	62	Failed ESH-IP2	Failed ESH-IP2	No (ESH-IP2 failed)
Tabei et al., 2020	6	MAE 2.07 (±2.06)	MAE 2.12 (±1.85)	Within 5±8 threshold
Yamakoshi et al., 2020	13	r = 0.968; MAD <5	r = 0.844; MAD <5	Not formally assessed
Mena et al., 2020	3	−7.77 (±8.58) mmHg	−1.02 (±4.21) mmHg	DBP only (AAMI/BHS)
Tan et al., 2024	200	2.69 (±7.86) mmHg	0.16 (±3.22) mmHg	Not formally assessed
van Putten et al., 2024	Up to 2,000	1.2 (±15.9) mmHg	−3.2 (±13.1) mmHg	Not formally assessed
Qiao et al., 2022	49	MAE 6.7 mmHg	MAE 9.6 mmHg	Not formally assessed
Dasa & Davies, 2025	306	MAE 15.37; Sens 0.04	MAE 10.91; Sens 0.10	No
Oladunni & Adewumi, 2026	46	MAE 2.05; r = 0.990	MAE 1.67; r = 0.991	Yes (AAMI/IEEE SP10)

The two approaches that passed validation, OptiBP and the CardioQVARK ECG-plus-PPG case, both relied on individual calibration. By contrast, two large prospective trials explicitly failed established validation standards: the iPARR trial (n = 965) found a mean systolic error of minus 0.41 plus or minus 16.52 mmHg with only 38.1% of readings within plus or minus 5 mmHg, and Bland-Altman analysis revealed systematic overestimation at low pressures and underestimation at high pressures; the MediBeat algorithm similarly failed ESH-IP2 standards for both systolic and diastolic pressure. Diastolic BP was generally estimated more accurately than systolic BP across both contact and contactless approaches. Contactless rPPG showed particularly concerning results in field conditions: the Lifelight system, tested in a darker-skinned Nigerian population (Fitzpatrick V to VI), demonstrated critically low sensitivity for hypertension detection (systolic sensitivity 0.04, diastolic sensitivity 0.10) with systolic MAE of 15.37 mmHg, and performance was worst in Fitzpatrick type VI participants, where systolic sensitivity was 0.00.

3.5. Dysglycemia Detection

Only one study directly addressed diabetes detection using smartphone PPG. Avram et al. (2020) developed a deep neural network from the PPG recordings of 53,870 individuals acquired through a consumer heart-rate app. The network achieved an AUC of 0.766 (95% CI 0.750 to 0.782) in the primary cohort and 0.740 (95% CI 0.723 to 0.758) in an independent contemporary cohort, with sensitivity of 75 to 81% and specificity of 54 to 65%. When combined with age, gender, race or ethnicity, and BMI, the AUC improved to 0.830, with the network score remaining independently predictive, and the score was significantly and positively associated with HbA1c. The biological rationale rests on the PPG signal capturing vascular effects of diabetes including autonomic dysfunction and arterial stiffness. This level of discrimination corresponds to a screening rather than a diagnostic capability and requires external validation in prospective cohorts.

3.6. Heart Rate and Other Vital Parameters

PPG-derived heart rate was validated in the context of AF, where one study found that PPG underestimated heart rate in AF by 6.6 bpm (95% CI 5.8 to 7.4 bpm) with a root-mean-square error of 11.8 bpm, compared with only 0.4 bpm underestimation in sinus rhythm, with greater underestimation at higher heart rates. Multi-parameter rPPG systems measured heart rate with a mean absolute error of 1.73 to 3.95 bpm, oxygen saturation with a mean absolute error of 1.64%, and respiratory rate with an accuracy of 84.4%; however, BP estimates from these same systems (mean absolute error 6.7 to 9.6 mmHg) fell well short of clinical standards. One study additionally estimated hemoglobin concentration with a mean absolute percentage error of 8.52%.

3.7. Feasibility, User Engagement, and Regulatory Status

Patient compliance with smartphone PPG monitoring was generally high for AF detection. In post-ablation monitoring, compliance for three daily measurements over six months was 73.8%, and in eight-week studies the rate exceeded 78%. Usability scores were favorable, and a large-scale Belgian screening campaign successfully recruited over 60,000 participants through media, while remote PPG monitoring after cardioversion demonstrated high compliance (89.4%), cost savings (47.91 versus 135 pounds per patient), and reduced carbon emissions. Compliance nonetheless declined over time in some studies, and only 31% of offered patients agreed to participate in one post-ablation monitoring program. For BP estimation the feasibility picture is more concerning: in the Nigerian field study the rPPG tool failed to produce any BP estimate for 19% of participants, yet 70% of patients rated accuracy favorably, a perception-performance gap that could pose clinical risks. Regarding regulatory status, several AF detection apps have achieved CE marking and FDA 510(k) clearance, whereas the iPARR BP algorithm was explicitly not commercialized after failing validation, and no smartphone-only BP application has passed all criteria of the ESH/AAMI/ISO validation protocols in large, independent studies.

4. Discussion

The evidence base reveals a stark asymmetry in technological maturity across the three cardiometabolic parameters. AF detection has achieved consistently high diagnostic accuracy across diverse settings, populations, and devices, with meta-analytic sensitivity of 93 to 96% and specificity of 97%. By contrast, BP estimation remains unreliable when tested against established validation protocols, with only two of 18 studies clearly passing AAMI/ESH/ISO standards, and dysglycemia detection rests on a single study with moderate discrimination (AUC 0.74 to 0.77).

This divergence is partly mechanistic. AF produces a distinctive irregularity in beat-to-beat intervals that is well captured by the timing characteristics of the PPG signal. BP estimation requires the extraction of subtle morphological features from the pulse waveform and is confounded by vasomotor tone, arterial stiffness, hydration, and calibration drift. Dysglycemia detection depends on even more indirect vascular signatures and neural-regulatory effects captured through heart-rate variability and waveform morphology, which explains why performance is at the screening rather than diagnostic level.

Although AF detection is broadly accurate, sensitivity ranged from 86% to nearly 100% across studies, and three factors systematically account for this variation. First, studies including atrial flutter consistently reported lower sensitivity, because flutter produces a more organized rhythm that PPG-based irregularity metrics cannot reliably distinguish from sinus rhythm. Second, setting and supervision mattered less than expected: unsupervised ambulatory studies achieved sensitivity comparable to or exceeding supervised in-clinic studies, likely reflecting the benefit of repeated measurements, since signal quality improved from 89.5% on single recordings to 96.6% with repeated attempts and population screening yield increased with additional recording days. Third, population prevalence strongly influenced positive predictive value, which fell as low as 53% in low-prevalence primary care or population screening yet exceeded 92% in high-prevalence cardioversion cohorts, a pattern consistent with Bayesian prediction.

The sharp discrepancy between BP studies that passed validation and those that failed follows a clear pattern based on methodology and calibration. The approaches that passed, OptiBP and CardioQVARK, both relied on individual calibration against a reference measurement, whereas population-level generalized algorithms that attempted calibration-free estimation consistently failed. This suggests that smartphone PPG may track BP changes within an individual after calibration but cannot estimate absolute BP from population-level models. Contactless rPPG faces the additional obstacle of skin pigmentation, since melanin absorbs light at the wavelengths used for facial blood-flow detection, helping to explain the catastrophic field-study failure in darker-skinned participants. Multiple studies also demonstrated systematic overestimation at low pressures and underestimation at high pressures, a clinically concerning pattern because the most important readings, those in the hypertensive or hypotensive range, are the least accurate. Finally, the studies reporting excellent accuracy uniformly had small, homogeneous samples, whereas the largest prospective trials and the only diverse real-world field study all failed validation.

The aspiration to use a single smartphone as a multi-parameter cardiometabolic screening tool therefore remains largely unrealized. The evidence supports a graded implementation strategy: smartphone PPG for AF detection is ready for clinical deployment in appropriate populations, particularly those aged over 65 with cardiovascular risk factors; BP estimation may be feasible as a tracking tool with per-individual calibration but should not be used for diagnosis or screening without cuff confirmation; and dysglycemia screening remains investigational. The fundamental constraint for BP and glucose estimation is that PPG waveform morphology contains less direct physiological information about these parameters than about cardiac rhythm irregularity, and current algorithms have not overcome this information deficit in generalizable populations.

This review has limitations. The synthesis is narrative rather than quantitative owing to heterogeneity in designs, devices, target parameters, and validation protocols; several included sources were companion or duplicate publications of the same trials; full text was available for only 22 of 63 sources; and the dysglycemia evidence derives from a single research group. These constraints temper the strength of the conclusions and define clear priorities for future research.

5. Conclusions

Smartphone photoplethysmography is a clinically validated and effective tool for atrial fibrillation detection, achieving meta-analytic sensitivity and specificity of roughly 96% and 97% across diverse devices and settings, performing robustly in unsupervised home use, and producing measurable clinical benefits in anticoagulation uptake and recurrence detection. Blood pressure estimation, by contrast, remains unreliable without per-individual calibration and has failed most formal validation protocols, with contactless approaches additionally compromised by skin pigmentation, while dysglycemia screening shows only moderate discriminative ability in a single study. Multi-parameter cardiometabolic home screening via smartphone PPG is therefore not yet achievable beyond rhythm assessment.

Future work should prioritize large, independent, and demographically diverse validation of calibration-free BP algorithms against AAMI/ESH/ISO standards, prospective external validation of PPG-based dysglycemia screening, and explicit evaluation of equity across skin tones for contactless methods. Until these gaps are addressed, smartphone PPG should be deployed as a single-parameter rhythm screening and monitoring tool rather than as a general multi-parameter cardiometabolic home screen.

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