

Remote Photoplethysmography-Based HbA1c Estimation for Community Screening of Type 2 Diabetes Mellitus: Screening Tool or Diagnostic Alternative?

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Abstract

Type 2 diabetes mellitus (T2DM) remains a major global health burden, with a high proportion of undiagnosed cases, particularly in community settings with limited access to laboratory testing. Remote photoplethysmography (rPPG) has emerged as a non-invasive, camera-based technology with potential for scalable screening. This study aimed to evaluate the agreement, diagnostic performance, and clinical role of rPPG-derived HbA1c as a screening tool or diagnostic alternative for T2DM. A cross-sectional diagnostic validation study was conducted among adults in a community setting in Semanan Subdistrict, Jakarta. Participants underwent non-contact facial scanning using an rPPG system alongside standard laboratory measurements of HbA1c and blood glucose. Agreement was assessed using Bland–Altman analysis and Cohen’s Kappa. Diagnostic performance was evaluated using sensitivity, specificity, predictive values, and receiver operating characteristic (ROC) curve analysis. rPPG-derived HbA1c showed a significant mean difference compared with laboratory measurements (0.63%; $p < 0.001$; 95% CI: 0.34–0.93), indicating systematic bias. Categorical agreement was poor ($\kappa = 0.029$; $p = 0.403$). In screening analysis, sensitivity ranged from 65.38% to 97.37%, while specificity ranged from 8.91% to 59.55%, with consistently high negative predictive values ($\geq 82\%$). ROC analysis demonstrated an AUC of 0.668 ($p = 0.008$) for diabetes and 0.711 ($p < 0.001$) for prediabetes, indicating modest to acceptable discriminative ability. rPPG-based HbA1c estimation lacks sufficient agreement for diagnostic use. However, its relatively high sensitivity and scalability suggest that it may warrant further evaluation as a non-invasive screening tool for early detection and population-level risk stratification within mobile health settings.

Keywords: Remote Photoplethysmography, HbA1c, Type 2 Diabetes Mellitus, Screening, Diagnostic Accuracy

1. Introduction

Type 2 diabetes mellitus (T2DM) represents a major global public health burden, with rapidly increasing prevalence and substantial economic impact. It is estimated that 537 million adults worldwide (10.5%) were living with diabetes in 2021, with projections rising to 643 million by 2030 and 783 million by 2045 [1], [2]. Notably, nearly 240 million individuals remain undiagnosed, highlighting a critical gap in early detection [2]. The burden is particularly pronounced in low- and middle-income countries (LMICs), which account for nearly 80% of global diabetes cases [3]. In Asia and ASEAN regions, the prevalence continues to rise sharply, driven by rapid urbanization, lifestyle changes, and demographic transitions [4]. Indonesia is among the top countries with the highest number of diabetes cases, with

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national prevalence increasing from 6.2% in 2019 to 10.8% in 2021, placing it among the fastest-growing diabetes populations globally [2], [5].

In response to this growing burden, community-based screening strategies have been implemented to improve early detection and management of T2DM. In Indonesia, programs such as Posyandu and community-based health interventions (CBHI) aim to provide screening for blood glucose and non-communicable disease risk factors at the community level [6], [7]. However, despite these efforts, a substantial proportion of diabetes cases remain undiagnosed, with estimates indicating that up to 74% of individuals with diabetes in Indonesia are unaware of their condition [8]. This gap is further exacerbated by limited access to laboratory testing, the invasive nature of conventional methods such as HbA1c measurement, and suboptimal follow-up rates in real-world community settings [6]. These challenges underscore the need for scalable, accessible, and non-invasive screening tools that can be deployed effectively at the community level.

Remote photoplethysmography (rPPG) has emerged as a promising non-invasive technology capable of extracting physiological signals from facial video using standard camera devices. By analyzing subtle variations in light absorption related to blood volume changes, rPPG enables remote assessment of cardiovascular and potentially metabolic parameters [9], [10]. Advances in artificial intelligence and signal processing have further enabled the development of models that estimate glycemia-related parameters, including HbA1c, based on microvascular and autonomic signatures derived from photoplethysmographic signals [11], [12], [13], [14], [15]. Despite its potential, current evidence on the validity of rPPG for HbA1c estimation remains limited, with most studies focusing on contact-based PPG or lacking robust comparison with laboratory reference standards. Additionally, factors such as lighting variability, motion artifacts, and heterogeneity in real-world conditions continue to pose challenges to accuracy [16].

Given these gaps, there is a critical need to evaluate the performance of rPPG-based HbA1c estimation within real-world community settings. Therefore, this study aims to assess the agreement, diagnostic performance, and discriminative ability of rPPG-derived HbA1c compared with standard laboratory measurements in a community-based population. Specifically, the study seeks to determine whether rPPG can function as a screening tool or a diagnostic alternative for detecting type 2 diabetes mellitus, particularly in resource-limited and community-based environments.

2. Methodology

2.1. Study Design

This study employed an analytical observational design using a cross-sectional diagnostic validation approach to evaluate the agreement and diagnostic performance of remote rPPG-derived HbA1c measurements compared with standard laboratory methods.

2.2. Study Setting and Period

The study was conducted in a community-based setting in Kelurahan Semanan, West Jakarta, Indonesia, during April to May 2026. Data collection took place through organized health screening activities, ensuring standardized environmental conditions such as lighting, positioning, and measurement procedures.

2.3. Population and Sample

The study population consisted of adult individuals aged 18 years and above residing in the Semanan Subdistrict area. Participants were recruited using a community-based sampling approach through local outreach programs and primary care engagement to reflect real-world screening conditions. The minimum sample size was determined using the single proportion formula ($n = Z^2 \times p(1 - p)/d^2$). A 95% confidence level was used ($Z = 1.96$). Because prior community-based estimates of rPPG-derived HbA1c classification performance were limited, an expected diagnostic performance proportion of 50% ($p = 0.50$) was selected to provide the most conservative sample size estimate. The desired precision was set at 10% ($d = 0.10$). Based on these assumptions, the minimum required sample size was 96 participants. To account for approximately 20% potential data loss due to incomplete blood examination, unsuccessful rPPG acquisition, or poor signal quality, the target minimum sample size was increased to 120 participants. In the final analysis, 127 participants with complete paired rPPG and reference HbA1c data were included.

2.4. Inclusion and Exclusion Criteria

Participants were eligible for inclusion if they met all of the following criteria: adults aged ≥ 18 years, able and willing to provide written informed consent, and capable of complying with all study procedures, including facial scanning, physical examination, blood sampling, and completion of study-related questionnaires. Participants were additionally excluded if they had any clinically unstable medical condition that could affect physiological measurements, participant safety, or study participation. These conditions included: (1) acute infection accompanied by fever ($>38^{\circ}\text{C}$); (2) hospitalization within the previous 30 days; (3) acute cardiovascular events within the previous 6 months (e.g., myocardial infarction, stroke, decompensated heart failure); (4) severe anemia (hemoglobin <8 g/dL if documented in medical records); (5) advanced chronic kidney disease requiring dialysis; (6) active malignancy undergoing chemotherapy or radiotherapy; (7) severe liver disease (cirrhosis with clinical decompensation); (8) uncontrolled endocrine disorders known to substantially alter glucose metabolism; and (9) any physical or cognitive condition preventing completion of facial scanning, blood sampling, or study procedures.

Participants were excluded if any condition was present that could interfere with the accuracy of rPPG signal acquisition or the validity of glycemic assessment. These included facial conditions affecting the region of interest (ROI), such as injury, deformity, impaired microcirculation, or any abnormality that could distort optical signal detection. Individuals with facial tattoos, heavy cosmetics, or coverings that obstructed the camera's ability to capture facial signals were also excluded. Furthermore, participants who were unable to remain still or comply with standardized measurement procedures during data acquisition were excluded to minimize motion-related artifacts.

From a clinical perspective, individuals with conditions that could significantly alter glucose metabolism or HbA1c interpretation were also excluded. These included patients with Type 1 diabetes mellitus, a history of pancreatic injury or pancreatic surgery, and other conditions affecting pancreatic function. In addition, participants with severe systemic illnesses or unstable medical conditions, as judged by the investigator, were excluded to ensure safety and data integrity. The complete workflow of the study is illustrated in [figure 1](#).

2.5. rPPG System Description

rPPG measurements were obtained using an artificial intelligence-based facial scanning system, which generates HbA1c estimates directly from facial video signals using remote photoplethysmography principles. Participants underwent a non-contact facial scan lasting approximately 1–2 minutes using a smartphone-based camera under standardized conditions, including stable lighting, a fixed camera-to-face distance of approximately 25–50 cm, and minimal movement to ensure optimal signal acquisition. The system automatically detected and continuously tracked facial regions of interest (ROI) ([figure 1](#)), particularly the forehead and bilateral cheeks, which are known to provide stable and high-quality microvascular signals.

The captured RGB facial video signals were processed through a structured computational pipeline consisting of signal filtering, normalization, segmentation, and artifact reduction. Bandpass filtering (approximately 0.4–8 Hz) was applied to isolate pulsatile blood flow signals from environmental noise and illumination variability. The signals were then normalized to reduce inter-individual variability and segmented into short time windows (approximately 10 seconds), allowing multiple independent signal samples to be generated from a single recording. Motion artifacts were minimized through signal quality indexing and real-time ROI tracking, ensuring that only high-integrity signal segments were retained for analysis [\[17\]](#), [\[18\]](#).

From the processed signals, pulse waveforms were reconstructed based on subtle variations in light absorption corresponding to cyclic blood volume changes in superficial vessels. A set of high-dimensional features was then extracted from these waveforms, including temporal patterns (e.g., pulse interval variability), amplitude modulation, and frequency-domain characteristics reflecting microcirculatory and autonomic dynamics. These features formed the input for the artificial intelligence model [\[17\]](#), [\[18\]](#).

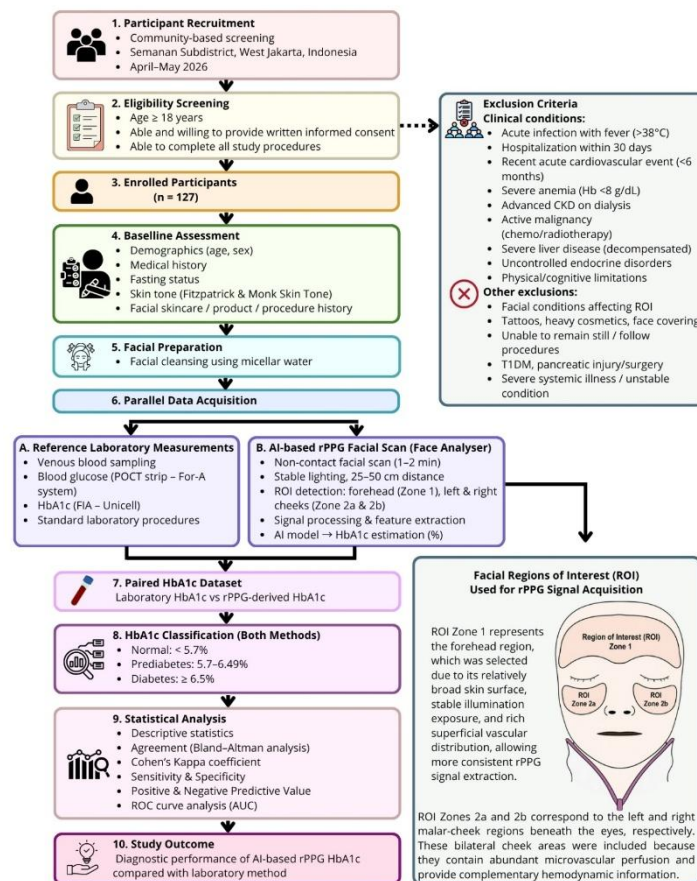


Figure 1. Flow Chart of the Study Process and Facial Regions of Interest (ROI) Used for rPPG Signal Acquisition.

HbA1c estimation was performed using a supervised machine learning regression model integrated within the system, incorporating fixed (state) coefficients for body weight and height as invariant input parameters. The model maps the extracted rPPG-derived features into a continuous HbA1c value by identifying patterns associated with long-term glycemic status. This mapping process leverages learned relationships between microvascular signal variability, autonomic modulation patterns, and metabolic profiles. The system incorporates internal quality control mechanisms, including signal quality thresholds and confidence scoring, to ensure that HbA1c outputs are generated only when signal reliability meets predefined criteria. As a result, the rPPG system produces a continuous HbA1c value (%) derived entirely from non-contact facial signal analysis through an end-to-end artificial intelligence framework [19].

2.6. Measurement and Classification

Laboratory measurements were conducted as the reference standard. Blood glucose levels were measured using a point-of-care strip-based method (For-A system), while HbA1c was measured using a fluorescence immunoassay (FIA) method (Unicell), aligned with standardized laboratory procedures. Glycemic classification was defined using established clinical thresholds, with diabetes defined as $\text{HbA1c} \geq 6.5\%$, prediabetes as HbA1c between 5.7% and 6.49% , and normal as $\text{HbA1c} < 5.7\%$ [20]. These cut-off values were consistently applied to both laboratory and rPPG-derived measurements to enable direct comparison in both numerical and categorical analyses.

2.7. Study Procedure

After obtaining written informed consent, participants underwent a structured assessment beginning with the collection of baseline information, including demographic characteristics (age and sex), medical history, and fasting status at the time of examination. In addition, skin tone was systematically documented as a potential confounding factor influencing rPPG signal acquisition. Skin tone classification was performed using two standardized approaches: the Fitzpatrick Skin Type scale (Type I–VI), based on melanin response to ultraviolet exposure, and the Monk Skin Tone (MST) scale (ranging from 1 to 10), which is designed to enhance inclusivity in artificial intelligence-based systems.

Participants were also asked about their history of facial product use, including skincare routines, sunscreen application, and any prior facial procedures or surgeries that could affect skin characteristics and signal acquisition.

Prior to rPPG measurement, participants' facial surfaces were cleaned using micellar water to remove makeup, oil, and other residues that might interfere with optical signal detection. Following baseline assessment, venous blood samples were collected by trained healthcare personnel using standardized aseptic techniques for laboratory measurement of HbA1c and blood glucose parameters. In parallel, each participant underwent a non-contact facial scan using the rPPG system under controlled conditions, including stable lighting, appropriate camera distance, and minimal movement to ensure optimal signal quality.

2.8. Environmental and Device Standardization

All rPPG measurements were conducted during daytime community health screening sessions in Jakarta under typical environmental conditions representative of the Indonesian dry season. Data collection was performed in shaded indoor or semi-indoor areas with stable ambient lighting and natural ventilation. Ambient temperatures during data collection were generally consistent with normal daytime conditions in Jakarta, ranging approximately from 28–34°C. Although illumination intensity (lux) and ambient temperature were not formally quantified using calibrated instruments, efforts were made to maintain consistent environmental conditions throughout data acquisition by avoiding direct sunlight exposure, excessive backlighting, and rapidly changing illumination sources.

To enhance external validity and reflect real-world implementation, participants used commonly available smartphone devices representative of the Indonesian consumer market. The most frequently recorded devices included Samsung Galaxy A72, Samsung Galaxy A33, Samsung Galaxy A15, Samsung Galaxy A10s, Samsung Galaxy M11, Samsung Galaxy Tab S8, Xiaomi 11T Pro, POCO X5 5G, Infinix Smart 9, and OnePlus 1. All devices were equipped with integrated front-facing RGB cameras operating under standard manufacturer specifications. Because the evaluated rPPG platform is designed for device-independent deployment, image acquisition was performed using the native camera hardware available on each smartphone without additional optical accessories or external sensors. This approach was intended to reflect practical real-world use rather than laboratory-based hardware standardization.

2.9. AI-Based HbA1c Estimation Model

The evaluated rPPG platform employs a proprietary artificial intelligence framework to estimate glycated hemoglobin (HbA1c) from facial video recordings. The system utilizes remote rPPG to capture subtle temporal variations in reflected light associated with pulsatile blood flow and microvascular perfusion. Facial video signals are extracted from predefined regions of interest, including the forehead and bilateral cheeks, followed by signal preprocessing, normalization, artifact reduction, and feature extraction.

According to the developer documentation available to the investigators, HbA1c estimation is not derived from direct biochemical measurement but rather from a multimodal predictive model integrating rPPG-derived vascular features, microcirculatory variability, waveform characteristics, autonomic-related parameters, and demographic inputs such as age, sex, body weight, and height. The algorithm subsequently generates an estimated HbA1c value expressed as a percentage (%).

The detailed model architecture, training dataset composition, feature selection process, internal validation procedures, and model development performance metrics remain proprietary and were not accessible to the investigators. Consequently, the present study was designed as an independent external validation of the final algorithm output rather than an evaluation of the model development process itself.

2.10. Statistical Analysis

All statistical analyses were performed using IBM SPSS Statistics and Microsoft Excel. Continuous variables were summarized as mean (standard deviation) or median (minimum–maximum) as appropriate, while categorical variables were presented as frequencies and percentages. Agreement between rPPG-derived and laboratory HbA1c values was assessed using Bland–Altman analysis, including calculation of mean difference (bias) and 95% limits of agreement. Categorical agreement was evaluated using Cohen's Kappa coefficient, with interpretation based on standard thresholds for agreement strength.

Diagnostic performance was assessed using four screening models based on standard HbA1c cut-off values ($\geq 6.5\%$ for diabetes and $\geq 5.7\%$ for prediabetes). Sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated for each model to evaluate the ability of rPPG to classify glycemic status. Statistical significance was assessed using a likelihood ratio-based 2×2 test, with a p-value < 0.05 considered statistically significant.

Receiver operating characteristic (ROC) curve analysis was additionally performed to evaluate the discriminative ability of rPPG-derived HbA1c. The area under the curve (AUC) was calculated for both diabetic and prediabetic classification models, along with 95% confidence intervals. The diagnostic performance based on AUC values was interpreted as follows: 0.50–0.60 (no diagnostic value), 0.60–0.70 (poor), 0.70–0.80 (acceptable), and 0.80–0.90 (good diagnostic performance). Higher AUC values indicate better discriminatory capability of the model in distinguishing between positive and negative cases [21].

2.11. Ethical Considerations

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Ethical approval was obtained from the Universitas Tarumanagara Health Research Ethics Committee (UTHREC No. 020-UTHREC/UNTAR/IV/2026), and the study was registered in ClinicalTrials.gov (NCT07502690). All participants provided written informed consent prior to participation. Data confidentiality was strictly maintained through anonymization, and no identifiable facial images were stored or used beyond signal processing purposes.

3. Results and Discussion

3.1. RESULTS

This study included 127 participants who met the eligibility criteria and had complete paired data for both rPPG face scan and laboratory measurements (figure 2, table 1).

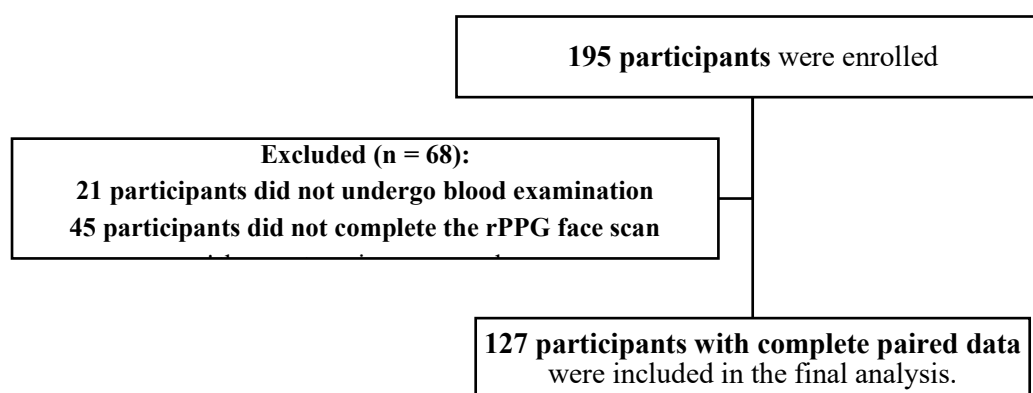


Figure 2. Flow Diagram of Participant Enrollment, Exclusion, and Final Inclusion in the Study

The mean age was 45.72 (10.93) years, with a predominance of female participants (68.5%). Most individuals had Fitzpatrick skin types IV–V and were classified within Monk Skin Tone levels 6–7. The mean HbA1c was 6.47 (0.60) % (rPPG) and 5.84 (1.73) % (laboratory), while the mean random blood glucose level was 106.12 (46.06) mg/dL (table 1).

Table 1. Participant Characteristics and Distribution of rPPG and Laboratory Glycemic Measurements

Variable	Category / Level	N (%)	Mean (SD)	Median (Minimum–Maximum)
Age, years	—	—	45.72 (10.93)	45 (18–80)
Gender	Male	40 (31.5)	—	—
	Female	87 (68.5)	—	—
Fitzpatrick Skin Type	Type III	6 (4.7)	—	—
	Type IV	41 (32.3)	—	—
	Type V	56 (44.1)	—	—

	Type VI	24 (18.9)	—	—
Monk Skin Tone (MST)	Level 4	1 (0.8)	—	—
	Level 5	10 (7.9)	—	—
	Level 6	55 (43.3)	—	—
	Level 7	41 (32.3)	—	—
	Level 8	15 (11.8)	—	—
	Level 9	5 (3.9)	—	—
Routine Facial Product Use	Sunscreen	36 (28.3)	—	—
	Powder	47 (37.0)	—	—
	Skincare	34 (26.8)	—	—
HbA1c (rPPG-derived), %	—	—	6.47 (0.60)	6.49 (4.66–7.90)
HbA1c (Laboratory), %	—	—	5.84 (1.73)	5.38 (4.00–12.88)
Random Blood Glucose (Laboratory), mg/dL	—	—	106.12 (46.06)	91 (67–297)

Referring to [table 2](#) and [figure 3](#), the agreement between HbA1c values derived from rPPG and standard laboratory measurements was first evaluated using the Bland–Altman method. The analysis showed a statistically significant mean difference of 0.63% ($p < 0.001$; 95% CI: 0.34–0.93), indicating a systematic bias between the two measurement approaches.

Table 2. Agreement and Diagnostic Performance of rPPG-Derived HbA1c Compared with Standard Laboratory Measurements using Bland Altman Test

Numerical Parameter	t	df	Sig. (2-tailed)	Mean Difference	Bland Altman Test	
					95% Confidence Interval	
					Lower	Upper
HbA1c (rPPG AI – Laboratory)	4.223	126	< 0.001	0.63268	0.3362	0.9291

Limit of Agreement: Minimal -2.68%; and Maximal 3.95%

As illustrated in [figure 3](#), the distribution of differences widens at higher mean HbA1c levels, suggesting increasing variability and potential proportional bias ([table 2](#), [figure 3](#)).

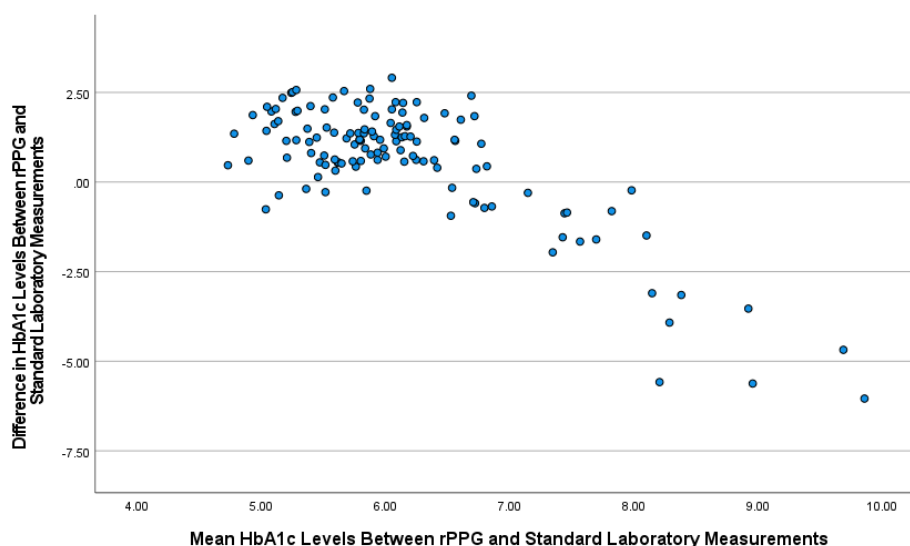


Figure 3. Agreement Analysis of rPPG-Derived and Laboratory-Measured HbA1c Using Bland–Altman Plot

Categorical agreement was subsequently assessed using the Kappa concordance test, applying standard laboratory cut-off values (diabetes: $\text{HbA1c} \geq 6.5\%$; prediabetes: $\text{HbA1c} \geq 5.7\%$). The analysis revealed a very low Kappa value ($\kappa = 0.029$; $p = 0.403$), indicating poor agreement between rPPG-based classification and laboratory-defined categories. This lack of concordance confirms that rPPG cannot accurately replicate clinical classification thresholds and is therefore not valid as a diagnostic replacement for the laboratory reference standard ([table 3](#), [figure 3](#)).

Table 3. Agreement and Diagnostic Performance of rPPG-Derived HbA1c Compared with Standard Laboratory Measurements using Kappa Concordance Test

Caterogical Paramater	Kappa Concordance Test			Value (Kappa)	Asymptotic Standard Error ^a	Approximate Significance
	Diabetic (HbA1c ≥ 6.5%)	Prediabetic (HbA1c 5.7–6.49%)	Normal (HbA1c < 5.7%)			
Diabetic (rPPG)	17 (13.4%)	10 (7.9%)	36 (28.3%)	0.029	0.033	0.403
Prediabetic (rPPG)	8 (6.3%)	2 (1.6%)	44 (34.6%)			
Normal (rPPG)	1 (0.8%)	0 (0.0%)	9 (7.1%)			

a. Not assuming the null hypothesis.

Despite these limitations, rPPG demonstrated potential utility as a screening tool when evaluated across four screening models based on the same HbA1c cut-off thresholds. In the diabetes vs diabetes model ($\geq 6.5\%$), sensitivity was 65.38% and specificity 54.46%, with a high negative predictive value (NPV) of 85.94%. In the diabetes vs prediabetes model, sensitivity improved to 71.05% with specificity 59.55% ($p = 0.001$), indicating better discriminatory ability when identifying individuals at elevated glycemic risk. In contrast, the prediabetes vs diabetes model ($\geq 5.7\%$ vs $\geq 6.5\%$) demonstrated very high sensitivity (96.15%) but extremely low specificity (8.91%), while the prediabetes vs prediabetes model ($\geq 5.7\%$) showed similarly high sensitivity (97.37%) with low specificity (10.11%). Across all models, NPV remained consistently high ($\geq 82\%$), whereas PPV was relatively low, indicating a tendency toward false-positive classifications (table 2, figure 3). Although rPPG-based HbA1c estimation does not meet the criteria for diagnostic equivalence due to poor agreement and low categorical concordance, its high sensitivity and strong NPV across standard HbA1c cut-off thresholds ($\geq 6.5\%$ and $\geq 5.7\%$) support its role as a community-based screening tool (table 4, figure 3).

Table 4. Agreement and Diagnostic Performance of rPPG-Derived HbA1c Compared with Standard Laboratory Measurements using Diagnostic Test Performance

Diagnostic Test Performance						
rPPG Measurement	Laboratory Measurement	Sensitivity (%)	Spesitifiy (%)	PPV (%)	NPV (%)	p-value*
Diabetic	Diabetic	65.38	54.46	26.98	85.94	0.069
Diabetic	Prediabetic	71.05	59.55	42.86	82.81	0.001*
Prediabetic	Diabetic	96.15	8.91	21.37	90.00	0.356
Prediabetic	Prediabetic	97.37	10.11	31.62	90.00	0.116

*Significance was tested using a likelihood ratio-based 2×2 test.

#Cut-off values: Diabetes: HbA1c $\geq 6.5\%$; Prediabetes: HbA1c $\geq 5.7\%$

Interpretation of screening models: Diabetic vs Diabetic: rPPG HbA1c $\geq 6.5\%$ compared against laboratory HbA1c $\geq 6.5\%$ (diabetes detection). Diabetic vs Prediabetic: rPPG HbA1c $\geq 6.5\%$ compared against laboratory HbA1c $\geq 5.7\%$ (detection of elevated glycemic risk, including prediabetes and diabetes). Prediabetic vs Diabetic: rPPG HbA1c $\geq 5.7\%$ compared against laboratory HbA1c $\geq 6.5\%$ (ability of a lower screening threshold to capture laboratory-confirmed diabetes). Prediabetic vs Prediabetic: rPPG HbA1c $\geq 5.7\%$ compared against laboratory HbA1c $\geq 5.7\%$ (prediabetes-or-higher screening model).

Further evaluation using receiver operating characteristic (ROC) analysis demonstrated variable discriminative ability depending on the diagnostic threshold. For the diabetic classification model (HbA1c $\geq 6.5\%$), the area under the curve (AUC) was 0.668 (95% CI: 0.560–0.776; $p = 0.008$), indicating statistically significant but poor discriminative performance according to standard AUC interpretation (0.60–0.70). In contrast, the prediabetic model (HbA1c $\geq 5.7\%$) showed a higher AUC of 0.711 (95% CI: 0.616–0.805; $p < 0.001$), representing acceptable diagnostic performance (0.70–0.80). The ROC curves (figure 4) illustrate that the prediabetic model demonstrates a more favorable balance between sensitivity and specificity, with the curve positioned further above the diagonal reference line (table 5, figure 4).

Table 5. Agreement and Diagnostic Performance of rPPG-Derived HbA1c Compared with Standard Laboratory Measurements using Area Under the Curve

	Model Diagnostic	Area	Std. Error ^a	Asymptotic Sig. ^b	95% Confidence Interval	
					Lower	Upper
Diabetic	The positive actual state is HbA1c min 6.5%	0.668	0.055	0.008	0.560	0.776
Prediabetic	The positive actual state is HbA1c min 5.7%	0.711	0.048	< 0.001	0.616	0.805

a. Under the nonparametric assumption, b. Null hypothesis: true area = 0.5

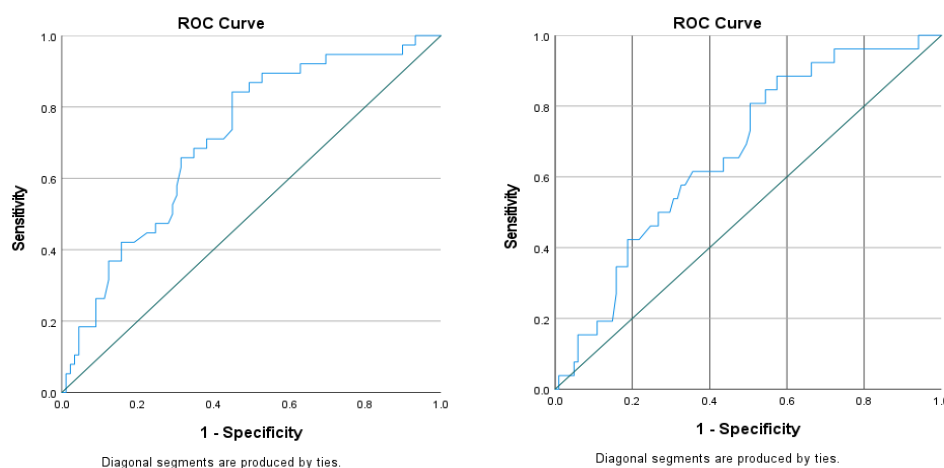


Figure 4. Receiver Operating Characteristic (ROC) Curves of rPPG-Derived HbA1c for Prediabetes (Left) and Diabetes (Right) Classification Based on Laboratory Reference Standards

The present study demonstrated a statistically significant mean difference between rPPG-derived and laboratory HbA1c (0.63%, $p < 0.001$), indicating systematic bias and limited agreement [22], [23]. This finding is consistent with prior optical-based measurement studies showing that glycemic status influences light-based physiological signals [17], [19], [24], [25]. For instance, Pu et al. reported a significant bias between SpO_2 and SaO_2 measurements in patients with elevated HbA1c, with a mean difference of 1.83 (0.55)% and significant correlation with HbA1c levels ($r = 0.307$; $p < 0.01$) [26]. Both studies suggest that optical signals are affected by underlying metabolic conditions, although Pu et al. focused on oxygen saturation, whereas the present study directly evaluated HbA1c estimation using facial rPPG.

The poor categorical agreement ($\kappa = 0.029$) observed in this study contrasts sharply with high-performing contact-based PPG studies. For instance, Nirala et al. reported accuracy of 97.87%, sensitivity 98.78%, and specificity 96.61% using toe PPG signals and SVM classification for diabetes detection [27]. The discrepancy highlights a key methodological difference: contact PPG captures stronger and more stable vascular signals compared to non-contact facial rPPG, which is more susceptible to noise, lighting variability, and motion artifacts. Thus, while both approaches rely on photoplethysmographic signals, their clinical validity differs significantly depending on acquisition method and environmental control [17], [24], [28], [29], [30], [31].

In terms of alternative diagnostic performance (screening tools), the AUC values in this study (0.668 for diabetes and 0.711 for prediabetes) indicate modest discrimination, particularly for early glycemic abnormalities. Compared with Avram et al., who achieved AUC values of 0.766–0.830 using smartphone-based PPG combined with deep learning and demographic variables, the current study shows lower performance [32].

Interestingly, the high sensitivity and high NPV observed in this study (especially for prediabetes (sensitivity up to 97.37%)) align with the screening characteristics of PPG-based systems reported in other studies. For example, Kim et al. demonstrated that PPG could achieve sensitivity of 84.0% in detecting diabetic neuropathy, supporting its role as an early screening tool [33]. The similarity lies in the high sensitivity for detecting abnormal physiological states, while

the difference is that the current study targets glycemic classification rather than complications, and exhibits lower specificity, suggesting a higher false-positive rate in face scan rPPG applications [27], [28], [33], [34], [35].

From a physiological perspective, the moderate performance of rPPG in this study is supported by evidence that PPG signals are strongly associated with vascular and metabolic changes rather than direct biochemical markers. Studies by Wei et al. demonstrated significant associations between PPG-derived indices and HbA1c ($p < 0.001$), as well as predictive value for diabetic complications [29], [34], [35]. Similarly, Liao et al. reported that PPG-derived harmonic components were associated with diabetic retinopathy risk, with a 1.8-fold increased risk in high-risk groups [36]. These findings suggest that rPPG captures vascular signatures of chronic hyperglycemia, which explains its ability to detect risk patterns rather than precisely quantify HbA1c values [27], [28], [33], [34], [35].

The variability observed in this study is also consistent with broader literature highlighting technical limitations of rPPG. Kraft et al. emphasized that rPPG signal accuracy is highly dependent on environmental conditions such as lighting, motion, and individual characteristics, leading to variability in real-world performance [17]. Similarly, Di Lerna et al. showed that rPPG performs well under controlled conditions but declines in uncontrolled “in-the-wild” environments. This aligns with the current study, which was conducted in a community setting, thereby reflecting realistic but less controlled conditions compared to laboratory-based validation studies [37].

Despite these limitations, the strength of face scan rPPG lies in its scalability and accessibility. Unlike laboratory HbA1c testing, which requires invasive blood sampling and infrastructure, rPPG can be performed using a smartphone camera in a matter of minutes. This is particularly relevant for community-based screening, where access to laboratory facilities is limited. Studies on mobile health (mHealth) systems suggest that smartphone-based PPG can enable continuous monitoring, early detection, and improved accessibility of healthcare services, especially in low-resource settings [19], [31]. This aligns with the present study, which demonstrates that rPPG can function as a front-line screening tool in community populations [19], [38]. But, the very low categorical agreement observed in this study ($\kappa = 0.029$) indicates that rPPG-derived HbA1c classifications do not reliably correspond to laboratory-defined glycemic categories. Therefore, the current implementation of rPPG-based HbA1c estimation should not be considered a diagnostic alternative to laboratory testing. Although the technology demonstrated relatively high sensitivity and negative predictive value in several screening scenarios, these findings should be interpreted cautiously given the poor agreement, systematic measurement bias, and modest ROC performance. Consequently, the present results support, at most, a hypothesis-generating role for rPPG in preliminary risk stratification, pending further technological refinement and external validation

The integration of rPPG into mobile phone applications represents a key opportunity for large-scale diabetes screening. Face scan technology can be embedded into mHealth platforms, allowing individuals to perform self-assessment anytime and anywhere. Prior studies have shown that users value the simplicity, convenience, and real-time feedback of such systems, although challenges remain in terms of accuracy, interpretation, and clinical integration [19], [31]. Wood et al. highlighted that while smartphone rPPG is promising for chronic disease monitoring, improvements in algorithm robustness, feedback clarity, and system integration are essential to enhance user trust and long-term adoption [24]. Therefore, the current study supports the role of face scan rPPG as a scalable, non-invasive screening approach, particularly for early detection of glycemic risk in community settings, while acknowledging the need for further technological refinement and validation [19], [38].

In community-based screening, the priority is to maximize sensitivity so that as many true positive cases as possible are captured, even at the expense of some false positives, whereas diagnostic confirmation in clinical settings places greater emphasis on specificity to avoid misclassifying healthy individuals as diseased. High sensitivity ensures that the instrument effectively “casts a wide net,” reducing the risk of missed cases and making it suitable for early case finding in asymptomatic or low risk populations. In this context, negative predictive value (NPV) is particularly important because it reflects the probability that an individual with a negative test result is truly free of disease, so a high NPV (as seen in the rPPG based HbA1c models here, with $NPV \geq 82\%$) supports confident reassurance of low-risk individuals and reduces unnecessary follow up testing. In contrast, positive predictive value (PPV) indicates the likelihood that a positive test result corresponds to true disease and tends to be lower when specificity is modest, which explains the relatively low PPV and higher false positive rate observed in the rPPG screening models; such behavior

is acceptable in screening but problematic for stand alone diagnosis, since diagnosis should minimize false positives by prioritizing high specificity and PPV to ensure accurate clinical decision making [39], [40], [41].

This study has several notable strengths and limitations. A key strength lies in its community-based design, which reflects real-world conditions and enhances the external validity of rPPG face scan implementation for large-scale screening. Additionally, the study employed comprehensive validation methods, including Bland–Altman analysis, Kappa concordance, diagnostic performance metrics, and ROC analysis, providing a robust and multidimensional evaluation of rPPG-derived HbA1c. The inclusion of skin tone stratification (Fitzpatrick and Monk Skin Tone scales) as well as documentation of facial product use (skincare, sunscreen, and face powder) further enriches the dataset by capturing factors that may influence optical signal acquisition [42]. However, it should be noted that these variables were collected for descriptive purposes only and were not included in confounding analysis due to limited and disproportionate sample distribution across categories, which may reduce statistical validity for subgroup comparisons.

Several limitations must also be acknowledged. The study was conducted in a single-center setting with a relatively limited sample size, which may restrict generalizability. The non-contact nature of rPPG introduces variability due to environmental factors such as lighting, motion artifacts, and facial surface conditions, potentially affecting signal quality and accuracy [17], [24]. HbA1c measurements obtained using the fluorescence immunoassay (FIA)-based point-of-care device were used as the reference comparator for evaluating rPPG-derived HbA1c estimates. Although FIA methods demonstrate acceptable analytical performance and are widely used in clinical screening and diabetes management, they do not constitute the definitive laboratory reference method, which is typically represented by NGSP-certified or IFCC-traceable HPLC assays [43], [44], [45], [46]. Furthermore, HbA1c estimation using rPPG is inherently indirect, relying on vascular and autonomic signal patterns rather than direct biochemical measurement, which may explain the observed systematic bias and low categorical agreement [27]. Finally, the study may have limited representation of extreme HbA1c values (up to 12.88%), which could affect model performance across the full spectrum of glycemic states [42]. In addition, although HbA1c estimation was performed using a supervised machine learning regression model, the incorporation of anthropometric parameters (particularly body weight, height, and body mass index (BMI)) remains limited. These variables are well-established determinants of insulin resistance, glucose metabolism, and the risk of Type 2 Diabetes Mellitus, and may significantly influence blood glucose dynamics and long-term glycemic control. Treating body weight and height as fixed (state) coefficients may not fully capture their dynamic interaction with metabolic status, potentially reducing model sensitivity and predictive accuracy. The absence of a more comprehensive integration of BMI and related anthropometric variability may therefore limit the robustness of HbA1c prediction and its clinical interpretability [47], [48], [49], [50], [51].

The relatively low specificity observed in several screening models suggests that implementation of rPPG-based screening may generate a substantial number of false-positive results, potentially increasing the demand for confirmatory laboratory testing. However, the practical impact of this phenomenon is difficult to quantify from the present study because referral burden depends on population prevalence, screening algorithms, healthcare resources, and local diagnostic pathways. Furthermore, limited published evidence currently exists regarding the downstream healthcare consequences of false-positive findings in rPPG-based HbA1c screening programs. Future implementation studies are therefore needed to evaluate the real-world cost-effectiveness, referral burden, and healthcare utilization associated with this technology.

4. Conclusion

This study demonstrates that rPPG-based HbA1c estimation has poor agreement with laboratory measurements and cannot be considered a diagnostic substitute for established biochemical methods. Although rPPG captures physiological signals associated with glycemic status, its outputs do not reliably correspond to clinical HbA1c classifications. Furthermore, the modest discriminatory performance (AUC 0.668–0.711) and very low agreement indicate that the technology has not yet achieved the accuracy required for clinical diagnosis. Therefore, any current application should be considered exploratory and complementary to, rather than a replacement for, laboratory-based testing. The principal finding of this study is that rPPG-derived HbA1c demonstrated poor agreement with reference HbA1c measurements and failed to achieve diagnostic equivalence. Any potential role in community screening should

therefore be regarded as exploratory and complementary to, rather than a replacement for, established laboratory-based testing.

Nevertheless, rPPG face scan technology holds strong potential as a non-invasive and scalable screening tool in community settings. Its practicality, ease of use, and compatibility with smartphone-based platforms make it particularly suitable for large-scale early detection and risk stratification of type 2 diabetes mellitus. With further refinement in algorithm development, improved signal stability, and integration into mobile health ecosystems, rPPG has the potential to support accessible and efficient community-level screening, especially in settings with limited access to laboratory services.

5. Declarations

5.1. Author Contributions

Conceptualization: S.B. and V.G.; Methodology: V.G.; Software: S.B.; Validation: S.B. and V.G.; Formal Analysis: S.B. and V.G.; Investigation: S.B.; Resources: V.G.; Data Curation: V.G.; Writing Original Draft Preparation: S.B. and V.G.; Writing Review and Editing: V.G. and S.B.; Visualization: S.B.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

5.3. Funding

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5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that artificial intelligence tools were used solely for minor grammatical and language refinement (similar to grammar-checking tools such as Grammarly). All aspects of the manuscript, including study design, data analysis, interpretation, and writing, were conducted and critically reviewed manually by the authors.

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