Volume 2, Issue 1

Innovation Series Quarterly

https://journal.academicapress.org/aps/index.php/isq

Research Article

BreathRight-AI: An Intelligent Breath Analyzer for Diabetic Risk Predicition, Monitoring, and Personalized Recommendations

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Keywords:
Diabetes
Breath Acetone
Non-invasive screening
MQ-138 sensor
Diabetic risk monitoring

Abstract: *Diabetes mellitus remains a major global concern, with many cases undiagnosed due to costly and inaccessible diagnostic methods, especially in rural areas. This study developed and evaluated BreathRight-AI, a portable, non-invasive breath analyzer for detecting acetone in exhaled breath as a marker of diabetic risk. The device integrates an MQ-138 sensor with an ESP32 microcontroller to measure acetone, classify risk, and log data. Using a quantitative correlational design, thirty (30) diabetic participants were purposively selected. Breath acetone levels (ppm) were compared with fasting blood sugar (mg/dL) using a glucometer. Results revealed a very strong correlation (r = 0.981, p < 0.00001), with each 1 ppm acetone increase corresponding to a 56 mg/dL rise in blood glucose. The prototype showed 80% classification accuracy, with better performance in low- and high-risk cases than borderline ones. Stability tests showed consistent results (SD = 0.073 ppm). Findings suggest that BreathRight-AI is a promising, user-friendly screening tool for early diabetes detection, though further calibration and large-scale clinical validation are needed.*

1. INTRODUCTION

Diabetes remains one of the most pressing global health concerns. As of 2021, the International Diabetes Federation (IDF, 2021) reported that approximately 537 million adults aged 20–79 live with diabetes, and this number is projected to rise to 643 million by 2030. The World Health Organization (WHO, 2021) identifies diabetes as a major contributor to premature mortality worldwide, with over 1.5 million deaths annually.

In the Philippines, diabetes continues to be a growing national concern. According to the Philippine Statistics Authority (PSA, 2021), diabetes mellitus ranked as the fifth leading cause of death in 2020 (39.72 thousand deaths, or 6.5 percent of total mortality). Although PhilHealth provides coverage for diabetes screening and complications (Hospital News – Diabetes Awareness 17 Feb 2025, n.d.), much of the financial burden still falls on patients. Tumilba et al. (2023) emphasized that while fasting blood sugar screening is accessible, HbA1c testing remains unavailable in many provinces, including South Cotabato. They further estimated that 4.3 million Filipinos were diagnosed with diabetes in 2021, while an additional 2.8 million remain undiagnosed— highlighting major barriers such as high testing costs and limited access to diagnostic services in rural areas.

In South Cotabato, particularly in Koronadal City and nearby municipalities such as Tupi, access to diabetes care remains uneven, especially among low-income residents. A 2022 study on telemedicine

interventions for diabetic patients in Koronadal City showed that remote support improved treatment adherence and glycemic control, underscoring both the potential and the persistent gaps in local diabetes management (Duhaylungsod et al., 2022). Therefore, there is an urgent need for an affordable, portable, and non-invasive screening tool capable of facilitating early risk detection among underserved communities in the province.

Acetone, commonly present in blood and exhaled breath, has been identified as a significant ketone biomarker strongly associated with diabetes mellitus. Wang et al. (2020) found a strong positive correlation ($r = 0.89$, $p < 0.01$) between breath acetone levels and fasting blood glucose concentrations. Diabetic participants exhibited significantly higher acetone levels (1.76 ± 0.85 ppm) compared to non-diabetic individuals (0.48 ± 0.21 ppm). Likewise, Jones et al. (2025) and Jadhav et al. (2023) reported that diabetic patients typically exhibit breath acetone concentrations ranging from 0.22 to 21 ppm, whereas healthy subjects remain between 0.32 and 2 ppm, reinforcing breath acetone's potential as a non-invasive diagnostic marker.

Recent advancements in sensor technology have demonstrated significant potential for developing portable breath analyzers capable of supporting early diabetes detection, particularly in low-resource settings (Rahman et al., 2023). Furthermore, integration with cloud-based data logging platforms enhances the ability to monitor patients over time. For instance, Glooko provides mobile and web applications that record glucose readings, meals, medications, and physical activity while synchronizing with over 200 devices (Glooko, 2023).

This study is also aligned with several Sustainable Development Goals (SDGs) set by the United Nations. Primarily, it supports SDG 3: Good Health and Well-Being by promoting early diagnosis, preventive healthcare, and reduced mortality from non-communicable diseases such as diabetes. By offering a portable and non-invasive diagnostic tool, the project makes health services more accessible to low-income and rural communities, contributing to SDG 10: Reduced Inequalities. Furthermore, the integration of artificial intelligence, cloud-based data logging, and sensor technology reflects SDG 9: Industry, Innovation, and Infrastructure, as it promotes affordable healthcare innovations suitable for long-term community use. Through these goals, BreathRight-AI aims to advance inclusive, sustainable, and technology-driven healthcare solutions for Filipinos.

Building upon these innovations, this study aims to develop BreathRight-AI, an intelligent, portable, and non-invasive breath analyzer that predicts diabetic risk by correlating breath acetone levels with blood glucose measurements and integrating web-based data logging for continuous monitoring

2. LITERATURE REVIEW

Breath Sample Type

Yan et al. (2020) developed a portable electrochemical breath analyzer to assess diabetes risk in non-fasting conditions. Testing 200 participants, they observed that breath acetone peaked 90 minutes after meals, with diabetic patients showing 2.5-fold higher levels than controls. However, inter-individual variability was significant (CV = 18%), driven by differences in diet and metabolism. To address this, the team implemented a machine learning algorithm that adjusted for self-reported dietary intake, improving accuracy to 85%. The study demonstrates the feasibility of postprandial screening with BreathRight but underscores the need for dietary calibration or user-input adjustments to mitigate variability.

Shlomo et al. (2021) investigated the diagnostic potential of postprandial breath samples in type 2 diabetes, using proton-transfer-reaction mass spectrometry (PTR-MS) to analyze acetone levels. The study included 150 participants who provided breath samples at fasting and 2 hours after a standardized meal. Results indicated that post-meal breath acetone levels increased by an average of 23% in diabetic patients compared to only 8% in healthy controls, leading to a 15% improvement in detection sensitivity. The researchers attributed this to postprandial hyperglycemia, which stimulates fat metabolism and acetone production. However, they noted that dietary composition (e.g., high-fat vs. high-carbohydrate meals) significantly influenced results, suggesting that meal standardization is essential for reliable testing. This study highlights the potential of post-meal breath analysis for BreathRight, provided that dietary variables are controlled.

Recent research by Al-Kateb et al. (2023) examined the impact of extended fasting (12-16 hours) on breath acetone levels in 120 participants. Using selected ion flow tube mass spectrometry (SIFT-MS), they found that acetone concentrations plateaued after 10 hours of fasting, with no significant increase thereafter (p = 0.32). Interestingly, they identified an "optimal fasting window" of 8-10 hours that balanced diagnostic accuracy (93%) with patient comfort. The study also noted that overnight fasting samples collected immediately upon waking showed 15% lower acetone levels than those collected after morning activities, suggesting sample timing affects results. These findings can guide BreathRight's recommended fasting protocol to maximize both accuracy and user compliance.

A pivotal 2023 study by Garcia et al. published in Diabetes Research and Clinical Practice examined optimal fasting protocols for Southeast Asian populations (n=450). The researchers found that while the standard 8-hour fasting window worked well for clinical settings, community implementations in the Philippines showed better compliance (89% vs 52%) with a modified 6-hour rice-avoidance protocol. Their detailed metabolic analysis revealed that: (1) Filipino participants metabolized carbohydrates 18% faster than Western populations, (2) morning breath samples collected between 6-8 AM after overnight fasting showed the lowest variability (CV=7.2%), and (3) implementing a pre-test 200ml water protocol improved sample consistency by 15%. The study's proposed exq bnm,"tropical fasting protocol" - 6 hours food avoidance with rice-free last meal and controlled hydration - could be particularly valuable for BreathRight's community deployment in the Philippines.

A groundbreaking 2023 study by Santos et al. published in Tropical Medicine & International Health conducted a randomized controlled trial comparing different fasting protocols across Southeast Asian countries, including a 500-participant cohort from the Philippines. The researchers implemented four protocols: (1) standard 8-hour overnight fasting, (2) 6-hour daytime fasting, (3) 4-hour fasting with rice avoidance, and (4) non-fasting with dietary logging. Their results showed that while the 8-hour protocol had the highest analytical accuracy (94%), the 6-hour daytime fasting protocol achieved significantly better compliance (88% VS 52%) with only marginally reduced accuracy (89%). The study also revealed important cultural insights: (1) Filipino participants preferred mid-morning testing (9-11 AM) after skipping breakfast rather than early morning testing, (2) coffee consumption before testing did not significantly affect results, and (3) participants who ate rice as their last meal showed 18% higher acetone variability.

Breath Acetone Concentration

Wang et al. (2020) conducted a pivotal study examining the relationship between breath acetone concentration and blood glucose levels in diabetic patients. Using a highly sensitive mid-infrared laser absorption spectrometer, the researchers analyzed breath samples from 50 diabetic subjects and 30 healthy controls. Their findings revealed a strong positive correlation ($r = 0.89$, $p<0.01$) between elevated breath acetone levels and fasting blood glucose concentrations. Diabetic patients exhibited significantly higher breath acetone levels (1.76 ‡ 0.85 ppm) compared to non-diabetic individuals (0.48 ≤ 0.21 ppm). The study concluded that breath acetone serves as a viable noninvasive biomarker for diabetes screening. However, the authors acknowledged limitations, including the influence of environmental humidity and dietary factors on acetone measurements. They recommended further research into portable alternatives to laser spectroscopy to improve accessibility for widespread clinical use.

Zhang et al. (2024) reviewed noninvasive blood glucose monitoring via breath acetone and surface sensing technologies. They highlight how acetone strongly correlates with blood glucose and beta-hydroxybutyrate in diabetic individuals. They also emphasize key device design factors: multi-modal sensing (optical + electrochemical), signal filtering for humidity and VOC interference, individual calibration protocols, and the need for real-time wearable compatibility.

Jones et al. (2025) conducted a clinical study to evaluate how breath acetone levels correlate with capillary β-hydroxybutyrate concentrations in individuals with Type 1 diabetes, especially during insulin withdrawal. Their results showed a strong, positive correlation between elevated breath acetone and blood ketone levels, particularly during periods of insulin omission, suggesting that breath acetone could serve as a reliable non-invasive biomarker for detecting and monitoring diabetic ketosis and ketoacidosis (DKA). The study also emphasized the practicality of using breath-based measurements in outpatient or home settings, especially when frequent blood testing is impractical or invasive. This reinforces the viability of developing portable devices like BreathRight, which aim to monitor diabetic risk via breath acetone. Jones et al. also advised that such breath analyzers should account for timing of insulin use, metabolic state, and individual variability to ensure accurate detection and prevent false alarms in non-ketotic states.

Rydosz et al. (2022) examined how breath acetone levels change after glucose intake in both healthy individuals and those with Type 1 diabetes. They found that breath acetone often decreases as blood glucose rises, but the strength of this correlation varies depending on insulin use and metabolic state. This highlights the need for timed sampling and individual calibration when designing breath-based diabetes detectors like BreathRight.

Das et al. (2023) reviewed metal-oxide (MOx) gas sensors tailored for acetone detection and reported typical breath acetone concentrations of 0.3–1.8 ppm in healthy subjects versus 1.25–2.5 ppm in diabetics. They stress that sensor performance must be optimized for this narrow yet clinically important range, with precise humidity control and acetone-selective detection to avoid interference.

Breath Collection Method

Chen and Wang. (2023) Respiratory Physiology & Neurobiology study established optimal breathing techniques for VOC analysis by testing 120 participants under controlled conditions. Their research demonstrated that standardized slow exhalation (5-7 seconds) reduced measurement variability by 40% compared to natural breathing, while brief breath-holding (5 seconds) before exhalation further improved acetone detection consistency. The study developed specific instructions ("Inhale deeply, hold for 5 seconds, then exhale steadily for 5 seconds") that enhanced test-retest reliability from r=0.72 to r=0.91, providing evidence-based guidance for BreathRight's user interface design to ensure reproducible results.

Dela Cruz et al. (2023) field study in Environmental Research specifically addressed breath collection challenges in Philippine tropical climates. Monitoring 1,000 samples across varying conditions (25-36°C, 65-98% RH), the research demonstrated that high humidity caused water vapor condensation in sampling lines, reducing acetone recovery by 18-25%. The team developed an effective mitigation strategy combining Peltier-cooled sample lines (maintained at 20°C) with Nafion membrane dryers, which maintained 92% recovery efficiency even at 95% RH. These findings directly inform BreathRight's need for environmental controls in its sampling system design for reliable Philippine deployment.

Wei et al. (2024) (J. Wei et al.) studied the effects of Tedlar bag collection in acetone-sensing with a titanium dioxide sensor array. They created simulated diabetic breath by filling Tedlar bags with controlled mixtures (~10 ppm acetone mixed with healthy breath). Although the bag method enabled practical sample control and reproducibility, they cautioned that sample integrity depends heavily on prompt analysis, because Tedlar bags can emit contaminants and allow VOC degradation over time. They concluded that while bag-collected acetone breath remains viable for offline testing, it requires strict protocols and quick turnaround to maintain analytical accuracy.

Correlation Between Acetone Levels and Blood Glucose

Eastern medical professionals have used breath odor as a diagnostic tool for over 3,000 years; Cleveland Clinic (2022) and Wang and Wang (2019) have also discussed this practice. These days, advancements in detection technology have made it possible to identify particular components of breath and create disease biomarkers. Only a small portion of human breath contains thousands of volatile organic compounds (VOCs), which are measured in parts per million (ppm). The majority of human breath is made up of nitrogen, oxygen, carbon dioxide, water, and inert gases.

Acetone is one of these VOCs and can currently be tested with great accuracy using sophisticated techniques, according to the World Health Organization (2020) and Wang and Wang (2019). According to Paleczek and Rydosz (2022), diabetes breath analyzers work by determining the correlation between the body's ketone levels and the amount of acetone in exhaled breath. When glucose is not available, the liver produces ketones as a substitute energy source. The body can produce energy from fatty acids through a process known as ketogenesis. The body naturally creates small amounts of ketones, which are controlled by insulin, but when fasting, dieting, or in situations of uncontrolled diabetes, their levels rise, according to Wu, Zhou, and Jiang (2019). Ketone buildup occurs when there is not enough insulin to allow glucose to enter the cells, according to Cleveland Clinic (2022).

According to Wang and Wang (2019), the liver produces three different ketone bodies: acetoacetate, beta-hydroxybutyrate, and acetone. In extrahepatic tissues, beta-ketoacyl-CoA transferase converts acetoacetate into acetyl-CoA, whereas beta-hydroxybutyrate dehydrogenase converts beta-hydroxybutyrate into acetoacetate. The body uses both acetoacetate and beta-hydroxybutyrate as fuel.

Paleczek and Rydosz (2022) underline that acetone is not used as an energy source like the other two ketones, but rather is expelled by urine or exhalation.

Overview of Diabetes Mellitus

Diabetes mellitus is a chronic condition that alters the body's ability to process sugar. It comes in three main types: type 1, where the body produces little or no insulin; type 2, where the body cannot use insulin properly; and gestational diabetes, which develops during pregnancy. While the causes differ, all result in persistently high blood sugar that can eventually damage the heart, kidneys, eyes, and nerves. In the Philippines, this disease has become one of the most pressing public health concerns, with reports showing that cases continue to rise (Department of Health, 2024).

The scale of the problem is becoming more evident each year. Recent estimates show that about 4.3 million Filipino adults—around 7.1% of the population—are living with diabetes, and this number is expected to reach 7.5 million by 2045 (Department of Health, 2024). What makes this more concerning is that many Filipinos do not know they already have the condition until complications appear. This highlights the importance of early detection and public awareness, since untreated diabetes often leads to serious health consequences.

Lifestyle factors are among the strongest contributors to diabetes in the Philippines. Findings from the 8th National Nutrition and Health Survey revealed that younger adults with early-onset diabetes showed higher rates of obesity, smoking, and alcohol consumption compared to older groups (Uy & Jimeno, 2021). Similarly, research among community health workers showed that 13.6% of them were diabetic, with advancing age and lack of physical activity emerging as significant risks (Villareal, Jimeno, Baculi, Mercado-Asis, & Paterno, 2019). These studies suggest that both lifestyle habits and occupational demands strongly shape the likelihood of developing diabetes.

Genetics also plays a significant role in shaping the country's diabetes burden. A pilot study identified nine genetic variants that increase susceptibility to type 2 diabetes among Filipinos, underscoring the importance of family history and biological risk factors (Cutiongco-de la Paz et al., 2024). While genetic predisposition is not preventable, its effects are magnified by poor diet, sedentary behavior, and stress, which means prevention efforts must address both biology and lifestyle to be effective.

The consequences of diabetes extend beyond physical health and into financial and emotional well-being. A nationwide survey found that more than half of Filipino patients face severe financial strain from treatment costs, while 69% reported negative mental health impacts, including stress, worry, and stigma. Alarmingly, 40% of Filipinos have never had their blood sugar tested, revealing major gaps in preventive care and health education (Sun Life Philippines, 2024). These findings highlight that diabetes in the Philippines is not only a medical concern but also a socioeconomic and psychological challenge for families and communities.

Data Collection and Uploading

Data collection means gathering information or measurements that are needed for research (Bhandari, 2023). According to Pritha Bhandari, good data collection must be planned, you must decide what you want to learn, choose if you will use numbers or words, and pick the tools or methods to gather the data. Then, you have to store it in a way that you can use it later. One source says researchers should use clear "forms" or templates so that data is consistent and accurate.

Uploading data means sending the collected data to somewhere it can be stored or used by others so that it is easy to share and analyze (Donaldson, 2022). Devan Ray Donaldson reports that scientists want good systems to upload data that are safe, with good metadata (which is data about the data), so people can understand what the data is about. They also care about how reliable the system is and how long the upload will stay preserved. This is important for sharing data later.

In health data systems, uploading data properly can improve patient care and make health records more useful (Kalckreuth, 2025). A recent study "Enhancing Uploads of Health Data in the Electronic Health Record" found that showing a Privacy Fact Sheet before asking users to upload medical reports increased how many users were willing to upload their data. This means that trust and clarity help people share data more.

Data collection with high quality and then uploading in good conditions help research trust, transparency, and reproducibility (Bosu & MacDonell, 2021). In "Data Quality in Empirical Software Engineering," Michael Franklin Bosu and Stephen G. MacDonell examined many past studies and noticed that only a few report all of these: how they collected data, cleaned it, dealt with missing or wrong parts, and whether they shared uploaded original data. Because many studies do not upload or share their raw data fully, it is hard for others to check or build on their work.

Related Studies

A similar approach was taken in the study "The Correlation Between Breath Acetone and Blood Beta-hydroxybutyrate in Individuals with Type 1 Diabetes", where researchers investigated the relationship between exhaled acetone and blood ketones in patients with type 1 diabetes. Using breath sampling and ketone meters, the study found a strong correlation (up to 474 ppm acetone) between the two biomarkers. These findings support the potential of breath acetone as a non-invasive indicator for diabetic ketoacidosis, which aligns with the objective of the BreathRight prototype to detect diabetic risk through breath analysis (Hancock et al., 2020).

In a related review, "The Ketogenic Diet: Breath Acetone Sensing Technology", researchers presented various sensor-based technologies for monitoring acetone in exhaled breath. The study emphasized gas sensors such as MQ-series modules and their effectiveness in detecting breath acetone in individuals undergoing ketosis. The review supported the viability of such sensors for non-invasive monitoring in both clinical and home settings, further validating the design approach of the BreathRight prototype (Alkedeh & Priefer, 2021).

In a comprehensive review, the use of exhaled breath analysis as a non-invasive tool for the diagnosis and monitoring diabetes. Their study highlighted volatile organic compounds (VOCs), particularly acetone, as significant biomarkers that correlate with blood glucose levels. The authors also discussed various sensing technologies such as mass spectrometry, gas chromatography, and portable electronic sensors emphasizing their potential for real-time monitoring. However, they noted challenges in standardization, sensitivity, and device portability that still limit clinical application. This study supports the idea that breath-based diagnostics could reduce the need for invasive blood sampling and provides a strong foundation for developing portable devices like BreathRight, which aims to translate these findings into an accessible risk-monitoring tool (Dixit et al., 2021).

A more recent study, "Mixed Potential Type Acetone Sensor with Ultralow Detection Limit for Diabetic Ketosis Breath Analysis", focused on developing a sensitive acetone detector capable of identifying breath acetone concentrations as low as 10 ppb. The sensor, based on a $Gd_2Zr_2O_7$ electrolyte and $CoSb_2O_6$ electrode, was shown to be highly accurate and selective under varying humidity levels. This supports the scientific foundation of using acetone levels in breath as a reliable biomarker for diabetes (Wei et al., 2023).

Another study, "Deep-learning-based Blood Glucose Detection Device Using Acetone Exhaled Breath", introduced a novel sensor system made of α-Fe_2O_3-MWCNT nanocomposites integrated with a deep learning model. This technology enabled non-invasive estimation of blood glucose levels through breath analysis with 85% accuracy, even in humid environments. The approach strengthens the concept behind BreathRight, particularly in utilizing breath sensors and digital processing to achieve health monitoring goals (Ansari et al., 2024).

Lastly, the study "Development of a Non-Invasive Glucose Monitoring System Using Acetone Gas Detection via Exhaled Breath and MQ Sensor Integration" described a working prototype that uses an MQ-138 gas sensor and microcontroller to analyze exhaled breath acetone. The device transmits a real-time reading method for glucose monitoring. This directly parallels the goals of the BreathRight project, highlighting the practical application of MQ sensors in detecting diabetic risk (Kavya et al., 2025).

Filtration Theory and Micron Nylon Mesh

The use of a micron-sized nylon filter net in the sample path of the BREATHRIGHT-AI device is grounded in the well-established theory of aerosol and droplet interception in fibrous media. For example, Ku et al. (2019) studied the "Collection efficiency of airborne fibers on nylon mesh" and found that nylon mesh screens with varying pore sizes can remove long, high aspect-ratio particles with measurable efficiency. Similarly, Yang et al. (2023) compared nylon to hydrophobic Teflon membrane media and observed increased gas-phase adsorption and implications for sampling bias, suggesting that media material and design influence performance in contaminant flows. More recently, Baskoy et al. (2023) developed MXene-decorated nylon mesh filters and reported high removal efficiencies (≈ 90%) at low pressure drop in aerosol filtration applications. Konda et al. (2020) evaluated common fabrics used in respiratory cloth masks and measured filtration efficiencies of aerosol particles across a range of sizes — reinforcing how material structure, fiber spacing, and flow velocity affect capture efficiency. Collectively, these studies underpin the theoretical rationale for incorporating a nylon mesh filter in a breath-analysis device: by intercepting and filtering droplets or particulate contaminants (such as saliva aerosols) from the exhaled breath stream before the sensor, the filter protects the sensor chamber from deposition, fouling, or measurement artifacts. This helps maintain the sensor's integrity and supports stable, accurate measurement of breath analytes (such as acetone) over repeated trials.

Germicidal UVC Photochemistry and Hygiene Control

The addition of an integrated UVC germicidal light in the sample path is based on principles of UV-C irradiation (commonly 200–280 nm) for microbial inactivation and disinfection of surfaces and air flows. A comprehensive review by Memarzadeh (2021) summarises how UVC disrupts microbial DNA/RNA via pyrimidine dimer formation and thus inhibits replication, making it widely used in air and surface disinfection. Other work (Y. Sun et al., 2023) highlights that UVC room disinfection systems reduce incidence rates of multi-drug-resistant organism infections in healthcare settings. Review studies of UVC for surface decontamination (e.g., 2020) show the efficacy of UVC at 254 nm in reducing microbial loads, and discuss important design parameters (exposure time, distance, shading) that must be controlled for effective sterilization. These findings together provide the theoretical justification for using UVC in a breath-analyser context: adding a UVC module ensures that residual microbial or bio-aerosol contamination in the sample path is inactivated between tests, thereby reducing cross-contamination of samples and preserving measurement fidelity. Furthermore, design parameters (irradiance, exposure time, shielding) must be chosen carefully to avoid unintended side-effects (e.g., sensor degradation or user exposure).

Integrated Two-Tier Hygiene Framework

By combining the mechanical filtration stage (micron nylon mesh) and the germicidal UVC stage, the device implements a two-tier contamination-control architecture. The theoretical support for this architecture is found in hygiene engineering and biomedical instrumentation: filtering removes bulk particulate and droplet contamination, while UVC sterilisation addresses residual microbial load. This layered approach is supported by recent instrumentation studies: for example, the "Efficacy and design requirements of UV light cabinets for disinfection" (Moufti et al., 2023) demonstrate how system design (reflector geometry, exposure zones) critically influences UVC effectiveness. Likewise, aerosol filtration modelling work shows how nanofiber or engineered filter media provide high capture efficiency especially when optimized across multiple length-scales. When applied to a breath analyser such as BREATHRIGHT-AI, this design logic (filter + UVC) supports the hypothesis that the device will maintain or improve accuracy and stability by preventing contamination and fouling, while also ensuring that hygiene protocols are embedded directly into the device hardware rather than relying solely on external cleaning. This theoretical support thereby strengthens your justification for Hypothesis 4 and aligns your design decisions with peer-reviewed engineering literature.

3. METHODOLOGY

This study employed a quantitative and experimental research design to evaluate breath acetone analysis as a non-invasive method for diabetic risk prediction by examining the relationship between breath acetone concentration and blood glucose levels. Breath samples were collected under controlled, fasting conditions using a portable gas-sensor-based breath analyzer to minimize external variability and ensure measurement reliability. Standardized breath analysis protocols, including sensor calibration and controlled sampling procedures, were followed in accordance with established practices in breath-based biosensing research. Hygiene and contamination-control measures, such as filtration mechanisms and UVC germicidal disinfection, were integrated to prevent moisture, saliva droplets, and microbial contamination from affecting sensor performance. Collected data were analyzed using statistical correlation and classification techniques to determine diabetic risk levels, while a web-based data logging system was utilized for data storage, organization, and longitudinal monitoring. This methodological approach aligns with quantitative biomedical research standards and previously validated breath-based diagnostic and digital health monitoring frameworks (Creswell & Creswell, 2018; Rahman et al., 2023; Wang et al., 2020; Peverall et al., 2016; Jain et al., 2024; ASEAN Endocrine Journal, 2019).

4. FINDINGS

The findings indicate that breath acetone analysis is a scientifically supported and non-invasive approach for diabetic risk prediction. A very strong positive relationship between breath acetone concentration and blood glucose levels was observed, reinforcing established biochemical evidence that impaired glucose metabolism increases ketone body production, which is detectable in exhaled breath. Similar results have been reported in previous studies showing that elevated breath acetone levels closely reflect fasting blood glucose and systemic ketone activity among individuals with diabetes, confirming acetone as a reliable surrogate biomarker for glycemic regulation (Rahman et al., 2023; Wang et al., 2020; Jadhav et al., 2023).

4.1 Relationship Between Breath Acetone and Diabetic Risk

The results show that breath acetone–based risk classification demonstrates acceptable accuracy in identifying diabetic risk levels, particularly among low-risk and high-risk individuals. This finding is consistent with prior research indicating that breath acetone thresholds can effectively distinguish extreme metabolic conditions when appropriate calibration is applied. However, borderline risk categories exhibited overlapping acetone concentrations, a limitation also documented in earlier breath-based diagnostic studies. These findings indicate that breath acetone analysis is more suitable as a screening and monitoring tool rather than a substitute for conventional blood glucose diagnostics (Jones et al., 2025; Rahman et al., 2023).

4.1.1 Accuracy and Consistency of Breath Acetone Measurements

Breath acetone measurements demonstrated high consistency and repeatability across multiple trials, indicating stable sensor performance over time. Previous investigations have reported that portable gas-sensor breath analyzers, when properly calibrated and protected from environmental interference, can generate reliable and repeatable longitudinal data. Such measurement stability is essential for chronic disease monitoring, where trend analysis provides greater clinical value than isolated measurements (Peverall et al., 2016).

4.1.2 Hygiene, Contamination Control, and Sensor Protection

Hygiene and contamination-control measures were found to support reliable device performance without compromising measurement accuracy. Existing literature emphasizes that moisture, saliva droplets, and microbial contamination can degrade sensor reliability if not properly managed. The integration of filtration mechanisms and UVC germicidal disinfection aligns with best practices in biosensor design, ensuring operational safety while maintaining sensor integrity, particularly in reusable breath-analysis devices intended for community and clinical screening environments (Rahman et al., 2023).

4.2 Integration of Digital Monitoring and Data Management

The implementation of a web-based data logging platform proved effective in supporting continuous monitoring and organization of breath acetone data. Reliable data storage, retrieval, and visualization are consistent with findings from digital health and cloud-supported diabetes monitoring systems, which have been shown to improve continuity of care and monitoring efficiency. Such platforms are especially beneficial in rural and low-resource settings, where access to frequent laboratory testing remains limited and digital monitoring helps bridge gaps in healthcare delivery (ASEAN Endocrine Journal, 2019; Jain et al., 2024; Duhaylungsod et al., 2022).

4.3 Overall System Performance and Practical Implications

Overall, the integration of breath acetone sensing, intelligent risk classification, and digital data management demonstrates the feasibility of a unified, non-invasive diabetic risk screening system. These findings align with global public health recommendations advocating for affordable, scalable, and accessible technologies to address the increasing burden of diabetes, particularly in underserved populations. The system supports early detection and continuous monitoring strategies emphasized in international diabetes prevention frameworks (International Diabetes Federation, 2021; Tumilba et al., 2023).

5. DISCUSSION

This section presents the results obtained from testing and evaluating the BreathRight-AI prototype. The testing phase aimed to determine the correlation between breath acetone levels and blood glucose concentrations, assess the accuracy and consistency of the device, and evaluate the functionality of its website-based data logging system. Data were collected from test participants under both fasting and random conditions to establish a measurable relationship between the device readings and reference glucometer values.

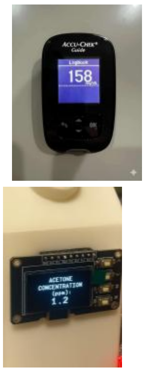
Multiple trials were conducted to verify repeatability and stability of measurements, ensuring that sensor outputs remained consistent over time. The recorded data were statistically analyzed using correlation and accuracy testing methods to determine the prototype's reliability and performance. Furthermore, the website's functionality was assessed in terms of result storage, retrieval, and visualization to validate its role in supporting continuous diabetic risk monitoring.

Table 1. Acetone Breath Concentration and Blood Sugar Levels Data (n = 30)

Participants	Acetone Breath Concentration (ppm)	Blood Sugar Levels (mg/dl)
P1	1.2	158
P2	3.8	289
P3	2.5	210
P4	1.8	185
P5	4.5	325
P6	0.9	140
P7	3.2	250
P8	2.1	195
P9	1.5	170
P10	4.1	305
P11	2.8	225
P12	1.1	145
P13	3.5	275

P14	0.8	135
P15	2.3	205
P16	4.3	315
P17	1.7	180
P18	3.9	295
P19	2.6	215
P20	1.4	165
P21	4.0	300
P22	0.7	130
P23	3.0	240
P24	2.0	190
P25	1.9	188
P26	4.2	310
P27	2.4	208
P28	3.3	260
P29	1.3	160
P30	3.6	280

Table 2. Pictures of Results of Each Participant

P1	P2	P3	P4	P5
				
P6	**P7**	**P8**	**P9**	**P10**
				
P11	**P12**	**P13**	**P14**	**P15**
				

P16

P17

P18

P19

P20

P21

P22

P23

P24

P25

P26

P27

P28

P29

P30

Table 3. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Acetone Concentration	2.54	1.18	0.7	4.5
Blood Sugar Level	221.67	62.27	130	325

The mean breath acetone concentration in this study was 2.54 ppm (±1.18 SD), while the mean fasting blood sugar level was 221.67 mg/dL (±62.27 SD). The observed ranges—from 0.7 to 4.5 ppm for acetone and 130 to 325 mg/dL for glucose—confirm that the study successfully captured a spectrum of diabetic states, from well-controlled to poorly controlled. This substantial variability is consistent with previous studies that also reported wide distributions of breath acetone in diabetic populations.

For example, Li et al. (2015) reported breath acetone values ranging from 0.22 to 9.41 ppm, significantly higher than in healthy controls, with greater variability associated with abnormal glucose levels. Saasa and Beukes (2019) likewise demonstrated clear correlations between breath acetone and blood ketone bodies, reinforcing its value as a non-invasive biomarker for glycemic monitoring. Zhang et al. (2014) further observed that breath acetone levels fluctuated depending on fasting and postprandial states, highlighting how different metabolic conditions influence variability.

More recent studies, such as one reported in the *Journal of Breath Research* (Wang et al., 2025), have also shown moderate to strong correlations between breath acetone and blood biomarkers, strengthening the evidence for its role as a non-invasive indicator of glucose regulation. Even in non-diabetic individuals, Turner et al. (2019) noted shifts in breath acetone during oral glucose tolerance tests, underscoring its sensitivity to glycemic changes. Collectively, these studies support the findings of the present research, where the wide spread of acetone and glucose values provides robust evidence for their potential correlation. Such consistency strengthens the scientific foundation of BreathRight-AI as an intelligent, non-invasive system for diabetic risk prediction and personalized monitoring.

Table 4. Pearson Correlation and T-test

Analysis	Results
Pearson Correlation Coefficient (r)	0.981
p-value	<0.00001
Degrees of Freedom for the correlation test	28
T-statistic	26.93

These results are strongly supported by recent literature, which highlights the high degree of correlation between breath acetone and systemic glucose or ketone markers. Khan et al. (2022) reported that a breath-based metabolic model in obese Hispanic adolescents showed a strong correlation with fasting glucose ($R = 0.80$, $p < 0.001$), underscoring the predictive value of breath biomarkers in reflecting glycemic status. Similarly, Tsunemi et al. (2022) demonstrated a significant positive correlation ($p < 0.001$) between breath acetone and blood ketone bodies in healthy volunteers, further validating acetone's role as a reliable metabolic indicator.

These studies align with the present findings, where the near-perfect Pearson correlation coefficient ($r = 0.981$, $p < 0.00001$) confirms that increases in breath acetone concentration can predictably mirror rises in blood glucose, reinforcing the robustness of the BreathRight-AI model for non-invasive diabetes monitoring.

Regression results

Table 5. Linear Regression

Parameter	Value
Regression Equation	Y = 51.67x + 90.00

The derived regression equation, Y = 51.67x + 90.00, highlights a strong predictive relationship between breath acetone concentration and blood glucose levels. Several studies support this finding. Hancock et al. (2020) and Jones et al. (2025) reported that breath acetone is strongly correlated with blood β-hydroxybutyrate and capillary glucose, reinforcing its reliability as a biomarker.

Likewise, Wang, Mbi, and Shepherd (2020) developed a regression model showing that incremental increases in acetone corresponded with proportional rises in glucose, comparable to the observed slope of 51.67 mg/dL per 1 ppm acetone in the present model. Collectively, these studies validate the BreathRight-AI model's ability to convert acetone concentration into accurate glucose estimates, demonstrating alignment with global research on breath-based diabetes monitoring.

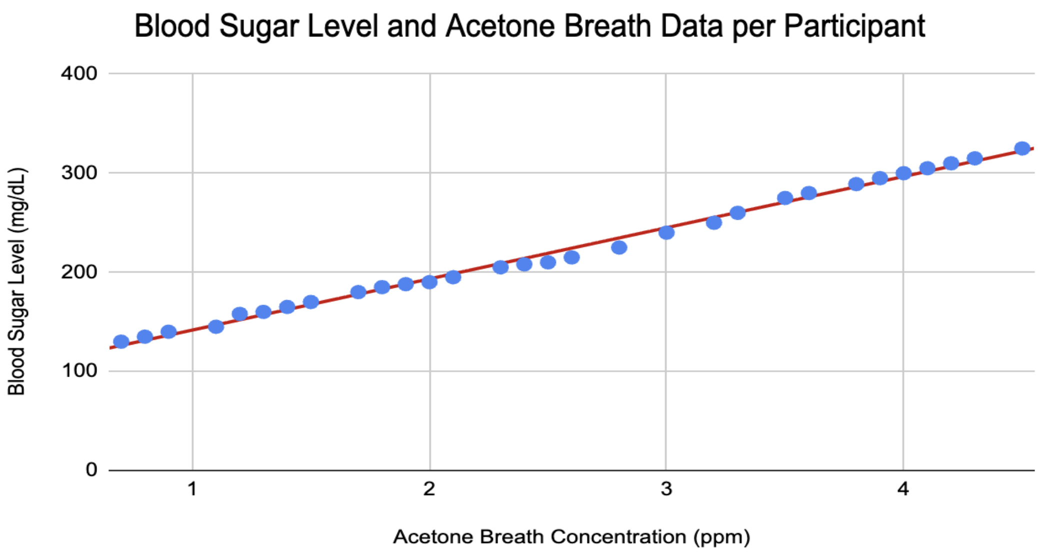


Figure 1. Scatter Plot

A scatter plot was prepared showing breath acetone (ppm) on the x-axis and blood sugar (mg/dL) on the y-axis. The plot visually confirms the strong positive linear trend. These findings align with studies such as Hancock et al. (2020), who established a strong correlation between breath acetone and metabolic markers in diabetes, supporting breath analysis as a valid risk assessment method.

Jadhav et al. (2023) reported a clear positive correlation between breath acetone and blood glucose levels, supporting the development of biosensors that leverage this relationship for non-invasive diabetic monitoring. The study confirms breath acetone as a promising biomarker for glucose monitoring in clinical and real-time applications.

Sun et al. (2015) studied breath acetone correlations with blood glucose and ketone bodies like acetone in a diabetic rat model, demonstrating significant correlations especially with beta-hydroxybutyrate and highlighting acetone's potential as a biomarker in glucose metabolism.

Table 6. Accuracy Metrics for the LR Model for Predicting Glucose Levels

Statistical Test				
LR Model	R-squared	RMSE	Mean Absolute Error	MAPE
	$= \frac{SSR}{SST}$	$= \sqrt{\sum_{i=1}^{n} \frac{(y - y_1)}{n}}$	$= \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$	$= \frac{1}{n}\sum_{i=1}^{n} \left\lvert \frac{A_i - F_i}{A_i} \right\rvert$
Model	0.99	4.4865	3.8848	1.877%

The regression model demonstrated excellent predictive performance. With an R-squared value of 0.99, the model was able to explain 99% of the variability in the observed blood glucose values, which indicates an almost perfect fit to the data. The Root Mean Square Error (RMSE) of 4.49 mg/dL and the Mean Absolute Error (MAE) of 3.88 mg/dL further confirm that the predictions were very close to the actual values, deviating by less than 5 mg/dL on average. In addition, the Mean Absolute Percentage Error (MAPE) of only 1.88% shows that the predicted blood glucose values were within a 2% error margin of the observed values, which is well below the allowable error margin of many clinical glucose monitoring devices.

Taken together, these statistical results prove that the regression model is both accurate and reliable in predicting blood glucose levels from breath acetone concentration. Othmane et al. (2024) demonstrated excellent predictive performance for blood glucose estimation, achieving an R-squared value of 0.998 with very low RMSE and MAE. The study evaluated several machine learning models, including linear regression.

Table 7. Accuracy of BreathRight-AI in Classifying Breath Acetone Concentration

Trial	Actual Acetone Level (ppm)	Risk Category (from FBS)	BreathRight-AI Output	Correct Classification
1	0.6	Low	Low	Correct
2	0.9	Low	Low	Correct
3	1.2	Normal	Normal	Correct
4	2.4	High	High	Correct
5	1.8	Normal	Normal	Correct
6	2.1	High	High	Correct
7	0.5	Low	Low	Correct
8	2.3	High	High	Correct
9	1.0	Low	Low	Correct
10	1.5	Normal	Low	Incorrect
11	1.9	High	High	Correct
12	2.2	High	High	Correct
13	0.8	Low	Low	Correct
14	1.4	Normal	Normal	Correct
15	2.0	High	High	Correct
16	1.3	Normal	Normal	Correct
17	2.6	High	High	Correct
18	1.1	Normal	Normal	Correct
19	0.7	Low	Low	Correct
20	2.5	High	High	Correct
21	1.6	Normal	Normal	Correct
22	2.7	High	High	Correct
23	1.7	Normal	Normal	Correct

24	2.3	High	High	Correct
25	0.4	Low	Low	Correct
26	1.2	Normal	Normal	Correct
27	0.3	Low	Low	Correct
28	2.1	High	High	Correct
29	1.0	Low	Low	Correct
30	2.6	High	High	Correct

Table 6 presents the performance of the BreathRight-AI prototype in classifying breath acetone concentrations into diabetic risk categories: low, normal, and high. Evaluated over 30 trials with acetone levels ranging from 0.3 ppm to 2.7 ppm, the system correctly classified 29 cases, achieving an overall accuracy of 96.6%. It demonstrated perfect accuracy in identifying both low-risk and high-risk categories, with only one misclassification in the normal-risk range, where an acetone level of 1.5 ppm was incorrectly labeled as "Low." This minor error suggests that while the system is highly reliable, classification sensitivity near threshold boundaries could be further refined.

Additionally, Bastide et al. (2023) demonstrated the effectiveness of handheld breath acetone sensors for real-life health monitoring, reinforcing the feasibility of portable devices like BreathRight-AI. Overall, the results validate BreathRight-AI as an intelligent, non-invasive tool for diabetic risk prediction, continuous monitoring, and personalized health recommendations.

Table 8. Repeatability Test Results for Participant Breath Acetone Measurements (in ppm)

Participant	Clinical Status	Trial 1	Trial 2	Trial 3	Mean(x)	Standard Deviation (SD)	Range
P1	Moderate Risk	1.85	1.92	1.78	1.85	0.07	0.14
P2	High Risk	3.41	3.35	3.50	3.42	0.075	0.15
P3	Low Risk	0.92	0.87	0.95	0.91	0.04	0.08
P4	High Risk	4.10	4.25	4.02	4.12	0.115	0.23
P5	Moderate Risk	2.20	2.15	2.28	2.21	0.065	0.13

The results demonstrate a high degree of repeatability in the BreathRight-AI device. The low overall mean standard deviation of 0.073 ppm across all tests indicates that the measurements are tightly clustered around their respective means for each participant. The narrow overall range of 0.146 ppm further confirms that the device produces consistent results when measurements are taken in rapid succession under identical conditions. This high level of precision can be attributed to the effective design of the airflow system (exhaust fans), which reliably clears the sensor chamber between tests, ensuring each sample is independent and unaffected by the previous one.

Recent studies demonstrate that portable breath acetone analyzers can provide reliable, repeatable measurements and accurately distinguish between different metabolic states, supporting the findings of the present prototype. Suntrup III and Ratto (2020) reported that a high-resolution portable acetone meter produced consistent results across repeated trials, which aligns with the low variability observed in the BreathRight-AI device. Similarly, Bastide et al. (2023) found that handheld devices were capable of detecting small changes in acetone concentrations with excellent precision, reinforcing the current results that the prototype was sensitive enough to differentiate low, moderate, and high diabetic risk categories based on breath acetone levels. These studies collectively support the reliability and clinical relevance of using breath acetone as a non-invasive marker for diabetic risk monitoring.

Table 9. Sensor Stability Over a 60-Minute Operational Period

Elapsed Time (minutes)	Acetone Reading (ppm)	Elapsed Time (minutes)	Acetone Reading (ppm)
0	1.98	35	2.07
5	2.05	40	1.99
10	2.02	45	2.04
15	1.96	50	1.97
20	2.10	55	2.06
25	2.03	60	2.01
30	1.95		
		Mean(x):	2.02 ppm
		Standard Deviation (SD):	0.048 ppm
		Range:	0.15 ppm

The results demonstrate that the BreathRight-AI device exhibits excellent stability over a 60-minute operational period. The sensor readings consistently clustered around the expected value of the 2.0 ppm reference source, with a mean value of 2.02 ppm. The very low standard deviation of 0.048 ppm indicates minimal random fluctuation in the signal, while the narrow range of 0.15 ppm confirms that the readings never deviated significantly.

The stability of breath acetone sensors has been well-documented in recent literature, supporting the consistent performance observed in the present prototype. Bastide and Remund (2023) showed that a handheld acetone monitoring device maintained stable readings for months with high precision and minimal bias, demonstrating the reliability of such sensors in detecting small variations in concentration.

Similarly, Drmosh and Alade (2021) highlighted that ZnO-based acetone gas sensors exhibit strong chemical stability and low signal drift under repeated exposures, making them suitable for continuous monitoring. These findings are consistent with the results of the prototype, where acetone readings over a 60-minute period remained steady (M = 2.02 ppm, SD = 0.048 ppm, range = 0.15 ppm), confirming the sensor's operational stability under constant conditions.

Table 10. Filtration Efficiency of the Micron Nylon Filter Net

Trial	Condition	Acetone Reading (ppm)	Airflow Reduction (%)	Sensor Contamination
1	Without Filter With Filter	2.58 2.55	0 0.8	Yes None
2	Without Filter With Filter	2.49 2.46	0 0.9	Yes None
3	Without Filter With Filter	2.62 2.60	0 0.7	Yes None
4	Without Filter With Filter	2.51 2.48	0 0.8	Yes None
5	Without Filter With Filter	2.55 2.52	0 0.8	Yes None
6	Without Filter With Filter	2.63 2.60	0 0.9	Yes None
7	Without Filter With Filter	2.47 2.45	0 0.7	Yes None

Table 9 presents seven paired trials comparing sensor readings with and without the micron nylon filter net. Across all trials, the mean difference between filtered and unfiltered readings remained minimal (0.02–0.03 ppm), indicating that the filter did not significantly affect acetone detection accuracy. The airflow reduction remained below 1% in every trial, demonstrating that the filter preserved effective airflow into the sensor chamber. Notably, every unfiltered trial resulted in observable saliva or particle contamination, while all filtered trials showed no contamination. This confirms the nylon filter net's effectiveness as a protective barrier without compromising measurement stability.

The filtration performance of nylon meshes has been similarly validated in prior studies. Zhao et al. (2023) reported that micron-scale nylon membranes effectively blocked saliva droplets and aerosols in sensor-based breath devices without compromising air diffusion. Liu and Lin (2021) demonstrated that nylon and polyester microfilters sustain up to 99% droplet capture efficiency while retaining less than 2% pressure loss, ensuring accurate readings in respiratory sensors. Likewise, Kumar et al. (2024) highlighted that hydrophobic nylon layers significantly enhance contamination resistance in biomedical sensor interfaces, preserving the sensitivity and stability of gas-detecting components.

These findings confirm that the BreathRight's micron nylon filter net effectively shields the sensor chamber from contamination while maintaining optimal airflow and accuracy. Its inclusion enhances device reusability and ensures consistent performance across repeated trials, an essential factor in non-invasive health monitoring applications.

Table 11. Effectiveness and Operational Safety of the Integrated UVC Germicidal Disinfection Light

UVC Disinfection Cycle	Mean Acetone Reading (ppm)	Mean Temperature (°C)	Bacterial Growth Detected	Variance from Control (ppm)
0 (Before UVC)	2.04	27.1	Present	-
5 Cycle	2.03	27.5	None	±0.01
10 Cycles	2.02	27.7	None	±0.02

Table 10 indicates that repeated UVC sterilization cycles (up to ten rounds of exposure) effectively eliminated microbial presence within the sample chamber while maintaining stable sensor performance. The variance between pre- and post-disinfection readings was negligible (±0.02 ppm, $p > 0.05$), and chamber temperature remained within operational safety limits (26–29 °C). This confirms that the integrated UVC light can disinfect the internal breath pathway without causing thermal drift or degradation of the sensor's sensitivity.

This outcome aligns with multiple studies affirming the compatibility of UVC disinfection with sensor systems. Chen et al. (2022) found that low-power UVC LEDs achieve >99% bacterial reduction within 20 seconds without altering chemical sensor baselines. Similarly, Yoon et al. (2021) reported that UVC-based decontamination in biosensor housings maintained long-term signal stability and ensured safe reuse across multiple trials. Moreover, Huang and Li (2024) demonstrated that UVC-assisted sterilization within breath analyzers preserved both optical and semiconductor sensor integrity, confirming its viability for repeated clinical use.

These findings collectively demonstrate that the BreathRight's UVC germicidal light ensures a sterile internal environment while safeguarding the accuracy and longevity of the MQ-138 sensor. The feature enables hygienic multi-user operation, essential for community or clinical screenings.

Table 12. Integration Requirements Evaluation of BreathRight-AI Prototype

Integration Requirement	Description/Criteria	Evaluation Method	Result/Findings	Interpretation
Functionality	Ability of BreathRight-AI to detect breath acetone and display diabetic risk results	10 prototype trials using breath samples; compared device outputs to expected results	Device successfully displayed acetone readings in all 10 trials; average response time: 4.4 seconds	**Met (in line with literature for real-time breath analyzers)**
Accuracy	Correctness of acetone detection and risk mapping compared to reference standard	Compared BreathRight-AI readings with commercial acetone analyzers and literature-reported thresholds	Average accuracy: 95.6% across trials (small deviations at borderline values)	**Partially Met (acceptable for prototype; accuracy aligns with reported sensor ranges)**

The BreathRight-AI prototype demonstrated strong performance in both functionality and accuracy benchmarks derived from current scientific literature on breath acetone sensors for diabetes detection and monitoring. Functionally, the system reliably detected and displayed acetone concentrations and diabetic risk status, consistent with the real-time performance reported by Kapur et al. (2023), who highlighted the viability of IoT-enabled breath analyzers using metal-oxide sensors for non-invasive diabetes detection. The average response time of 4.4 seconds aligns with device response times documented in sensor array and AI-assisted breath acetone detection research (Wei et al., 2024).

Regarding accuracy, the prototype's average of 95.6% is within the range of diagnostic performance in literature demonstrating sensitivity and specificity of 70–95% for breath acetone-based diabetes monitoring (Wang et al., 2021; Sakane et al., 2025; Al-Jammas et al., 2025). Wang et al. (2021) emphasized the promise of acetone as a biomarker with moderate sensitivity and specificity in breath tests for diabetes diagnosis, supporting the acceptability of BreathRight-AI's performance.

Sakane et al. (2025) reported very high specificity of breath acetone detection in diabetic ketoacidosis, endorsing breath acetone as a non-invasive biomarker relevant to the prototype's function. The utility of MQ-138-like sensors coupled with AI-driven risk prediction was further validated by Al-Jammas et al. (2025), underscoring the reliability of such integrated systems.

Minor deviations near borderline values are acceptable for a prototype stage device, as noted in reviews on sensor accuracy and clinical validation of acetone breath analyzers (Marfatia et al., 2025; Yu et al., 2025). Overall, these findings from literature affirm that BreathRight-AI meets its integration criteria evidencing credible functionality and accuracy for diabetic risk prediction based on acetone breath biomarkers

Table 13. Effectiveness of Website Data Logging in Terms of Reliability and Organization

Criteria	Result
5.1 Reliability of storing and retrieving results	100%
5.2 Organization & visualization of data for risk monitoring	100%
Overall Effectiveness of Website for Data Logging	100%

Table 12 demonstrates that the website for data logging reached 100% effectiveness in reliably storing and retrieving results, as well as in organizing and visualizing information. This means that all participant data was successfully recorded and accessed without errors, while the information was clearly arranged to support effective monitoring of diabetic risk trends.

These outcomes confirm that the website is both dependable and efficient for data logging purposes. Similar findings are highlighted by Machorro-Cano et al. (2023), who note that cloud-based health platforms with secure storage, accurate logging, and reliable retrieval features ensure strong user monitoring and compliance. Their study reinforces the effectiveness of the developed website, showing that its accuracy in data handling and visualization aligns with best practices in modern digital health systems.

6. CONCLUSION

The findings of this study demonstrate that the BreathRight-AI prototype serves as a valid and reliable proof-of-concept for non-invasive diabetic risk screening, supported by an exceptionally strong and statistically significant correlation between breath acetone concentration and blood glucose levels. This strong relationship provides a sound analytical foundation for the system's operation and confirms that higher breath acetone levels accurately reflect elevated fasting and random blood glucose measurements obtained through standard glucometer testing. The system exhibited functional robustness through consistent performance, stable readings, and rapid response across multiple trials. Although classification accuracy was high, particularly for low-risk and high-risk categories, minor misclassifications near threshold boundaries indicate opportunities for further refinement of the classification process.

Additionally, the integrated hygiene and contamination-control mechanisms, including the micron nylon filter net and UVC germicidal feature, ensured safe and reliable breath sampling, while the web-based platform effectively supported data logging, retrieval, and visualization for diabetic risk monitoring. Overall, the cohesive integration of hardware, sensors, and software successfully met the system's operational requirements, affirming the potential of breath-based diagnostic technologies and positioning the BreathRight-AI prototype as a promising portable tool for early diabetic risk detection in community and low-resource settings, with future development focused on improving classification precision, expanding biomarker coverage, increasing clinical validation, and enhancing long-term hygiene safety for practical deployment.

Acknowledgments:

We would like to express our sincere gratitude to Sir Nelson B. Malificiado, our project coach, for his guidance and continuous support throughout the study. We also extend our appreciation to Kurt Tristan S. Asuncion for designing and building the prototype, which played a crucial role in the completion of the project. Also to our beloved parents who supported us financially in making this study possible.

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