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Development and Effectiveness of the Diabet Alert Application for Detecting Abnormal Blood Glucose Levels in Patients with Diabetes Mellitus

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ABSTRACT

Introduction: Abnormal blood glucose levels are a common problem in patients with diabetes and require early detection to prevent complications. Digital health technology may facilitate rapid and accessible glucose abnormality screening. This study aimed to evaluate the diagnostic performance and agreement of the Diabet Alert application compared with GlucoCheck in detecting abnormal blood glucose levels.

Methods: This diagnostic evaluation study involved 102 participants. Blood glucose classification using Diabet Alert was compared with GlucoCheck as the reference method. Diagnostic performance was assessed using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy. Agreement was evaluated using observed agreement and Cohen's kappa, while the McNemar test was used to assess differences in paired classifications.

Results: Diabet Alert demonstrated a sensitivity of 94.3%, specificity of 20.0%, PPV of 87.2%, NPV of 37.5%, and overall accuracy of 83.3%. The observed agreement was 83.3%, while Cohen's kappa was 0.122 (p = 0.058), indicating low agreement after accounting for chance agreement. The McNemar test showed no statistically significant difference between the two classification methods (p = 0.099)

Conclusion: Diabet Alert demonstrated high sensitivity and PPV, indicating good ability to detect abnormal blood glucose levels. However, its low specificity and NPV indicate limited ability to correctly identify normal glucose levels. Therefore, Diabet Alert has potential as a screening tool for early detection of abnormal blood glucose levels, but further refinement and validation are needed before it can replace standard glucose measurement.

Keywords: Diabet Alert; Blood Glucose; Diabetes Mellitus; Diagnostic Performance; Sensitivity

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INTRODUCTION

Diabetes mellitus (DM) is a metabolic disease characterized by impaired insulin production or insulin resistance[1]. Indonesia ranks fifth globally in terms of the number of people with diabetes, with more than 19 million cases recorded in 2021[2]. Impaired insulin function can lead to abnormal blood glucose levels, particularly hypoglycemia and hyperglycemia[3]. These conditions often go unrecognized by patients[4] and may increase the risk of serious complications. Diabetes-related complications have been reported to contribute to more than two million deaths worldwide.

Experts predict that the number of people with diabetes will double over the next 12–15 years[5]. According to the Basic Health Research (*Riskesdas*), the prevalence of diabetes mellitus (DM) increased in almost all provinces in Indonesia, from 1.5% in 2013 to 2.0% in 2018 [6]. Unhealthy lifestyles, including smoking, alcohol consumption, frequent intake of high-fat and high-sugar junk food such as sugary beverages, cakes, and fried foods, as well as physical inactivity, increase the risk of DM among individuals aged 30–40 years[7].

People with DM are at increased risk of developing both hyperglycemia and hypoglycemia[3]. Hyperglycemia is characterized by elevated blood glucose levels, defined as ≥200 mg/dL for random plasma glucose or ≥126 mg/dL for fasting plasma glucose [8], whereas hypoglycemia is generally defined as a blood glucose level <70 mg/dL [4]. DM is a major risk factor for cardiovascular disease [9], and intensive glycemic control has been shown to reduce the risk of cardiovascular events [10]. In 2021, diabetes and its complications were associated with more than two million deaths globally, with elevated blood glucose contributing to approximately 11% of cardiovascular deaths[11]. Beyond cardiovascular consequences, substantial fluctuations in blood glucose levels may induce cellular dysfunction and structural damage in the brain[12], potentially resulting in acute neurological manifestations that require prompt recognition and timely management[13].

Unrecognized and untreated hypoglycemia may progress to severe neuroglycopenia, characterized by cognitive dysfunction, loss of consciousness, and, in some cases, seizures or epilepsy[4]. Approximately 83.8% of events potentially associated with hypoglycemia have been attributed to drug-related interactions, while the remaining 16.2% may contribute to hyperglycemia[3]. Most hypoglycemic episodes are associated with excessive insulin therapy, a history of infection, and inadequate food intake[14]. Because hypoglycemia and hyperglycemia can present with different clinical manifestations, individuals with diabetes need to recognize these symptoms to initiate appropriate management promptly[15]. However, only 59.4% of people with diabetes have demonstrated adequate knowledge of hypoglycemic symptoms[16]. Consequently, many patients rely on self-monitoring blood glucose devices (glucometers) to detect fluctuations in blood glucose levels [17]. Nevertheless, access to glucometers remains limited, with only 6.7% of patients with diabetes reported to own a glucometer, while 93.3% do not have access to one[18].

This situation is partly attributable to the relatively high cost of glucometers, which may limit their accessibility for many individuals[19]. To address this challenge, strategic interventions are needed to promote the adoption of health technologies[20], particularly affordable and accessible approaches for detecting abnormal blood glucose levels[21]. The development of technologies capable of analyzing patient data has demonstrated substantial potential to improve the quality of care and patient health outcomes[22]. Nevertheless, although 91% of patients reported that they always or frequently experienced symptoms when their blood glucose levels were low, symptom-based recognition alone may not be sufficient for reliable detection[23]. Previous research has also demonstrated that patients at risk of hypoglycemia can be identified using accurate predictive models, which may facilitate the implementation of timely and targeted preventive interventions[24].

Hypoglycemia is classified into three levels: level 1, defined as a glucose concentration of 54–<70 mg/dL (3.0–3.9 mmol/L); level 2, defined as <54 mg/dL (<3.0 mmol/L); and level 3, characterized by severe hypoglycemia accompanied by mental or physical impairment requiring assistance from another person[25]. Level 1 hypoglycemia is typically associated with autonomic symptoms, including anxiety, tremor, palpitations, diaphoresis, paresthesia, and hunger[26]. Level 2 hypoglycemia is characterized predominantly by neuroglycopenic symptoms, such as impaired concentration, headache, blurred vision, dizziness, confusion, seizures, speech disturbances, and restlessness. Severe hypoglycemia may progress to profound mental impairment and loss of consciousness[27]. Several factors have been associated with impaired awareness of hypoglycemia, including older age, longer diabetes duration[28,29], and a history or increased frequency of severe and recurrent hypoglycemic episodes[25,30].

In contrast, patients with diabetes experiencing hyperglycemia may present with excessive thirst, frequent urination, fatigue, pruritus, and weight loss[31]. In mild cases, these symptoms may remain unrecognized, whereas they become more apparent as hyperglycemia worsens [32]. Severe hyperglycemia may manifest as

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polyuria, polydipsia, weight loss, and neurological symptoms, including lethargy, neurological deficits, altered mental status, and coma. In diabetic ketoacidosis, additional manifestations may include nausea, vomiting, abdominal pain, fruity-smelling breath, and compensatory hyperventilation [32]. However, to date, there is limited development of a dedicated system specifically designed to assist patients with diabetes in recognizing symptoms of both hypoglycemia and hyperglycemia.

The Diabet Alert application was developed to detect hypoglycemia and hyperglycemia based on differences in symptoms experienced by patients and to provide appropriate guidance on actions to take during these conditions. The advancement of health technology and mobile applications offers opportunities to develop accessible and user-friendly tools for early detection of blood glucose abnormalities. As a mobile health (mHealth) application, Diabet Alert is designed to provide practical guidance for identifying potential blood glucose abnormalities in patients with diabetes mellitus. This study aimed to develop and evaluate the effectiveness of the Diabet Alert application in detecting abnormal blood glucose levels among patients with diabetes mellitus.

METHODS

Study Design and Setting

This study employed a comparative diagnostic accuracy design with a cross-sectional paired-measurement approach to evaluate the performance of the Diabet Alert application in detecting abnormal blood glucose levels among patients with diabetes mellitus. The study commenced with the development of Diabet Alert, a web-based digital application designed to identify potential hypoglycemia and hyperglycemia based on patient-reported symptoms. The application was developed collaboratively by researchers, an internal medicine specialist, experienced diabetes care nurses, and a programmer, with clinical input regarding symptom selection, assessment criteria, and the classification algorithm. Diabet Alert generates one of three classifications: potential hypoglycemia, potential hyperglycemia, or no identified glucose abnormality. Each participant was assessed using both Diabet Alert and GlucoCheck under standardized conditions, allowing direct comparison of the application's symptom-based classification with blood glucose measurements obtained from GlucoCheck. This paired design was selected to evaluate the diagnostic performance and agreement of Diabet Alert while minimizing the influence of inter-individual variability

Population and Sample

The study population comprised patients diagnosed with diabetes mellitus who received care at the Internal Medicine Outpatient Clinics of Luwuk Regional General Hospital and Anutapura Regional General Hospital, Palu. A total of 102 patients were included, comprising 88 patients (86.3%) from Luwuk Regional General Hospital and 14 patients (13.7%) from Anutapura Regional General Hospital. Participants were selected based on predefined inclusion criteria, including adult patients with diabetes mellitus who were able to communicate their experienced symptoms and undergo blood glucose assessment. Each participant underwent symptom assessment using the Diabet Alert application and blood glucose measurement using GlucoCheck as the reference comparator.

Data Collection Methods and Instruments

Diabet Alert

The study instruments consisted of the Diabet Alert application, GlucoCheck device, and a data collection form. Diabet Alert is a symptom-based digital application developed to support the early detection of potential hypoglycemia and hyperglycemia in patients with diabetes mellitus. The symptom items were developed based on the American Diabetes Association (ADA) Standards of Care in Diabetes, clinical references on the manifestations of hypoglycemia and hyperglycemia, and clinical review by an internal medicine specialist and experienced diabetes care nurses.

The symptom items included manifestations of hypoglycemia, such as sweating, tremor, palpitations, hunger, anxiety, dizziness, weakness, impaired concentration, and confusion. Hyperglycemic symptoms included polyuria, polydipsia, increased hunger, fatigue, blurred vision, and unexplained weight loss. Warning signs of severe hyperglycemia, including fruity-smelling breath and poorly healing wounds, were also incorporated into the assessment. Nonspecific symptoms were not used as the sole basis for classification but were interpreted in conjunction with other reported symptoms to improve the clinical relevance of the application's classification.

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Diabet Alert processed the selected symptoms using a predefined algorithm and generated an initial classification of potential hypoglycemia, potential hyperglycemia, or no identified glucose abnormality based on the reported symptoms. GlucoCheck was used as the reference comparator to obtain blood glucose measurements in mg/dL. A data collection form was used to record participant characteristics, reported symptoms, Diabet Alert classifications, and GlucoCheck measurements. These instruments were subsequently used to evaluate the diagnostic performance of Diabet Alert in detecting abnormal blood glucose conditions.

Data Collection Procedures

The study was conducted from January to August 2026 and comprised three main stages. Development of the Web-Based Diabet Alert Application. Diabet Alert was developed collaboratively by a multidisciplinary team comprising researchers, an internal medicine specialist, experienced diabetes care nurses, and a programmer. The development process included establishing the symptom database, developing the classification algorithm, designing the user interface, and integrating the system into a web-based application for patient symptom assessment.

Validation and Feasibility Testing. The developed application underwent expert review by an internal medicine specialist, experienced diabetes care nurses, and an information technology expert. The evaluation covered the relevance and clarity of symptom items, the accuracy of the classification algorithm and workflow, system functionality, interface design, navigation, and usability. Expert feedback and recommendations were used to revise and refine the application.

Application Trial. The application was initially tested using simulated hypoglycemia and hyperglycemia cases to assess its functionality and usability. Following finalization, each participant underwent symptom assessment using Diabet Alert and blood glucose measurement using GlucoCheck as the reference comparator. The results from both methods were subsequently compared to evaluate the diagnostic performance and agreement of Diabet Alert

Data Analysis

Data were analyzed using statistical software with a significance level of $p < 0.05$. Participant characteristics and reported symptoms were summarized descriptively using frequencies and percentages for categorical variables and mean ± standard deviation (SD) or median (interquartile range [IQR]) for continuous variables.

The diagnostic performance of Diabet Alert was evaluated by comparing its symptom-based classifications with blood glucose measurements obtained using GlucoCheck as the reference comparator. Classifications were categorized as hypoglycemia, normoglycemia, or hyperglycemia according to predefined clinical thresholds. Diagnostic performance was assessed using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy.

Agreement between Diabet Alert and GlucoCheck was assessed using Cohen's kappa, while the McNemar test was applied to evaluate differences in paired classification proportions. Analyses were conducted separately for the detection of hypoglycemia and hyperglycemia. The findings were presented in tables to summarize the diagnostic performance and agreement of Diabet Alert in detecting abnormal blood glucose conditions.

Ethical Considerations

The study received ethical approval from the Health Research Ethics Committee of Poltekkes Kemenkes Palu, under ethical approval number No. 000911/KEPK POLTEKKES KEMENKES PALU/2026. All participants were informed about the study objectives, potential benefits, and procedures before undergoing the assessments. Participant confidentiality was strictly maintained, and all collected data were used solely for academic and research purposes

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RESULTS

Distribution of Participant Characteristics and Clinical Variables

Table 1. Presents the Demographic and Clinical Characteristics of the 102 Participants

Characteristics	Categories	Total (N=102)
Hospital of admission	RSU Luwuk	88 (86.3)
	RS Anutapura Palu	14 (13.7)
Sex	Male	33 (32.4)
	Female	69 (67.6)
Age, years		57.90 ± 11.34
Duration of diabetes, years		3 (4)
Type of antidiabetic medication	Oral	67 (65.7)
	Insulin	31 (30.4)
	Oral + insulin	4 (3.9)

Most participants were recruited from RSU Luwuk (86.3%) and were female (67.6%). The mean age was 57.90 ± 11.34 years, with a median diabetes duration of 3 years (IQR 4). Oral antidiabetic medication was the most frequently used treatment (65.7%), followed by insulin therapy (30.4%) and combined oral and insulin therapy (3.9%).

Evaluation of the Diagnostic Performance of the Diabet Alert Application

Table 2. Diagnostic Performance and Agreement of the Diabet Alert Application Compared with GlucoCheck in Detecting Abnormal Blood Glucose Levels

Parameter	Diabet Alert	GlucoCheck	Diagnostic Performance/ Agreement	p-value
Normal, n (%)	8 (7.8)	15 (14.7)	—	—
Abnormal, n (%)	94 (92.2)	87 (85.3)	—	—
Total, n (%)	102 (100.0)	102 (100.0)	—	—
Sensitivity	—	—	94.3%	—
Specificity	—	—	20.0%	—
Positive Predictive Value (PPV)	—	—	87.2%	—
Negative Predictive Value (NPV)	—	—	37.5%	—
Overall Accuracy	—	—	83.3%	—
Observed Agreement	—	—	83.3%	—
Cohen's Kappa (κ)	—	—	0,122	0.058
McNemar Test	—	—	—	0,099

Diabet Alert demonstrated high sensitivity (94.3%) but low specificity (20.0%) compared with GlucoCheck. Among 87 participants classified as abnormal by GlucoCheck, 82 were correctly identified by Diabet Alert, while 5 were missed. Conversely, among 15 participants classified as normal by GlucoCheck, only 3 were correctly identified as normal, whereas 12 were classified as abnormal by Diabet Alert. The PPV was 87.2%, while the NPV was 37.5%, with an overall accuracy of 83.3%. Although the observed agreement between the

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two methods was 83.3%, Cohen's kappa demonstrated only slight agreement (κ = 0.177, p = 0.058). McNemar's test indicated no statistically significant difference in paired classification proportions (p = 0.143).

DISCUSSION

Effectiveness of the Diabet Alert Application in Detecting Abnormal Blood Glucose Levels

The findings demonstrated that Diabet Alert had high sensitivity in detecting abnormal blood glucose conditions. Sensitivity reflects the ability of a diagnostic tool to correctly identify individuals with the target condition[33], and higher sensitivity indicates a greater capacity to detect true abnormal cases [34]. High sensitivity is associated with a lower risk of false-negative results, in which a test incorrectly classifies an individual with an actual abnormality as normal[35]. A low false-negative rate is particularly important for screening applications because it reduces the likelihood of missing clinically relevant cases [36]. In this study, the false-negative rate of Diabet Alert was only 5.7%, indicating that the application successfully identified the vast majority of abnormal blood glucose cases detected by GlucoCheck.

However, the high sensitivity of Diabet Alert was accompanied by low specificity (20.0%). Specificity refers to the ability of a diagnostic tool to correctly identify individuals who do not have the target condition [37]**.** In this study, this finding indicates that only 20% of participants who were classified as having normal blood glucose levels by GlucoCheck were correctly identified as normal by Diabet Alert. The combination of high sensitivity and low specificity suggests that the application tends to favor an abnormal classification when symptoms indicative of glucose disturbances are reported. Such a conservative approach may be appropriate for an early detection and warning system, as prioritizing sensitivity can reduce the likelihood of overlooking potentially abnormal conditions and facilitate timely follow-up assessment[38–40].

The Positive Predictive Value (PPV) of 87.2% indicates that, among the 94 participants classified as having abnormal blood glucose levels by Diabet Alert, 82 were confirmed as abnormal by GlucoCheck, while 12 represented false-positive results. In contrast, the Negative Predictive Value (NPV) was only 37.5%, indicating that of the eight participants classified as normal by Diabet Alert, only three were confirmed as normal by GlucoCheck, whereas five were actually abnormal (false-negative results). These findings suggest that a positive (abnormal) classification generated by Diabet Alert is considerably more reliable than a negative (normal) classification. Thus, the application appears more suitable for screening and early warning of potential glucose abnormalities than for confirming normal blood glucose status.

The findings showed that overall accuracy and observed agreement between Diabet Alert and GlucoCheck were both 83.3%, indicating that the two methods produced the same classification for most participants. However, the Cohen's kappa coefficient (κ = 0.122; p = 0.058) indicated only slight agreement between the two methods after accounting for chance agreement. The McNemar test yielded p = 0.099 (>0.05), indicating that although Diabet Alert and GlucoCheck did not produce identical classifications for all participants, the difference in the proportions of normal and abnormal classifications was not statistically significant. Overall, these findings support the potential of Diabet Alert as an early screening tool for identifying possible blood glucose abnormalities, although further refinement and validation are required to improve its agreement with standard glucose measurements**.**

Interpretation of Key Findings

The findings demonstrated that Diabet Alert has good capability in detecting abnormal blood glucose levels, supporting its potential use as an early screening tool. However, the application showed limited ability to correctly identify normal glucose conditions; therefore, normal results should be confirmed using a reference glucose measurement. Overall, Diabet Alert shows promise for supporting the early detection of blood glucose abnormalities, although further refinement of its classification algorithm is needed to improve diagnostic performance and reduce false-positive results.

Comparison with Previous Studies

These findings are consistent with previous evidence reported by[41;42;43], indicating that symptoms experienced by patients with diabetes mellitus can provide useful information for identifying potential abnormalities in blood glucose levels. The present findings further support the potential of Diabet Alert as a symptom-based digital tool to assist in the early identification of possible blood glucose abnormalities.

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Limitations and Cautions

This study has several limitations. GlucoCheck was used as the reference comparator, and the sample distribution was predominantly concentrated in the abnormal glucose category. These factors may have influenced the interpretation of Diabet Alert's diagnostic performance, particularly its predictive values and overall agreement. Future studies should include a larger, more diverse, and more balanced sample to improve the robustness, validity, and generalizability of the findings.

CONCLUSION

The Diabet Alert application demonstrated potential as a screening tool for detecting abnormal blood glucose levels. The application showed good ability to identify abnormal glucose conditions, although its ability to correctly classify normal conditions remains limited. Therefore, Diabet Alert may support early detection of glucose abnormalities, but further refinement and validation are needed before it can be used as a substitute for standard glucose measurement.

DECLARATIONS

Ethics approval: The study received ethical approval from the Health Research Ethics Committee of Poltekkes Kemenkes Palu, under ethical approval number No. 000911/KEPK POLTEKKES KEMENKES PALU/2026. All participants were informed about the study objectives, potential benefits, and procedures before undergoing the assessments. Participant confidentiality was strictly maintained, and all collected data were used solely for academic and research purposes

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