Jurnal Teknokes
Homepage: teknokes.org; Vol. 18, No. 3, pp. 198-206, September 2025;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

RESEARCH PAPER

OPEN ACCES

Smart Screening Technology for Diabetes Risk: FFQ and FINDRISC Integration in a Digital Platform

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ABSTRACT

Diabetes mellitus (DM) is a growing metabolic and autoimmune-related disease whose early onset is increasingly observed among young adults, including the university students in Indonesia. The existing screening models are either costly, invasive, or fail to integrate lifestyle data, leaving a gap for practical yet scalable solutions in this population. This study introduces a smart screening technology that combines the Food Frequency Questionnaire (FFQ) and the Finnish Diabetes Risk Score (FINDRISC) within a digital platform to capture both dietary patterns and individual risk factors. A cross-sectional design was applied to 110 undergraduates, chosen to reflect young adults most vulnerable to lifestyle-related DM risks. Data were collected entirely online to ensure feasibility and low-cost scalability in campus and public health programs. Multiple linear regression revealed that both individual factors (age, gender, BMI, physical activity, family history) and dietary patterns were significant predictors of DM risk (β = 0.312; β = 0.389; p < 0.001), explaining 37.4% of the variance. Compared to prior studies that relied solely on clinical or genetic markers, this integration highlights the added predictive value of dietary data in digital risk screening. With 70.9% of respondents at moderate and 25.5% at high risk, the findings underscore the urgent need for early intervention among Indonesian students. The proposed model offers practical applications through university health centers, mobile apps for student lifestyle monitoring, and peer-based preventive education. Future work should extend to biomarker validation and adaptive algorithms to enhance predictive accuracy and applicability across diverse populations.

PAPER HISTORY

Received August 01, 2025
Revised August 28, 2025
Accepted Sept 18, 2025
Published Sept 30,2025

KEYWORDS (ARIAL 10)

Diabetes Mellitus;
Smart Screening;
Individual Factors;
Dietary Pattern;
Early Detection;
FINDRISC;
FFQ

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I. INTRODUCTION

Diabetes mellitus (DM) is a global health emergency, with prevalence rising each year and straining healthcare systems. The International Diabetes Federation reported 537 million adults with diabetes in 2021, projected to reach 643 million by 2030 [1]. In Indonesia, a parallel escalation was observed: the Consensus on Management and Prevention of Type 2 Diabetes Mellitus highlighting prevalence increases tied to dietary changes and sedentary lifestyles [2], [3]. These shifts, accelerated by urbanization and modernization, reshape food environments and physical activity, driving metabolic disorders. While prior literature has documented global and national burdens extensively, a sharper research gap lies in early detection strategies tailored for young adults, especially the university students in Indonesia.

University students represent a particularly vulnerable cohort. Their transitional lifestyle, marked by high intake of fast food and sugar-sweetened beverages, irregular meals, and sedentary behavior, accelerates metabolic risk factors early in life [4], [5]. Indonesian studies reinforce these concerns: [6] highlighting direct links between dietary habits and DM onset, while [7] emphasizing the urgency of early health promotion. However, despite such evidence, students remain understudied in diabetes risk research, particularly in relation to integrated screening using validated tools such as the Food Frequency Questionnaire (FFQ) and Finnish Diabetes Risk Score (FINDRISC). This insufficiency constitutes a clear research gap, as behaviors formed during university years may persist into adulthood without intervention.

The existing literature underscores both intrinsic and extrinsic contributors to DM risk. Genetic predisposition, BMI, and family history interact dynamically with lifestyle factors to exacerbate insulin resistance and accelerate DM onset [8], [9]. Western-pattern diets rich in processed, calorie-dense foods heighten these risks [4], [10], with meta-analytic confirmation linking such diets to DM in adolescents and young adults. Local studies in Public Health Center settings mirror these associations [6]. The coherence between global and local findings indicates both the urgency and feasibility of tailored screening in Indonesian youth.

Screening tools provide promising low-cost interventions. FINDRISC has proven accuracy, with

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Indonesian modifications yielding AUC of 80.9% (NCEP-ATP III) and 88.9% (IDF), sensitivity of ~74-90%, and specificity of ~75% [11]. While FFQs reliably estimate dietary patterns among youth [12], [13], [14], [15], [16], the existing applications have treated these tools separately. Studies among young adults applying FINDRISC alone found most classified as low risk, with a minority at moderate-to-high risk [17], [18], but omitted dietary assessment. The novelty of this study lies in integrating FFQ and FINDRISC within a single digital platform, offering more robust stratification by combining biological, behavioral, and nutritional dimensions.

Advances in digital health amplify this integration. SmartEdge architecture improves diabetes prediction by 5% via ensemble machine learning [19], and multimodal large language models enhance accuracy by merging text, imaging, and temporal data [20]. Mobile health interventions have already reduced HbA1c in type 2 DM patients [21]. Embedding FFQ-FINDRISC into such platforms promises scalable, low-cost screening for students. Importantly, contextual validation remains essential, as cultural norms shape risk factor reporting, as shown in Uganda [22] and Iran [23].

This study explicitly addresses two gaps: the lack of integrated FFQ–FINDRISC screening in university populations and the absence of culturally validated digital platforms for early DM risk. Guiding this research is the question: *Can the integration between FFQ and FINDRISC within a digital platform provide a valid, scalable, and low-cost approach to early diabetes risk detection among Indonesian university students?*

The practical implications are significant. For Indonesian universities, such smart screening can strengthen preventive health infrastructure, enable early lifestyle modification, and foster a healthier generation before diabetes becomes entrenched. By situating the research within biomedical engineering and health informatics, this study advances both scientific knowledge and public health practice.

II. MATERIALS AND METHOD

A. Dataset

This study analyzed data from 110 active Indonesian undergraduate students recruited through convenience sampling due to accessibility within university networks and feasibility during data collection constraints. While this approach limits representativeness and generalizability, it provides an initial exploratory basis for testing the integrated FFQ-FINDRISC platform in a student setting. All participants were in normal physical condition and provided informed consent via an online form before participation.

The dataset consisted of three main modules: (1) individual factors (age, gender, BMI, physical activity, family history of DM), (2) dietary patterns measured using a validated Food Frequency Questionnaire (FFQ), and (3) diabetes risk assessed using the Finnish Diabetes Risk Score (FINDRISC). The FFQ captured frequency and types of food consumed, adapted to include local dietary items relevant to Indonesian students (e.g., fried snacks, instant noodles, sweetened beverages). FINDRISC was linguistically adapted to ensure clarity in describing activity levels and dietary components. Both instruments were delivered through a digital platform to enable automated scoring and minimize human error.

Table 1. Operational definitions, parameters, instruments, and scoring categories for study variables

No	Research Variable	Operational Definition	Parameter (Dataset Code)	Instrument	Score Category
1	**Control Variable: Individual Factors**	Demographic and lifestyle characteristics influencing DM risk	1) Age 2) Gender 3) BMI 4) Physical Activity 5) Family History of DM	Self-administered questionnaire	Categorized based on median split or tertiles depending on analysis
2	**Independent Variable: Dietary Pattern**	Assessment of the type and frequency of food consumed to maintain health and nutritional status	1) Type of Food 2) Meal Frequency	Food Frequency Questionnaire (FFQ)	1 = High (>452) 2 = Moderate (236-343) 3 = Low (<128)
3	**Dependent Variable: Risk of Diabetes Mellitus (DM)**	Assessment to determine the risk of developing DM	1) Age 2) Gender 3) Body Mass Index 4) Waist Circumference (derived from BMI & self-report) 5) Dietary Pattern 6) Physical Activity 7) Family History of DM	Finnish Diabetes Risk Score (FINDRISC) Questionnaire	1 = Low risk (≤6) 2 = Moderate risk (7-11) 3 = High risk (≥12)

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B. Data Collection

Data collection was conducted entirely online through a digital platform. Participants entered demographic details and self-reported anthropometric measurements (height and weight) for BMI calculation. Recognizing the risk of recall and social desirability bias in self-reported measures, the survey included standardized instructions, visual guidance for measurement, and anonymized responses to minimize bias. Physical activity was reported as the frequency of ≥30 minutes/day of moderate-to-vigorous exercise. Family history of DM was documented as present or absent.

The FFQ required reporting intake frequency of major food groups including fruits, vegetables, whole grains, processed foods, sugary drinks, and high-fat foods, with local examples provided for clarity. The FINDRISC module automatically computed scores from responses covering age, BMI, waist circumference (derived from BMI and self-report), daily fruit/vegetable consumption, physical activity, antihypertensive use, history of elevated blood glucose, and family history of DM.

C. Data Processing

An integrated smart screening algorithm processed all responses in real time, following a standardized pipeline: completeness checks and outlier removal; numerical coding of categorical variables; conversion of FFQ frequencies into standardized scores with classification into low, moderate, or high dietary patterns; automated FINDRISC scoring with categorization into low (≤6), moderate (7-11), or high (≥12) risk levels; and integration of FFQ and FINDRISC results into a combined dataset for statistical analysis. This digital approach minimized manual scoring, enhanced reproducibility, and reflected engineering principles of automation, interoperability, and accuracy as illustrated in Fig. 1.

D. Data Analysis

Data analysis was performed using IBM SPSS Statistics v25. Descriptive statistics summarized the characteristics of individual factors, dietary patterns, and DM risk distribution. Pearson's Chi-square tests assessed associations between categorical variables and DM risk categories. Multiple linear regression was selected to determine the simultaneous effects of individual factors and dietary patterns on DM risk because it allows assessment of predictive contributions of both intrinsic (e.g., BMI, family history) and extrinsic (dietary) factors within one model. Alternative models such as logistic regression were considered, but linear regression was deemed appropriate given the continuous composite risk scores generated by the FINDRISC instrument. Statistical significance was set at $p < 0.05$. The final model reported regression coefficients and the coefficient of determination (R^2) to quantify explained variance.

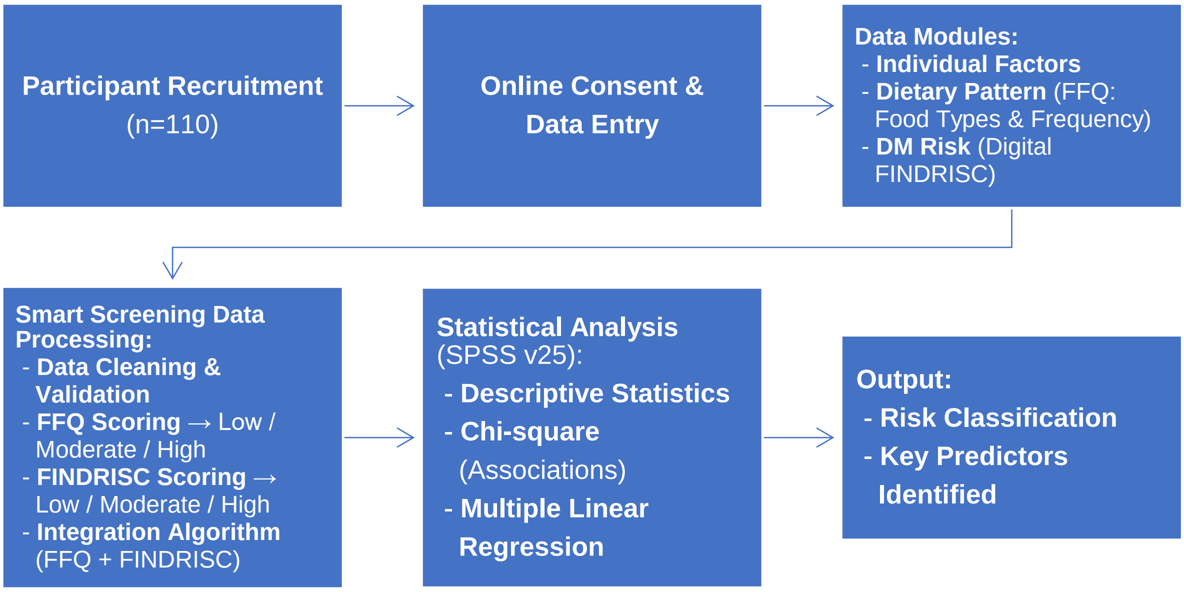

Fig. 1. Automated workflow integrating FFQ and FINDRISC for real-time diabetes risk classification

III. RESULTS

1. Demographics (Individual Factors)

The smart screening platform automatically captured and classified demographic and lifestyle data from 110 undergraduate students in real time. Participants were aged 17-22 years (51.8%) or 23-28 years (48.2%), mirroring the typical age distribution of Indonesian undergraduates. Gender was balanced (54.5% female, 45.5% male). BMI profiling showed 36.4% with normal weight, 39.1% overweight, and 24.5% obese, with excess weight flagged as a metabolic risk marker. Notably, nearly two-thirds exceeded the normal BMI range, consistent with rising overweight and obesity prevalence among Indonesian young adults [24].

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The platform also identified 48.2% as physically inactive and 54.5% with a family history of DM. These findings suggest that undergraduates, who are often considered healthy, already carry substantial intrinsic and lifestyle-related risk factors. While automation ensures efficiency and scalability, reliance on self-reported anthropometric data may introduce bias, warranting validation through clinical measures.

2. Dietary Pattern Analysis

The Food Frequency Questionnaire (FFQ) module within the smart screening platform automatically converted self-reported consumption frequencies into quantifiable dietary scores. Participants' intake of fruits, vegetables, whole grains, processed foods, sugary drinks, and high-fat items was transformed into weighted values, aggregated into composite scores for dietary pattern classification.

Results showed that 52.7% of students fell into the moderate dietary pattern group, reflecting a mix of healthy and less healthy foods but with potential caloric excess. Another 38.2% were categorized as high dietary pattern, flagged by the algorithm as elevated metabolic risk due to frequent intake of processed, high-sugar, and high-fat items. Only 9.1% achieved a low dietary pattern score, associated with nutrient-dense intake and lower risk.

Automated FFQ scoring eliminated manual coding, minimized human error, and ensured consistent thresholds across respondents. This real-time processing not only accelerated classification but also enabled scalability for larger populations. Importantly, the dominance of moderate-to-high risk groups is consistent with prior studies on Indonesian students, which highlight limited fruit and vegetable consumption alongside increasing fast-food dependence. By situating findings within this broader nutrition transition, the platform demonstrates its potential as both a risk-detection and public health monitoring tool for young populations in Indonesia.

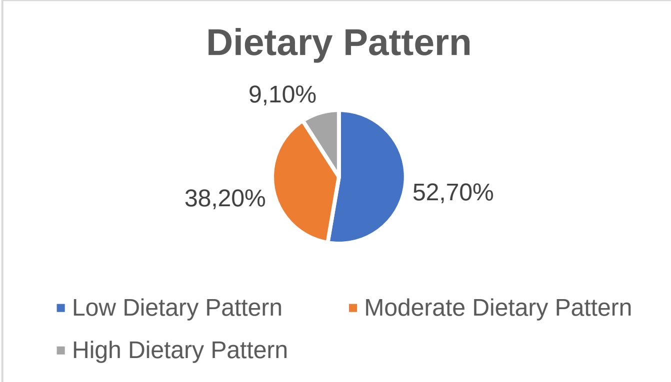

Fig. 2. Automated FFQ scoring system classifying dietary patterns into risk-based categories

3. DM Risk Classification (Smart Screening Output)

The integrated smart screening system, which combined FFQ-based dietary scoring with the Finnish Diabetes Risk Score (FINDRISC), automatically classified the risk profiles of all 110 participants in real time. The algorithm-generated output (Table 2) showed that 70.9% of students were in the moderate risk category, 25.5% were at high risk, and only 3.6% were classified as low risk.

These results highlight a concerning pattern: nearly all students already face some degree of diabetes risk, with a negligible proportion in the low-risk group. This clustering into moderate and high categories aligns with national data showing increasing prediabetes prevalence among Indonesian youth [24]. Comparable international findings in Malaysia and China also indicate elevated risks among young adults when lifestyle and dietary factors are jointly considered [25].

Although the digital algorithm enabled rapid, reproducible classification, the absence of manual or clinician cross-validation limits accuracy assurance. Still, the convergence between overweight/obesity, inactivity, and poor diet suggests the system captures meaningful health risk clusters warranting preventive interventions among university populations.

Table 2. A Summary of Participant Characteristics Based on Diabetes Mellitus (DM) Risk Level

Variable	**Low Risk n (%)**	**Moderate Risk n (%)**	**High Risk n (%)**	**p-value**
Age				0.548
17-22 years old	1 (1.8%)	41 (71.9%)	15 (26.3%)	
23-28 years old	3 (5.7%)	37 (69.8%)	13 (24.5%)	
Gender				0.167
Male	0 (0.0%)	36 (72.0%)	14 (28.0%)	
Female	4 (6.7%)	42 (70.0%)	14 (23.3%)	
BMI				0.000***
Normal	4 (10.0%)	36 (90.0%)	0 (0.0%)	
Overweight	0 (0.0%)	35 (81.4%)	8 (18.6%)	
Obese	0 (0.0%)	7 (25.9%)	20 (74.1%)	
Physical Activity ≥30 min/day				0.004**
Yes	4 (7.0%)	45 (78.9%)	8 (14.1%)	
No	0 (0.0%)	33 (62.3%)	20 (37.7%)	
Family History DM				0.646
None	1 (2.0%)	37 (74.0%)	12 (24.0%)	

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Variable	Low Risk n (%)	Moderate Risk n (%)	High Risk n (%)	p-value
Yes	3 (5.0%)	41 (68.3%)	16 (26.7%)	
Individual Factors				0.002**
Low	0 (0.0%)	2 (100.0%)	0 (0.0%)	
Moderate	4 (5.2%)	61 (79.2%)	12 (15.6%)	
High	0 (0.0%)	15 (48.4%)	16 (51.6%)	
Dietary Patterns				0.000***
Low	4 (40.0%)	6 (60.0%)	0 (0.0%)	
Moderate	0 (0.0%)	51 (87.9%)	7 (12.1%)	
High	0 (0.0%)	21 (50.0%)	21 (50.0%)	

(Source: IBM SPSS 25.00 output, 2025)

*p-value taken from Pearson Chi-Square test

4. Hypothesis Testing (Key Predictor Identified)

The regression engine embedded within the analysis pipeline identified both Individual Factors and Dietary Patterns as significant predictors of diabetes mellitus (DM) risk (Table 3). The Individual Factors module, encompassing BMI, physical activity, and family history, produced an unstandardized coefficient of B = 0.312 and a standardized coefficient of β = 0.303 ($p < 0.001$). This highlights the role of weight status and activity level as foundational determinants of metabolic health in young adults. More prominently, the Dietary Patterns module yielded a stronger predictive value (B = 0.389; β = 0.491; $p < 0.001$), underscoring nutrition as the dominant factor in shaping early DM risk within this population.

Table 3. Multiple Linear Regression Model Results for the Prediction of Diabetes Mellitus Risk

Variable	B	SE	Beta	t	p-value
Individual Factor	0.312	0.079	0.303	3.927	0.000
Dietary Pattern	0.389	0.061	0.491	6.359	0.000
$R^2 = 0.374$					

(Source: IBM SPSS 25.00 output, 2025)

When both modules were integrated, the regression model achieved a coefficient of determination ($R^2 = 0.374$), indicating that approximately 37.4% of the variance in DM risk could be explained by the combined predictors. This outcome closely aligns with prior evidence suggesting that lifestyle and diet together account for 30-45% of variance in early diabetes risk. The result validates the engineering rationale for merging FFQ-derived dietary scores with FINDRISC outputs, as the combination captures both behavioral and biological risk dimensions in a scalable manner.

Nevertheless, the statistical model has methodological constraints. No diagnostic tests for multicollinearity or interaction effects were performed, which weakens confidence in the independence of predictors. For instance, a synergistic relationship between BMI and high-fat dietary intake may intensify risk beyond their separate contributions, yet such effects remain unexplored here. Addressing these limitations in future studies, through robustness checks, longitudinal designs, and biomarker validation, would enhance causal inference and strengthen clinical relevance. Overall, these findings affirm that automated integration of dietary and lifestyle data provides not only efficiency but also meaningful predictive accuracy, though further refinement is required before clinical deployment.

IV. DISCUSSION

A. Individual Factors and Diabetes Mellitus (DM) Risk

The prevalence of diabetes mellitus risk among Indonesian university students observed in this study highlights an urgent public health concern. Using the FINDRISC instrument, the majority of respondents were categorized as moderate risk (70.9%) and a substantial proportion as high risk (25.5%). These findings are in line with the International Diabetes Federation's (2021)[1] report emphasizing that the productive age group is increasingly vulnerable to diabetes due to sedentary behavior and dietary shifts.

Regression results confirmed that individual factors such as age, gender, body mass index (BMI), physical activity, and family history of DM were significant predictors of risk (β = 0.312; $p < 0.001$). This outcome corroborates prior studies [8], [9], which demonstrated the interplay of genetic predisposition, overweight status, and low activity in shaping young adults' metabolic vulnerability. Nevertheless, the strength of predictors is not uniform across studies. Furthermore, a study [25] found that BMI consistently emerges as the strongest risk factor for type 2 DM, while others [26], [27] highlighted that overweight status induces insulin resistance and chronic inflammation. Evidence even suggests BMI may outweigh advanced maternal age as a predictor of gestational diabetes [28] and exert intergenerational effects [29]. However, not all findings align; for example, a previous [30] reported that underweight individuals with diabetes had markedly elevated risk for tuberculosis, showing that BMI is not a uniformly linear predictor of adverse outcomes. Similarly, [31] found that while BMI ≥ 25 kg/m² increases diabetes risk in Ethiopia, other factors such as older age, illiteracy, smoking, and hypertension can act as equally strong determinants, suggesting contextual variability in BMI's predictive strength.

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

These contrasts underscore the need to interpret predictors contextually rather than confirmatorily. For example, while this study supports BMI as a central determinant, the lack of biomarker validation or control for synergistic effects (e.g., BMI × high-fat diet) limits internal validity. Similarly, reliance on self-reported anthropometric data introduces recall and desirability bias. The cross-sectional design prevents causal inference, which reduces the explanatory power compared to longitudinal approaches. Thus, although the smart screening platform effectively integrates individual risk factors with dietary data, future iterations must incorporate objective biomarkers and temporal tracking to enhance reliability.

From a practical standpoint, these findings suggest that universities could integrate digital risk screening into student health services, enabling early detection and targeted counseling. At a policy level, the Ministry of Health may adapt such platforms for nationwide screening of productive-age adults, provided methodological refinements and equitable digital access are secured.

B. Dietary Pattern and Diabetes Mellitus (DM) Risk

Dietary patterns were found to significantly influence DM risk ($\beta = 0.389$; $p < 0.001$). The prevalence of unhealthy dietary patterns (38.2%) among students aligns with research in developing nations, where frequent consumption of high-calorie, processed, and high-sugar foods elevates DM risk [32], [33]. International literature further confirms that such diets are strongly linked to the onset of T2DM and cardiometabolic complications [34].

Yet, the relationship is not uniform across studies. [35] reported no significant association between fast-food consumption and visceral adiposity among Bangladeshi T2DM patients, suggesting that the impact of diet may vary by cultural or lifestyle contexts. Similarly, [36] found that in preschool-aged children, environmental factors such as stress, pollution, and food accessibility were stronger predictors of DM risk than diet, which showed only borderline significance. In another context, [37] observed that dietary modification in Iranian T2DM patients produced no immediate improvements in eating habits or glycemic outcomes, with significant effects emerging only after sustained family-centered empowerment over three months. Together, these studies highlight that dietary risk operates conditionally, amplified or attenuated by environment, age, and social support.

Our results therefore cannot be interpreted in isolation. Discrepancies may arise from differences in physical activity, stress exposure, socioeconomic background, or family support systems, all of which can mediate dietary impacts. This supports the argument for holistic assessment models that integrate not only food frequency but also psychosocial and environmental determinants of metabolic health [38].

The integration of FFQ within the smart screening platform represents technical advancement, enabling real-time dietary risk profiling alongside FINDRISC scoring, thereby improving reproducibility and scalability. However, efficiency should not obscure limitations. The platform remains reliant on self-reported data, subject to recall and social desirability biases [39]. Moreover, without biomarker validation such as HbA1c or lipid panels, claims of predictive accuracy remain provisional [40].

Generalizability is also constrained. The focus on university students may not capture dietary and environmental realities of non-student young adults, limiting external validity. These methodological issues partly explain divergence across studies and underscore the need for longitudinal designs incorporating biomarker validation and diverse populations.

From a policy standpoint, embedding dietary assessment into digital health infrastructures could strengthen prevention programs at campus and community levels. For example, integrating personalized feedback into university nutrition services or national health applications could align with Indonesia's digital health roadmap. Still, equitable scaling demands attention to privacy, algorithm transparency, and access barriers to avoid reinforcing health disparities.

V. CONCLUSION

This study assessed the influence of individual factors and dietary patterns on diabetes mellitus (DM) risk among university students using an integrated smart screening model. Both dietary patterns ($\beta = 0.491$; $p < 0.001$) and individual factors ($\beta = 0.303$; $p < 0.001$) emerged as significant predictors, with the combined model explaining 37.4% of the variance ($R^2 = 0.374$). A high prevalence of risk was identified, as most students were categorized as moderate risk (70.9%). Beyond quantifying these associations, the study validated the feasibility of a digital platform for non-invasive, scalable risk stratification in young adults.

While these findings are promising, several limitations must be acknowledged. The cross-sectional design restricts causal inference, and reliance on self-reported data introduces recall and social desirability biases. Furthermore, the single-university sample constrains generalizability to broader populations. These methodological constraints may account for inconsistencies with prior research and highlight the need for more robust validation.

Future research should adopt longitudinal designs that monitor glycemic outcomes over time and incorporate biomarker assessments (e.g., HbA1c, lipid profiles, fasting insulin) to strengthen predictive accuracy. Beyond methodological refinements, implementation must address ethical and cultural considerations, particularly regarding data privacy, unequal digital access, and the integration of dietary assessments into diverse community settings. For Indonesia, where DM prevalence among young adults is rapidly increasing, scaling such a tool requires alignment with local dietary habits, digital literacy levels, and public health priorities.

Overall, this study contributes to the intersection of digital health engineering and public health nutrition by demonstrating how smart screening can operationalize

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p-ISSN: 1907-7904

early DM risk detection. However, its broader impact depends on embedding these tools into community-based strategies, such as targeted nutrition education, university health programs, and youth-focused prevention policies, so that technology not only identifies risk but also drives sustainable behavioral change in populations most vulnerable to DM.

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DOI: https://doi.org/10.35882/teknokes.v18i3.109

e-ISSN: 2407-8964
p-ISSN: 1907-7904

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DOI: https://doi.org/10.35882/teknokes.v18i3.109