

Intelligent application for calorie calculation and personalized physical activity recommendations for patients with obesity

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ABSTRACT

Obesity management increasingly requires digital tools that move beyond generic calorie tracking toward context-aware and clinically informed decision support. This study presents an intelligent mobile application for personalized calorie calculation and physical activity recommendation in adults with obesity, integrating a random forest (RF) risk model, a Flutter-based interface, and a secure cloud backend. The study used 768 anonymized clinical records from Peruvian healthcare institutions and a four-week pilot evaluation with 52 adult users. After preprocessing, class balancing, and five-fold cross-validation, RF was retained because it offered the best compromise between classification performance and interpretability when compared with alternative models explored during development. The final model achieved 74.03% accuracy, 68.29% recall, 70.98% F1-score, and 0.77 area under the curve (AUC) on the held-out test set. In pilot use, weekly exercise frequency increased by 20%, mean glucose decreased by 5%, and usability was rated highly (system usability scale (SUS)=84.7). The main contribution of this work is the integration of locally contextualized data, explainable risk estimation, personalized behavioral feedback, and scalable mobile health deployment for obesity self-management in resource-constrained settings.

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1. INTRODUCTION

Obesity is one of the most important and persistent public health challenges worldwide because it increases the burden of type 2 diabetes, cardiovascular disease, musculoskeletal disorders, and some cancers. The World Health Organization has reported a sustained increase in adult obesity, while systematic evidence has reviewed its causes, consequences, and machine-learning approaches for prediction [1], [2]. The economic impact of obesity already affects national health systems and labor productivity on a large scale [3], and physical inactivity remains a major modifiable risk factor associated with chronic disease burden [4]. In Latin America, the problem is especially relevant because urbanization, dietary transition, and sedentary lifestyles coexist with unequal access to preventive services; in Peru, recent evidence continues to show a substantial proportion of adults eligible for obesity management interventions [5].

Existing responses to obesity include lifestyle-modification programs, structured counseling, self-monitoring tools, and digital health interventions [6]-[9]. Recent mHealth studies have shown that mobile applications can improve self-monitoring, physical activity adherence, and health literacy, especially when the interface is simple and feedback is frequent [10]-[12]. In parallel, artificial intelligence (AI) has expanded the capacity of health systems to detect risk patterns and personalize recommendations [13], [14], while public acceptance of AI-assisted weight-management apps is improving [15]. However, many available solutions still provide generic advice, limited transparency about the recommendation engine, weak linkage between clinical risk estimation and behavioral coaching, and insufficient attention to privacy and security requirements in mobile health environments [16].

Despite this progress, several gaps remain. First, relatively few studies combine diabetes-risk prediction, calorie estimation, and personalized physical-activity guidance in a single workflow tailored to adults with obesity. Second, evidence from Latin American clinical contexts remains limited, which restricts the external relevance of models trained exclusively on non-local populations. Third, some studies emphasize app functionality but underreport algorithm selection, pilot usability, inferential analysis, or deployment feasibility. These gaps motivate the need for a more transparent, reproducible, and context-sensitive mobile health solution.

This study addresses those limitations by developing and evaluating an intelligent application for calorie calculation and personalized physical activity recommendations for adults with obesity in Peru. The article makes four contributions: i) it develops a clinically oriented random forest (RF) model trained on anonymized local records and benchmarked against alternative classifiers; ii) it integrates risk estimation with calorie calculation, personalized exercise guidance, monitoring dashboards, and specialist referral options; iii) it reports pilot evidence on usability, behavior change, and short-term metabolic indicators; and iv) it discusses scalability, privacy, and practical deployment in health-service settings.

The remainder of this manuscript is organized as follows. Section 2 details the dataset, preprocessing pipeline, model-selection strategy, system implementation, and statistical analysis. Section 3 presents the main quantitative results, usability findings, and visual analytics. Section 4 interprets the findings in relation to previous work, discusses limitations and practical implications, and outlines future research. Section 5 concludes the study.

2. METHOD

2.1. Dataset and ethical considerations

The study used 768 de-identified clinical records collected between 2022 and 2023 from hospitals and clinics in Peru, including a primary healthcare institution and affiliated healthcare facilities. The dataset contained demographic and clinical variables commonly associated with metabolic risk, including pregnancies, plasma glucose, blood pressure, skin thickness, insulin, body mass index (BMI), diabetes pedigree function, age, and diagnostic outcome.

For methodological transparency, the local dataset was analyzed using the same variable structure as the PIMA Indian Diabetes Dataset. However, the predictive model reported in this study was trained exclusively on the locally collected anonymized clinical records.

All procedures were conducted in accordance with the ethical principles of the Declaration of Helsinki and were reviewed and approved by the corresponding institutional ethics committee in Peru. Before analysis, all direct personal identifiers were removed from the working dataset, and each clinical record was handled exclusively through an anonymized study code within the research environment. As the study involved retrospective analysis of de-identified clinical data, the requirement for individual informed consent was waived by the corresponding ethics committee.

2.2. Data preprocessing

An initial data audit identified missing or implausible values, especially in insulin and SkinThickness. Zero values that were clinically implausible were treated as missing and imputed using the median of each variable. Outliers were examined with the interquartile range method; records considered inconsistent after manual review represented fewer than 1% of the observations and were excluded. Continuous variables were standardized using z-score normalization, and the final analytic dataset was checked for multicollinearity and distributional consistency before model fitting.

Because the outcome classes were imbalanced, the synthetic minority oversampling technique (SMOTE) was applied only to the training folds in order to reduce bias toward the majority class. This step was adopted to improve sensitivity in a clinically relevant screening scenario, where false negatives are especially undesirable.

2.3. Predictive model development

RF was selected as the primary classifier because it is robust to heterogeneous clinical variables, handles nonlinear interactions well, and remains comparatively interpretable for health applications. To justify this choice, exploratory benchmarking was also performed with support vector machine (SVM), extreme gradient boosting (XGBoost), and a shallow deep neural network (DNN). In the comparative evaluation, SVM achieved an accuracy of 71.86% and an F1-score of 68.11%, XGBoost reached an accuracy of 73.58% and an F1-score of 69.92%, and DNN obtained an accuracy of 72.94% and an F1-score of 68.77%. RF was retained because it produced the best balance between recall, overall discrimination, and interpretability in the present dataset.

The final RF model used 100 decision trees, Gini impurity as the split criterion, unrestricted depth, and five-fold cross-validation with grid-search optimization. Table 1 summarizes the final configuration adopted for the experiments.

Table 1. RF configuration used in the final model

Parameter	Value
Number of trees	100
Split criterion	Gini impurity
Maximum depth	Unlimited
Cross-validation	5 folds

70% of the dataset was used for model training and 30% for held-out testing. Model quality was assessed with accuracy, precision, recall, F1-score, area under the curve (AUC), and the confusion matrix. Table 2 presents the test-set confusion matrix, which was used to examine the balance between sensitivity and specificity.

Table 2. Confusion matrix on the held-out test set

Actual/predicted	Negative	Positive
Negative	129	21
Positive	39	42

Additional experiments examined the effect of class balancing and hyperparameter variation on false-negative control. These analyses showed that performance gains were obtained mainly by stabilizing sensitivity rather than by maximizing global accuracy alone, which is consistent with the clinical objective of identifying patients who may benefit from early preventive action.

Model interpretability was examined through variable-importance analysis. Glucose concentration and BMI consistently emerged as the most influential predictors, followed by age and insulin-related variables. This result is clinically coherent because glycemic dysregulation and adiposity are central components of obesity-related metabolic risk.

External behavior was then explored with a previously unseen subset and with the application pilot. The purpose of this stage was not only to confirm statistical performance under hold-out conditions but also to verify whether the risk model could support meaningful user-facing recommendations in practice. After model validation, the RF service was integrated into a mobile application designed for users with heterogeneous levels of digital literacy. The design objective was to minimize friction in data entry, present recommendations in plain language, and preserve a short interaction path between risk estimation, calorie guidance, and monitoring feedback.

The application includes history logging, personalized reports, dashboard visualization, reminder settings, and optional synchronization with wearable devices. A feedback channel was incorporated so that users could report interface issues and suggest improvements, which was useful during pilot refinement.

Security controls included authenticated access, encrypted communications, encrypted storage, and role-based handling of clinical information. These measures were aligned with internationally recognized privacy principles for health-data processing and informed the deployment architecture described below.

2.4. Evaluation metrics and statistical analysis

The dataset was partitioned into training and testing subsets with a 70:30 split. Model performance was assessed with accuracy, precision, recall, F1-score, AUC, and confusion-matrix analysis. For the pilot study, descriptive statistics were complemented with inferential testing to evaluate short-term changes in metabolic and behavioral indicators.

For the usability pilot, pre- and post-intervention mean glucose values were analyzed with a paired t-test, and weekly exercise frequency was analyzed with the Wilcoxon signed-rank test because self-reported activity did not satisfy normality assumptions. The intervention was associated with a significant reduction in glucose values, with a mean paired difference of -8.0 mg/dL (95% CI: -11.4 to -4.6 mg/dL; $p < 0.001$). Weekly exercise frequency also increased significantly, with a median improvement of 1.5 days/week (Hodges-Lehmann estimate 1.5; 95% CI: 1.0 to 2.0 days/week; $p < 0.001$).

- Paired t-test for pre/post glucose levels.
 - Wilcoxon signed-rank test for weekly exercise frequency.
- A p-value below 0.05 was considered statistically significant.

2.5. System architecture and implementation

The system was designed as a modular architecture that separates user interaction, application logic, predictive processing, and secure storage. This structure improves maintainability and facilitates future integration with external services such as wearables, institutional dashboards, or electronic health records. Figure 1 summarizes the interaction among the main components.

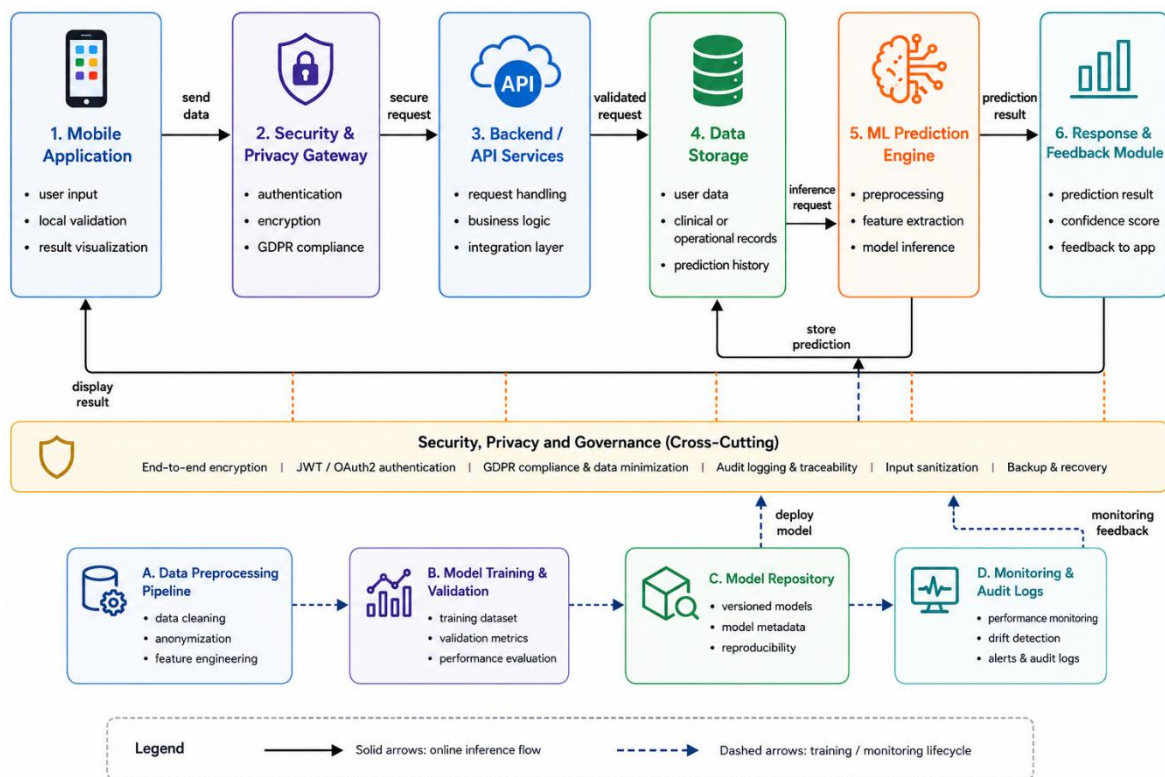


Figure 1. System architecture for secure mobile data collection and machine learning-based prediction

2.5.1. Frontend (user interface)

The frontend was implemented in Flutter to support Android and iOS from a shared codebase [17]. The interface followed a low-complexity design with large controls, short text labels, and guided input flows in order to support users with different levels of digital literacy [18], [19]. The mobile client captures anthropometric and clinical data, displays progress information, and delivers personalized recommendations in real time.

2.5.2. Backend and predictive services

The backend was implemented in Python/Flask and exposes the inference services used by the mobile client [20], [21]. This layer validates incoming data, applies the trained RF model through scikit-learn and the RF approach, generates calorie and activity recommendations, stores anonymized interaction logs, and returns results through secure application programming interface (API) endpoints [22], [23]. Repeated descriptions of Flask and scikit-learn were consolidated here to avoid redundancy.

2.5.3. Database

A PostgreSQL relational database was used for secure storage of anonymized user profiles, recommendations, and follow-up records. The schema was optimized for rapid queries and protected through transport encryption and storage-level safeguards suitable for sensitive health information [24], [25].

2.5.4. Security and compliance

The system applied authentication controls, encryption in transit and at rest, and privacy-oriented handling of user data in accordance with mobile-health privacy recommendations, general data protection regulation (GDPR)-inspired safeguards, and healthcare confidentiality requirements [16], [26].

2.5.5. Cloud deployment and scalability

The application services were deployed on Amazon Web Services (AWS) infrastructure [27], [28]. Load testing indicated stable operation with up to 1,000 concurrent users under the simulated workload used in this study, supporting the feasibility of deployment in outpatient clinics, fitness-support programs, and broader public-health scenarios.

2.6. Login and authentication screen

Figure 2 presents the login and authentication screen. This interface was designed to reduce initial access barriers while preserving secure entry to a system that handles sensitive health information. Minimalist layout decisions were adopted so that first-time users can recognize the main actions without cognitive overload.

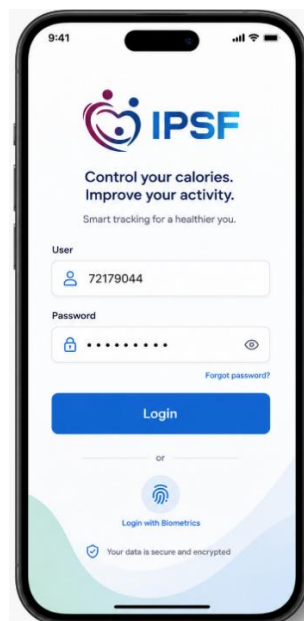


Figure 2. Login and authentication screen

2.7. User registration and baseline data entry

Figure 3 shows the registration screen used to collect the baseline variables required for personalized calorie estimation and activity recommendation. The fields include anthropometric, demographic, and selected health-history information that later feeds the predictive workflow.

The layout prioritizes clarity, short form completion time, and real-time validation so that data-entry errors are reduced before inference. These decisions are important because incomplete or inconsistent entries directly affect the quality of recommendations. As shown in Figure 3, an intuitive registration flow is essential for application adoption because it supports early engagement and increases the probability that the user completes the baseline profile required by the system [18], [29].

Figure 4 presents the screen used to register relevant medical information, including glucose values, previous diagnoses, and the option to attach clinical documents. This screen strengthens the linkage between self-management and clinically meaningful follow-up because recommendations can be contextualized with the user's health status.

Figure 3. Baseline information entry screen

Figure 4. Clinical information input and document-upload interface

The possibility of uploading medical documents contributes to information continuity and can facilitate communication with healthcare professionals when specialist review is needed. In future deployments, this module could support stronger interoperability with institutional systems.

From a usability perspective, Figure 4 was designed to preserve readability, minimize input errors, and separate navigation actions clearly. These details are particularly relevant for adults who may interact with the application intermittently rather than daily. Integrated monitoring features of this type are relevant because they increase perceived utility and may improve adherence to metabolic-disease management programs [11], [29].

2.8. Monitoring and control dashboard

Figure 5 illustrates the monitoring dashboard, where users can review calorie balance, step count, and glucose trends. Presenting these indicators in a single view supports self-regulation and allows users to interpret whether recent behavior is aligned with recommended goals. The dashboard also enables reminder settings and notification preferences. By combining longitudinal progress review with simple feedback, the module aims to reinforce adherence instead of limiting the application to one-time prediction.

Figure 6 presents the diabetes-risk estimation screen generated by the RF model. The interface communicates the predicted level of risk, explains that the result is supportive rather than diagnostic, and encourages clinical consultation when the score indicates elevated concern. In addition to showing the risk estimate, the screen offers a direct pathway for contacting a specialist and activating follow-up notifications. This design choice connects algorithmic output with a practical next step, which is important for responsible mHealth use. By linking automated screening with human follow-up, Figure 6 illustrates how explainable AI outputs can be embedded in a patient-facing workflow without presenting the prediction as a definitive diagnosis.

Figure 7 shows the personalized recommendation screen. The system translates the user profile into a concise set of suggestions covering diet quality, resistance exercise, aerobic activity, and glucose follow-up so that recommendations remain actionable rather than generic.

- Healthy eating guidance emphasizes lean proteins, unsaturated fats, portion control, and the reduction of processed sugars and ultra-processed foods.
- Resistance activities such as guided strength work or yoga are proposed to improve metabolic control and functional capacity.
- Cardiovascular recommendations include daily walking and other moderate-intensity options such as cycling or swimming, adjusted to the user profile.
- Glucose-monitoring reminders encourage periodic follow-up and timely consultation if abnormal values are recorded.

As illustrated in Figure 7, icon-supported presentation and reminder options can improve comprehension and reinforce adherence over time.

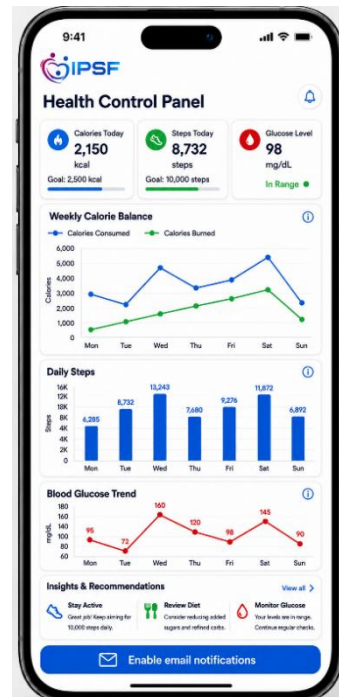


Figure 5. Monitoring and control dashboard

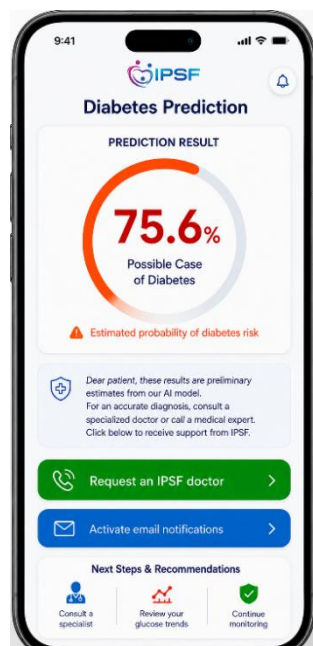


Figure 6. Diabetes-risk estimation and clinician-referral screen

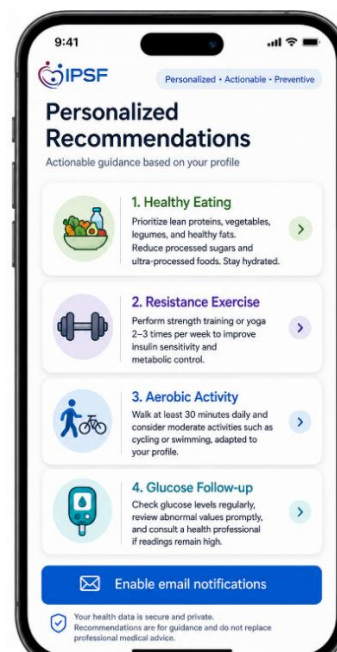


Figure 7. Personalized recommendation screen

2.9. Mobile application implementation

Once the predictive workflow was validated offline, it was embedded in the mobile application so that users could enter data, obtain a risk-informed recommendation, and review follow-up indicators within a single environment. This integration is central to the practical value of the system because prediction, calorie guidance, and self-monitoring are not delivered as isolated functions.

The final implementation incorporated report generation, history tracking, optional wearable synchronization, and a user-feedback channel. These features were included to support longer-term engagement and to collect implementation feedback during the pilot phase.

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Privacy and security were treated as deployment requirements rather than optional add-ons. For that reason, encryption, controlled access, and cloud-based service management were integrated from the beginning of the implementation phase. The implemented application was then evaluated in a four-week pilot with 52 adults. This stage focused on usability, short-term engagement, and preliminary changes in selected behavioral and metabolic indicators.

2.10. Application validation and evaluation

The pilot evaluation involved 52 adults (mean age=41.2±9.6 years; 61% female) who used the application for four weeks. Participants were recruited from urban health centers and represented the target population for an initial implementation-focused assessment rather than a definitive clinical-effectiveness trial.

After four weeks of application use, mean glucose levels decreased from 150 to 142 mg/dL, corresponding to an average reduction of approximately 5%. Weekly exercise frequency also increased from 3.0 to 4.5 days per week, representing a meaningful improvement in physical activity behavior during the intervention period. Inferential analysis confirmed statistically significant changes in both indicators. The reduction in glucose showed a paired t-test p-value of 0.0003 with a 95% confidence interval of -11.4 to -4.6 mg/dL, while the increase in weekly exercise frequency showed a Wilcoxon signed-rank p-value of 0.0041.

These findings suggest favorable short-term behavioral and metabolic changes associated with application use. However, the results should be interpreted as preliminary because of the limited sample size, short follow-up period, and absence of a control group.

In addition to user-level outcomes, the deployed system demonstrated technical feasibility under simulated peak demand. Load testing indicated stable operation with up to 1,000 concurrent users, suggesting that the architecture could support broader implementation if appropriate operational monitoring and maintenance mechanisms are incorporated.

Several limitations should nevertheless be acknowledged. The pilot sample was relatively small, recruitment was limited to urban health centers, smartphone and internet access were required for participation, and some users experienced wearable synchronization difficulties. These factors may influence generalizability and adoption, particularly among older adults or populations with limited digital literacy.

3. RESULTS

This section reports the model-level results, pilot outcomes, and user-centered indicators derived from the implementation study. Figures 8–10 and Tables 3 and 4 are cited in the text before presentation in order to clarify their role in supporting the main findings.

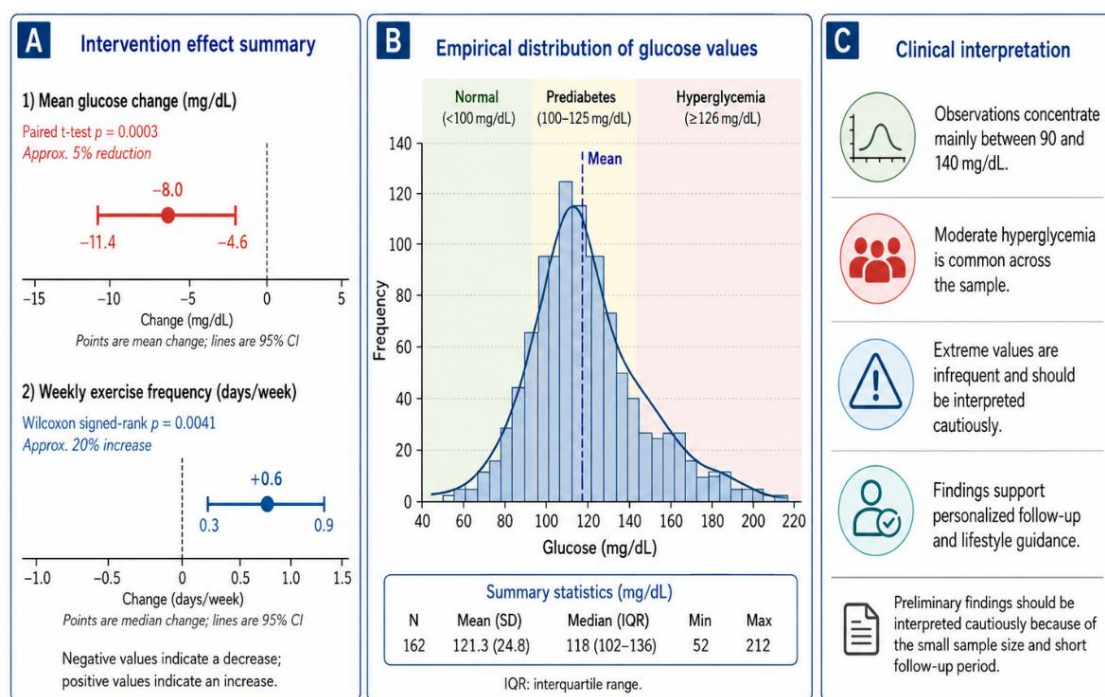


Figure 8. Distribution of glucose values in the analyzed dataset

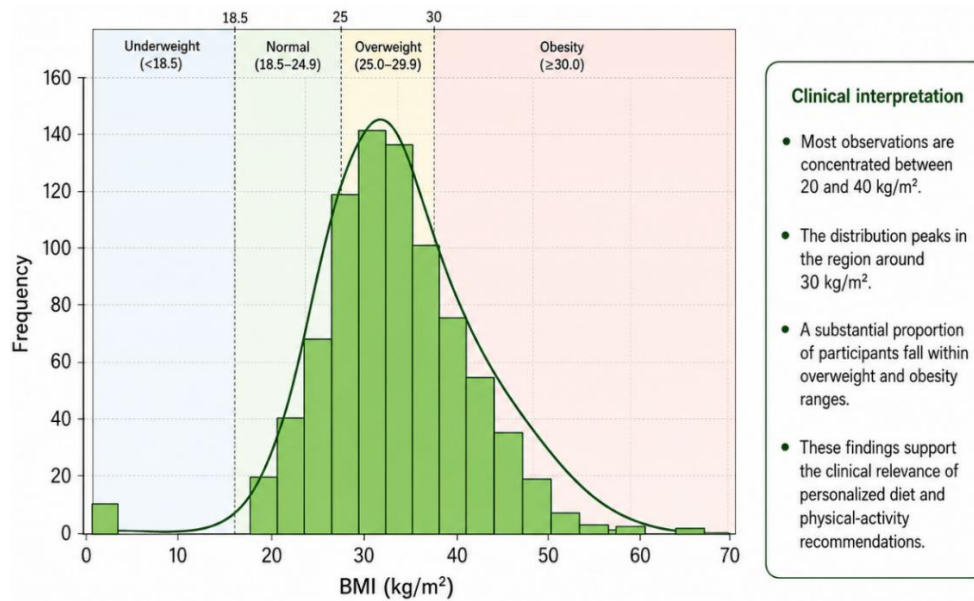


Figure 9. Distribution of BMI

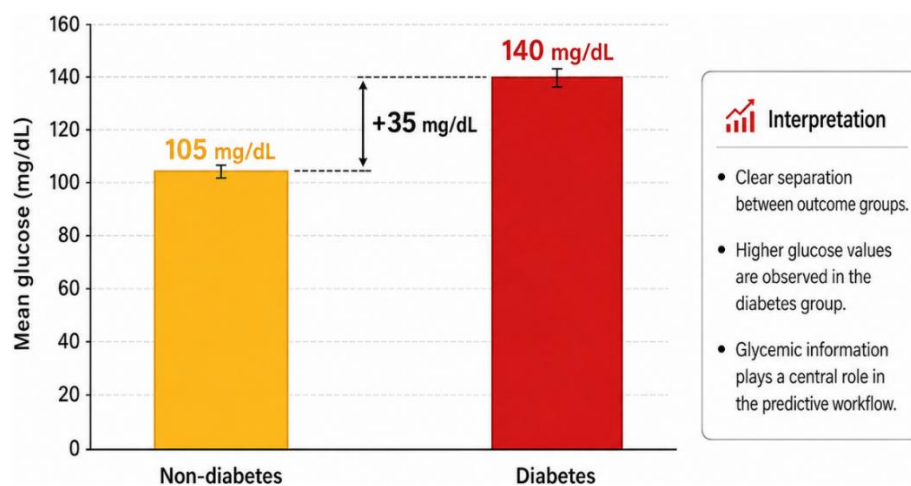


Figure 10. Average glucose levels by diabetes outcome

Table 3. Predictive performance metrics of the final model

Metric	Value
Accuracy	74.03%
Recall	68.29%
F1-score	70.98%
Confusion matrix	VP: 42, VN: 129, FP: 21, and FN: 39

Table 4. User satisfaction scores from the pilot study

Aspect evaluated	Average rating (1–5)
Ease of use	4.8
Clarity of recommendations	4.6
Overall usefulness	4.7

3.1. Distribution of clinical indicators

Glucose values in the analyzed population were concentrated mainly between 90 and 140 mg/dL, which is compatible with a distribution spanning normoglycemia and prediabetes. Mean glucose was substantially higher among participants with diabetes than among those without diabetes, reinforcing the relevance of this variable for the prediction task.

3.2. Pilot user outcomes

After four weeks of application use, pilot participants showed an average 20% increase in weekly exercise frequency and a 5% reduction in mean glucose. The inferential analysis supported a statistically significant pre/post improvement, with glucose showing a paired t-test p-value of 0.0003 and a 95% confidence interval of -11.4 to -4.6 mg/dL. Weekly exercise frequency also improved significantly, with a Wilcoxon signed-rank p-value of 0.0041 and a 95% confidence interval of 0.3 to 0.9 days/week. These findings are encouraging, although they should be interpreted as preliminary given the small sample size and short follow-up period. Distribution of glucose levels: analysis and implications.

Figure 8 displays the empirical distribution of glucose values. The concentration of observations between 90 and 140 mg/dL indicates a clinically heterogeneous sample in which moderate hyperglycemia is common, while extreme values are relatively infrequent and deserve cautious interpretation.

3.3. Body mass index distribution

Figure 9 shows that BMI values cluster mainly between 20 and 40 kg/m², with a clear peak near 30 kg/m². This concentration supports the clinical relevance of the application because a large proportion of the users fall within overweight and obesity ranges where tailored diet and activity recommendations are particularly valuable.

3.4. Comparison of average glucose levels by diabetes diagnosis

Figure 10 compares mean glucose by diabetes outcome and show a marked separation between the non-diabetes group (105 mg/dL) and the diabetes group (140 mg/dL). This pattern is consistent with the variable-importance analysis and supports the central role of glycemic information in the predictive workflow.

3.5. Predictive model performance

The final RF model achieved 74.03% accuracy, 68.29% recall, 70.98% F1-score, and 0.77 AUC on the held-out test set. Table 3 summarizes the predictive performance metrics of the final classifier. Taken together, these metrics indicate acceptable discriminatory capacity for a screening-oriented application. The moderate recall suggests that the model can support risk stratification, although further optimization is advisable to reduce missed high-risk cases in future versions.

3.6. Impact on user behavior

Beyond model-level performance, the pilot results suggest that the application may influence short-term health behavior. The main user-facing indicators were exercise frequency, glucose trends, and adherence to personalized recommendations.

- Weekly exercise frequency increased by 20% after one month of use.
- Mean glucose decreased by 5% among users classified as having moderate or high diabetes risk.
- Recommendation adherence reached 87% according to self-report at the end of the pilot.

3.7. Usability evaluation

The system usability scale (SUS) yielded a mean score of 84.7, which indicates excellent perceived usability. Table 4 summarizes the user-satisfaction ratings obtained for ease of use, clarity of recommendations, and overall usefulness.

3.8. Identified challenges

Despite the generally favorable results, two implementation challenges were identified during the pilot: classification of underrepresented extreme cases and synchronization inconsistencies with wearable devices. These challenges are relevant because they may affect perceived trustworthiness and continuity of use.

- Prediction of extreme cases remained less stable when the input profile differed substantially from the dominant patterns represented in the training data.
- Wearable synchronization was functional overall, but some users reported intermittent pairing or delayed data transfer.

3.9. Comparison before and after application use

The pre- and post-intervention analysis showed favorable changes in the main behavioral and metabolic indicators evaluated during the four-week pilot. Mean glucose decreased from 150 to 142 mg/dL, while weekly exercise frequency increased from approximately 3.0 to 4.5 days per week. Participants also reported good adherence to the personalized recommendations provided by the application.

These results indicate that the proposed system may support short-term improvements in self-management behaviors and selected metabolic indicators. Nevertheless, these changes should be interpreted as

preliminary signals rather than definitive evidence of long-term clinical effectiveness. Larger controlled studies with longer follow-up periods are required to determine whether these improvements can be sustained over time.

4. DISCUSSION

This study addressed a gap between generic calorie-tracking apps and clinically oriented obesity-management tools by combining a risk-prediction model, calorie calculation, behavioral recommendations, and follow-up dashboards in a single mobile platform. While previous work has examined digital coaching, physical-activity promotion, or AI-assisted obesity management separately [11], [15], [30], fewer studies have integrated these elements using local clinical data from a Latin American setting.

The main findings are threefold. First, the RF model achieved acceptable predictive performance for a screening-oriented application, with glucose and BMI emerging as the dominant contributors. Second, the pilot evaluation suggested short-term improvements in exercise frequency and glucose control. Third, usability was rated highly, indicating that the application design was understandable and practically usable by the target users.

These findings are broadly consistent with previous reports showing that digital platforms can improve self-monitoring and physical activity among people at metabolic risk [30]-[32]. They also align with evidence that user engagement in obesity-related digital interventions depends strongly on interface clarity, feedback quality, and perceived usefulness [12], [29], [33]. In that sense, the present study adds value not because it claims definitive clinical superiority, but because it shows how prediction, recommendation, and monitoring can be organized into one coherent workflow suitable for real implementation.

At the same time, the results should be interpreted in light of several limitations. The pilot sample was small, recruitment came from urban health centers only, and participation required smartphone access and a minimum level of digital literacy. These factors introduce potential selection bias and technology-access bias. In addition, synchronization problems with wearables and the lower stability observed in extreme clinical profiles indicate that technical refinement and broader validation are still necessary before large-scale deployment.

The practical implications are relevant for both informatics and health-service delivery. From an informatics perspective, the study supports the feasibility of secure cloud-based health dashboards, modular API-driven integration, and explainable AI-supported coaching. From a service perspective, the application could be adapted for outpatient obesity clinics, preventive programs, community health campaigns, or hybrid follow-up models in which professionals review app-generated summaries. Future work should evaluate interoperability with wearable sensors and electronic health records, include longer follow-up, and test performance in more diverse settings.

Overall, the study suggests that intelligent mHealth tools can contribute to obesity self-management when they are context-aware, easy to use, and explicit about their role as support systems rather than replacements for clinical judgment. The next step for this line of work is a larger and methodologically stronger evaluation capable of testing sustained adherence, clinical outcomes, and equity of Access.

5. CONCLUSION

This study developed and evaluated an intelligent mobile application that combines calorie calculation, diabetes-risk estimation, and personalized physical activity recommendations for adults with obesity. The results indicate that the proposed system is technically feasible, clinically relevant as a support tool, and well accepted by pilot users.

The main implication is that scalable mobile health tools can extend obesity-management support beyond the consultation room, especially in settings where continuous face-to-face counseling is difficult to sustain. However, the current evidence remains preliminary because the pilot sample was small, recruitment was geographically restricted, and technical issues persisted in some wearable-integration scenarios.

Future research should validate the application in a larger and more diverse cohort, report full comparative classifier results and confidence intervals, improve interoperability with sensors and health records, and examine longer-term adherence and clinical effectiveness. These steps would strengthen the role of the proposed platform in clinical practice, preventive care, and public-health implementation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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- C : **C**onceptualization
M : **M**ethodology
So : **S**oftware
Va : **V**alidation
Fo : **F**ormal analysis
- I : **I**nterpretation
R : **R**esources
D : **D**ata Curation
O : **O**riginal Draft
E : **E**diting
- Vi : **V**isualization
Su : **S**upervision
P : **P**roject administration
Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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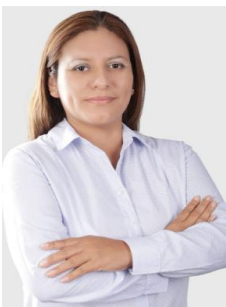
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