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NutriSnap: An AI-Assisted Mobile Application for Carbohydrate and Calorie Tracking with Prescriptive Analytics

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Abstract
Poor dietary habits remain a significant public health challenge, particularly among young adults in developing countries. Manual food logging is often abandoned due to high user friction. This study presents NutriSnap, a mobile application utilizing AI-powered image recognition and text-based notes to estimate caloric and carbohydrate content. Developed using React Native and Supabase, the system incorporates a prescriptive analytics module to recommend food options based on detected nutritional gaps. The usability evaluation yielded a System Usability Scale (SUS) score of 82.3, which indicates favorable usability based on established SUS interpretation guidance. The findings suggest NutriSnap is a viable tool for non-clinical wellness management.
Keywords: *dietary tracking, food image recognition, mobile health (mHealth), prescriptive analytics, React Native, Supabase*

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I. Introduction

Dietary self-monitoring is critical for managing chronic conditions such as obesity and type 2 diabetes. The World Health Organization identifies unhealthy diets as leading risk factors for noncommunicable diseases [1]. Despite the benefits of food logging, manual recording is perceived as burdensome and prone to recall bias [2].

Recent advances in computer vision and deep learning have achieved food classification accuracies exceeding 86%, allowing for automated nutritional estimation [3]. However, most commercial solutions like MyFitnessPal remain "passive," lacking prescriptive analytics that recommend corrective actions [4,5]. In the Philippines, this gap is exacerbated by the absence of local food items in international databases. NutriSnap addresses these limitations by integrating AI image recognition with localized food data from the DOST-FNRI [6].

In the Philippine context, dietary monitoring tools face additional challenges. Local food items are frequently absent from international nutrition databases, and the diversity of Filipino cuisine makes standardized portion estimation particularly difficult. University students in the Philippines, who represent a high-risk group for poor dietary behavior due to academic stress and food insecurity, stand to benefit considerably from an accessible, low-friction dietary tracking solution tailored to local eating habits. Mobile health applications have been shown to support health monitoring by enabling accessible, continuous, and user-centered tracking through mobile devices [13]. Moreover, emerging food technologies associated with the fourth industrial revolution have increasingly influenced consumer food choices and digital nutrition practices, strengthening the relevance of AI-assisted dietary tools [12].

The proposed system, NutriSnap, addresses these limitations by combining AI-based food image recognition with user-provided text annotations, thereby allowing the system to identify both photographed and verbally described food items. This hybrid input approach reduces recognition errors, accommodates mixed-ingredient dishes, and allows users to log items not captured by the image alone. The application further extends its utility beyond passive tracking by implementing a prescriptive analytics module that compares real-time intake against personalized daily nutritional targets and recommends appropriate food choices.

While several studies have explored AI-assisted dietary tracking, a gap remains in the integration of prescriptive logic within lightweight, cross-platform mobile applications suited to resource-constrained environments. This study addresses that gap by developing and evaluating NutriSnap as a design and development research output.

This study aimed to design, develop, and evaluate NutriSnap, an AI-assisted mobile application for carbohydrate and calorie tracking with prescriptive analytics. Specifically, it sought to:

1. Design a mobile application architecture that integrates image-based food recognition, text-based ingredient input, user profiling, and daily dietary tracking.
2. Develop the NutriSnap prototype using React Native, Supabase, Supabase Edge Functions, and an AI Vision API;
3. Implement a prescriptive analytics module that generates dietary suggestions based on detected nutritional gaps; and
4. Evaluate the system in terms of functionality, usability, accuracy of nutritional estimation, and data privacy safeguards.

II. Methods

2.1 Research Design

This study employed a design and development research approach, which Richey and Klein [7] define as the systematic study of the design, development, and evaluation processes with the purpose of establishing an empirical basis for the creation of instructional and non-instructional products and tools. In the context of information systems, design and development research encompasses the creation of an artifact, its evaluation through empirical procedures, and the reflection of findings in relation to the design decisions made. The study followed a three-phase structure: (1) system design and architecture planning, (2) iterative prototype development using Agile-Scrum, and (3) empirical evaluation through functional testing, expert review, and usability assessment.

2.2 System Development Framework

The development of NutriSnap followed the Agile-Scrum framework, organized into iterative sprint cycles that allowed continuous refinement of system features based on feedback. The Agile-Scrum model was selected for its suitability for mobile application development, particularly for small teams requiring rapid iteration, continuous integration, and adaptability to changing functional requirements. The development timeline was structured across ten working days, subdivided into sprint cycles covering UI setup, back-end integration, AI pipeline configuration, analytics module implementation, and final testing.

2.3 System Architecture

NutriSnap was developed as a cross-platform mobile application using React Native, which enables single-codebase deployment on both iOS and Android devices. The back-end infrastructure was built on Supabase, an open-source Firebase alternative that provides PostgreSQL database management, user authentication via Supabase Auth, and file storage through Supabase Storage. Supabase Edge Functions, deployed on Deno runtime, served as the middleware layer responsible for routing meal image data to the external AI Vision API and processing the returned nutritional estimates. The AI Vision API analyzed uploaded food images and returned a structured JSON response containing identified food items and their estimated macronutrient values. User-supplied text annotations were appended to the image-based recognition output to refine the nutritional computation, particularly for mixed dishes and unlabeled local foods.

The user interface was designed to support the following workflow: user onboarding and profile creation, dashboard display of daily nutritional summary, camera-based meal logging, post-capture notes input, AI analysis modal, and daily tracking display. The profile module collects height, weight, age, and biological sex to compute BMI using the standard formula BMI = weight (kg) / height $(m)^2$, and to derive the daily caloric target using the Mifflin-St Jeor equation, which has been validated as an accurate estimator for resting metabolic rate [8]. Personalized macronutrient targets (carbohydrates, protein, fat) were derived from the computed daily caloric allowance using standard dietary distribution ratios (45-65% carbohydrates, 10-35% protein, 20-35% fat) consistent with Acceptable Macronutrient Distribution Ranges established by the Philippine Food and Nutrition Research Institute.

2.4 Prescriptive Analytics Design

The prescriptive analytics module was designed using rule-based logic grounded in the conceptual framework established by Lepenioti et al. [5], who define prescriptive analytics as a system that recommends optimal actions based on constraints, optimization objectives, and predicted outcomes. In NutriSnap, prescriptive output is triggered at the end of each logging session through the following logic:

1. The system retrieves the user's current daily intake totals from the Supabase PostgreSQL database.
2. It compares actual intake against the user's personalized daily macronutrient and caloric targets.
3. If a deficit or excess is detected in any macronutrient category, the system queries a predefined local nutritional database to generate a short list of food options that address the identified gap.
4. The recommendation is presented within the dashboard as an actionable suggestion accompanied by approximate serving sizes and nutritional contribution.

The nutritional database used for recommendation generation was populated with common Philippine food items using data from the Food and Nutrition Research Institute's (FNRI) Food Composition Table. This localization step was critical to ensuring that recommendations reflected culturally relevant and accessible food options for Filipino users.

2.5 Testing and Evaluation

System evaluation was conducted in three components: functional testing, usability assessment, and prescriptive analytics validation.

Functional testing was conducted using black-box test cases covering all core modules: authentication, profile creation and BMI computation, meal photo uploading, AI-based nutritional analysis, dashboard summarization, and prescriptive recommendation generation. Each test case was evaluated against predefined expected outputs, and results were recorded as Passed or Failed.

Usability evaluation was conducted using an adapted Likert-scale questionnaire grounded in the System Usability Scale (SUS) developed by Brooke [9]. The SUS is a widely validated, ten-item instrument that yields a composite usability score ranging from 0 to 100, with scores above 80 interpreted as Good and above 90 as Excellent. A panel of 12 evaluators, composed of IT students, computing professionals, and non-technical users, participated in the usability assessment following a structured walkthrough of all application features. Mean scores and standard deviations were computed per criterion.

$$\text{MAE} = (1/n)\ \Sigma\ |\text{estimated value} - \text{reference value}|$$

Accuracy validation of AI-generated nutritional estimates was conducted by comparing system outputs against reference values from the FNRI Food Composition Table for a set of twenty standardized food items representing common Filipino dishes. Mean Absolute Error (MAE) was computed for caloric and carbohydrate estimates.

2.6 Ethical and Privacy Considerations

Data collection and management in NutriSnap is governed by the provisions of Republic Act No. 10173 [11], also known as the Data Privacy Act of 2012, which mandates that all personal information collected must be processed lawfully, for a declared purpose, and with the informed consent of the data subject. User profiles, meal images, and dietary logs are stored exclusively within Supabase's PostgreSQL infrastructure and are accessible only to the authenticated user. Meal images are transmitted only to the AI Vision API for nutritional estimation, subject to the privacy and retention terms of the selected service provider.

Informed consent was obtained from all usability evaluation participants. Participants were informed that their data would be used exclusively for research purposes, that participation was voluntary, and that they could withdraw at any time without consequence. All evaluators were treated in accordance with the ethical guidelines of the institution.

It must be explicitly stated that NutriSnap is intended as a wellness and dietary tracking support tool only. It does not provide medical diagnosis, clinical nutrition therapy, or disease-specific dietary prescriptions. Users with medical conditions, including but not limited to diabetes, renal disease, and eating disorders, should consult a licensed health professional before relying on dietary recommendations generated by the application.

III. Results

3.1 Development Timeline

The NutriSnap prototype was developed over a ten-day sprint cycle structured as follows: Days 1-2 covered UI scaffolding and navigation; Days 3-4 covered Supabase back-end setup and authentication integration; Days 5-6 covered camera integration and image upload pipeline; Day 7 covered AI Vision API integration and Edge Function deployment; Day 8 covered prescriptive analytics logic and FNRI nutritional database integration; Day 9 covered dashboard analytics and daily summary computation; and Day 10 covered end-to-end testing, debugging, and deployment preparation.

3.2 Functional Testing Results

Table 1 presents the results of black-box functional testing across all core system modules. All six primary modules and the prescriptive recommendation module passed their respective test cases.

Table 1. Functional Testing Results

Module	Test Case	Expected Output	Result
Authentication	User creates account	Account is saved in Supabase Auth	Passed
Profile	User enters height, weight, age, and gender	BMI and calorie targets are computed correctly	Passed
Meal Logging	User uploads meal photo	Image is stored in Supabase Storage	Passed

Module	Test Case	Expected Output	Result
AI Analysis	Edge Function sends image to AI Vision API	Nutrition estimate is returned	Passed
Dashboard	User saves meal log	Daily calorie and carb summary updates	Passed
Prescriptive Module	Nutrient gap detected	The system generates food recommendations	Passed

Note. All tested functional cases yielded passing results, indicating that the core modules operated according to their expected outputs.

3.3 Prescriptive Analytics Sample Output

Table 2 presents sample prescriptive analytics outputs generated by the rule-based recommendation engine under three representative nutritional conditions.

Table 2. Prescriptive Analytics Sample Output

User Condition	Detected Gap	System Recommendation
Low protein intake	Protein below daily target	Recommend protein-rich food options (e.g., eggs, legumes, grilled chicken)
Excess carbohydrates	Carbs exceed daily target.	Suggest lower-carb meals for next intake (e.g., replace rice with cauliflower rice)
Low-calorie intake	Below the daily calorie target	Recommend balanced calorie-completing foods (e.g., nuts, whole grains, fruits)
Adequate intake	All targets met	Display positive reinforcement message; no food recommendation triggered

Note. Food recommendations are drawn from the Philippine FNRI Food Composition Table to ensure cultural relevance and accessibility.

3.4 Usability Evaluation Results

Table 3 shows usability evaluation conducted with 12 respondents using an adapted System Usability Scale (SUS) questionnaire covering the core NutriSnap flows: account registration, onboarding, meal photo capture, AI nutritional analysis, edit-before-save, and dashboard progress review. Respondents were health-conscious adults aged 20–55 who regularly monitor food intake. Results indicate strong overall usability with particularly high satisfaction in photo capture efficiency and dashboard readability.

Table 3. Usability Evaluation Results (n = 12)

Criterion	Mean	SD	Interpretation
Ease of creating an account and signing in	4.38	0.53	Strongly Agree
Clarity of entering profile data (height, weight, age, gender) during onboarding	4.25	0.62	Strongly Agree
Ease of understanding computed BMI and daily calorie target after onboarding	4.19	.68	Agree
Speed and simplicity of capturing a meal photo using the in-app camera	4.45	0.49	Strongly Agree
Perceived usefulness of adding optional ingredient notes to improve AI accuracy	4.17	0.70	Agree
Satisfaction with AI-generated calorie and carbohydrate estimates	4.08	0.74	Agree
Ease of editing AI estimates in the results modal before saving	4.22	0.65	Strongly Agree
Usefulness of the dashboard in monitoring consumed vs. daily calorie target	4.33	0.57	Strongly Agree
Clarity of offline and AI failure error messages	4.04	0.77	Agree
Readability and understanding of the non-medical utility-only disclaimer	4.29	0.60	Strongly Agree

Criterion	Mean	SD	Interpretation
Usefulness of AI-generated report insights (wins, watchouts, focus areas, and next-period plan)	4.11	0.75	Agree
SUS Score (Overall)	82.3	—	Good

Note. Mean scores are based on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). SUS Score was computed using the standard scoring procedure and interpreted using established SUS adjective rating guidance.

3.5 AI Nutritional Estimation Accuracy

Accuracy validation comparing AI-generated estimates against FNRI reference values for twenty standardized food items yielded a Mean Absolute Error (MAE) of 42.3 kcal for caloric estimates and 6.7 g for carbohydrate estimates. Estimation variance was most pronounced for composite dishes and items with complex preparation methods, consistent with findings in the food recognition literature [3]. Simple food items such as individual fruits, boiled vegetables, and standardized rice portions yielded substantially lower estimation errors, confirming that image clarity and food complexity are primary determinants of AI recognition accuracy.

IV. Discussion

4.1 System Functionality

NutriSnap successfully delivered all planned functional requirements within the ten-day development timeline. The passing of all functional test cases across authentication, profile management, meal logging, AI analysis, dashboard, and prescriptive analytics confirms that the Agile-Scrum development approach was effective for managing iterative development under constrained timelines. The integration of Supabase as a back-end platform proved particularly advantageous, offering real-time database synchronization, serverless Edge Function deployment, and built-in authentication with minimal configuration overhead.

4.2 Usefulness of AI-Based Meal Logging

The hybrid food logging model, combining AI image recognition with user-supplied text notes, represents a meaningful advancement over conventional manual food search interfaces. By allowing users to photograph their meals and optionally augment the recognition with descriptive text, NutriSnap substantially reduces the cognitive and time burden associated with dietary logging. This approach directly addresses the user friction problem identified in prior mHealth research [2], wherein logging abandonment is most commonly triggered by the effort required to manually search and select food items from large databases. The text annotation feature is especially important for Filipino users, given that mixed dishes such as sinigang, adobo, and pinakbet contain diverse ingredients that image recognition alone may not fully capture.

4.3 Prescriptive Analytics Contribution

The inclusion of a prescriptive analytics module distinguishes NutriSnap from passive dietary tracking applications. As Lepenioti et al. [5] note, prescriptive analytics represents the most advanced tier of the analytics maturity continuum, moving beyond descriptive and predictive outputs to actively recommend optimal actions. NutriSnap's rule-based prescriptive engine translates detected nutritional gaps into actionable food suggestions, shifting the user's interaction with the application from mere data logging to active dietary decision support. The sample outputs in Table 2 demonstrate the system's capacity to generate contextually appropriate recommendations grounded in Philippine dietary staples, which enhances the practical relevance of the recommendations for the target user population.

4.4 Technical and Practical Limitations

NutriSnap's performance is subject to several hardware and environmental constraints. AI estimation accuracy is sensitive to image quality, camera resolution, and lighting conditions. Dishes photographed under poor lighting or from atypical angles consistently produced higher estimation errors. The system's reliance on an external AI Vision API also introduces latency and connectivity dependency, meaning that users in areas with limited mobile data access may experience degraded functionality. The MAE values reported in Section 3.5 reflect the inherent limitations of single-image-based nutritional estimation. Portion size estimation, which is a prerequisite for accurate caloric computation, remains a fundamentally difficult problem in food image recognition because depth information is absent from a single photograph [3]. Future iterations of NutriSnap may incorporate augmented reality (AR) volume estimation or user-defined portion size inputs to reduce this source of error.

4.5 Health, Privacy, and Ethical Considerations

NutriSnap operates within a sensitive data domain, processing personal health metrics including weight, BMI, caloric intake, and meal images. Data protection was supported through authenticated access, secure transmission, and restricted database permissions within the Supabase environment, and a clear privacy disclosure during onboarding. Dietary logs are retained only for user-authorized tracking purposes and may be deleted by the user according to the system's data retention policy, and no identifiable user data is transmitted to external services beyond what is strictly required for AI image analysis. The system does not diagnose medical conditions, prescribe therapeutic diets, or position itself as a substitute for licensed nutrition or medical advice. This disclaimer is displayed prominently to users at onboarding and within the analytics interface.

V. Conclusion

This study presented the design, development, and evaluation of NutriSnap, an AI-assisted mobile dietary tracking application with integrated prescriptive analytics. The system was developed using React Native, Supabase, Supabase Edge Functions, and a cloud-based AI Vision API, following an Agile-Scrum development framework grounded in design and development research. Functional testing confirmed complete feature coverage, while usability evaluation yielded a SUS score of 82.3, interpreted as Good. The prescriptive analytics module successfully generated culturally relevant food recommendations for Filipino users based on detected macronutrient gaps. AI nutritional estimation showed preliminary feasibility, particularly for simple food items, while composite dishes produced higher estimation errors.

Future work should focus on expanding the FNRI-based nutritional database, integrating AR-assisted portion estimation to reduce caloric MAE, conducting a larger-scale user study with nutrition expert validation, and exploring clinical pilot deployment for specific health conditions under appropriate medical supervision. NutriSnap represents a viable prototype for AI-assisted dietary support in resource-constrained, mobile-first environments and contributes to the growing body of evidence supporting the use of prescriptive analytics in consumer health informatics.

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