A SMART AI-POWERED MOBILE SYSTEM TO PREVENT DIABETES IN HOMELESS COMMUNITIES USING COMPUTER VISION AND PERSONALIZED NUTRITIONAL RECOMMENDATIONS

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ABSTRACT

Diabetes affects homeless populations at rates similar to the general population (8%), but homeless individuals receive significantly less medical attention and face higher complication rates due to food insecurity and lifestyle instability. VitalityShield addresses this challenge through a Flutter-based mobile application that provides AI-powered food analysis and personalized diabetes prevention recommendations. The system integrates three core components: an OpenAI GPT-4 Vision food scanner for nutritional analysis, an AI recommendation service using GPT-4o-mini for personalized dietary suggestions, and interactive health analytics for progress tracking [1]. Key challenges included achieving accurate food recognition across varying image qualities and generating practical recommendations for populations with limited food access. Experimental results demonstrated 83.25% accuracy in nutritional analysis and moderate practicality scores (3.4/5) for recommendations. While limitations exist in accessibility and accuracy, VitalityShield offers significant advantages over traditional outreach methods by providing scalable, 24/7 diabetes prevention support that adapts to individual dietary patterns, potentially reducing diabetes risk in vulnerable homeless communities.

KEYWORDS

Diabetes Prevention, Homeless Populations, Artificial Intelligence, Computer Vision, Mobile Health Applications

1. INTRODUCTION

The difficulties of chronic illness have long been an issue in vulnerable communities, especially among the homeless [2]. With daily survival concerns–especially food insecurity– taking precedence, health often becomes a secondary priority. This constant struggle for basic survival leaves little time for the homeless to worry about chronic disease care. Notably, type 1 and type 2 diabetes pose a huge threat to homeless communities, as almost 75% of homeless people have no health insurance, putting them at a greater risk for health complications (Elder & Tubb, 2014). Although the prevalence of diabetes in the homeless and general population is roughly the same, at about 8% (Bernstein et al., 2015), homeless people with diabetes were markedly less likely to obtain medical attention (Wiens et al., 2024). Due to the reduced likelihood of receiving screening care, homeless people also have much higher rates of macrovascular complications (Sharan et al., 2023) compared to the non-homeless, with rates of hospitalization in homeless

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minors reaching up to 14 times that of non-homeless minors (Sakai-Bizmark et al., 2020). With food being one of the major priorities for homeless individuals, these food insecure populations are more prone to poor health because of their chaotic lifestyle of homelessness (Elder & Tubb, 2014; Hernandez et al., 2019). To address the growing concern of diabetes care in homeless communities, we aim to develop a mobile application dedicated to reducing the risk of diabetes and promoting a healthier diet in homeless communities [3]. We recognize that the problem has two sides: the large proportion of people with diabetes in homeless communities, and the lack of treatment homeless communities receive. For our mobile application, we strive to decrease the proportion of homeless people with diabetes, however we would also like to find solutions to increasing medical support for these communities in the future.

Three existing methodologies address diabetes prevention in homeless populations with varying approaches and limitations. Campbell et al.'s systematic review (2020) identified effective outreach programs including screening teams and shelter-based monitoring, but these suffer from high costs, limited reach, and scheduling barriers that exclude many homeless individuals with chaotic lifestyles. Recent SMS intervention trials (2020-2024) achieve behavior improvements through automated messaging, with the SupportMe trial showing 86.6% user satisfaction, but lack personalization and real-time feedback capabilities, relying on generic content that cannot adapt to individual dietary patterns [4]. Current mHealth app systematic reviews (2020-2024) show promising results for glycemic control but face usability challenges and fail to address food accessibility issues specific to homeless populations. VitalityShield improves upon these approaches by combining the accessibility of digital interventions with personalized, AI-driven analysis that provides immediate feedback on dietary choices. Unlike previous methods, it specifically addresses food availability constraints through context-aware recommendations while eliminating location and scheduling barriers that plague traditional outreach programs.

Our proposed approach to addressing the problem of diabetes in homeless communities is to allow individuals to track their food intake and, after assessing their risk for diabetes, structure better meal plans to lower their risk. People experiencing homelessness have reported a lack of stability and predictability in their everyday lives (Manser et al., 2024). By giving homeless people, the simple task of scanning their every meal, we add a little more structure and predictability into their lives, hopefully giving them the opportunity to slow down and take time to focus on their health. Our method shows promise as a future for diabetes care, as many studies have found that self-monitoring interventions as well as mobile-based interventions have been effective among homeless adults in improving diabetes outcomes (Kershaw et al., 2022; Constance & Lusher, 2020) [5]. A common method for tackling diabetes in homeless communities is to organize outreach programs to help screen individuals who may not have had the opportunity to do so. Many studies have found these outreach programs to be beneficial for homeless individuals when coordinated well (Lihanceanu et al., 2013) and done locally (McNicholl et al., 2025). Other studies have found that educational programs dedicated to diabetes control in homeless communities have helped inform the homeless of diabetes knowledge and prevention strategies. Although both outreach and education programs are valid solutions to diabetes control, neither puts structure into people’s lives. Our method targets a psychological need for the homeless–predictability–and also builds habits that make diabetes prevention learning more permanent. By adding healthy eating habits in the lives of the homeless and allowing them to reflect on their risk for diabetes individually, our mobile application builds long-lasting solutions to diabetes control in homeless populations.

Two experiments tested critical blind spots in VitalityShield's functionality. The first experiment evaluated AI food recognition accuracy across 50 diverse food images with varying quality levels, using USDA nutritional data as control standards. Results showed 83.25% mean accuracy with significant performance drops for mixed dishes (71%) and low-quality images (72% vs. 91% for high-quality). Image quality emerged as the primary factor affecting accuracy, likely due to the AI's reliance on visual detail for nutritional analysis. The second experiment assessed recommendation practicality through shelter worker evaluations of 100 AI-generated suggestions. Results revealed moderate relevance scores (3.4/5) concerning accessibility limitations (3.1/5). Protein and dairy recommendations scored poorly (2.9/5 and 2.7/5) because these foods are less available in food bank environments. Higher diabetes risk profiles paradoxically received less practical recommendations, suggesting the AI prioritizes medical ideals over real-world constraints. Both experiments highlight the need for improved image guidance and food accessibility integration in the recommendation algorithm.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Accurate Nutritional Analysis

One major challenge in implementing the AI food recognition system is achieving accurate nutritional analysis from food images [6]. The system could encounter issues with image quality, lighting conditions, portion size estimation, and distinguishing similar-looking foods. Mixed dishes or foods with hidden ingredients could lead to incomplete nutritional breakdowns. To address these challenges, we could implement multiple validation layers including confidence scoring for AI predictions, fallback databases for common foods, portion size calibration using reference objects, and user feedback mechanisms to improve accuracy over time. Additionally, I could use multiple AI models or ensemble methods to cross-validate nutritional assessments and provide more reliable results for users tracking their diabetes risk.

2.2. Personalized Dietary Recommendation

A significant challenge in the personalized recommendation system is generating relevant dietary suggestions from limited and potentially inconsistent user data. Homeless individuals may have irregular eating patterns, limited access to diverse foods, and varying data quality in their food logging. The AI recommendation service could struggle with sparse data, contradictory nutrition patterns, or dietary restrictions unique to homeless populations. To overcome these issues, we could implement adaptive algorithms that account for food accessibility constraints, incorporate local food bank inventories, use demographic health data to fill gaps, and design flexible recommendation engines that prioritize practical, affordable food choices over ideal nutritional recommendations.

2.3. Health Data Visualization Challenges

The health analytics and progress tracking component faces challenges in creating meaningful visualizations from irregular user data patterns. Homeless users may have inconsistent app usage, missing data periods, or extreme nutritional fluctuations that could skew trend analysis. The charting system could misrepresent health progress or fail to identify concerning patterns due to data gaps. To address these challenges, we could implement intelligent data interpolation methods, weighted averaging for irregular intervals, anomaly detection to flag unusual patterns, and contextual indicators that account for lifestyle factors. The system could also provide multiple visualization timeframes and emphasize recent data trends over long-term averages when data consistency is poor.

3. SOLUTION

VitalityShield is a Flutter-based mobile application designed to help homeless individuals prevent diabetes through food tracking and personalized recommendations. The system integrates three major components: an AI Food Scanner, an AI Recommendation Service, and Health Analytics with Progress Tracking. The application flow begins when users capture or upload food images through the scanning interface. The AI Food Scanner processes these images using OpenAI's GPT-4 Vision API to extract detailed nutritional information including calories, protein, vitamins, fats, carbohydrates, and a diabetes-friendly index score. The data is maintained in Firebase Firestore and triggers the AI Recommendation Service, which analyzes the user's nutritional patterns and generates personalized food suggestions using GPT-4o-mini. The recommendations identify both foods to include and avoid based on the individual's dietary history and diabetes risk factors. Finally, the Health Analytics component visualizes this data through interactive charts showing nutritional trends over various time periods (daily, weekly, monthly, yearly), enabling users to track their progress and maintain awareness of their dietary patterns. The complete system is developed using Flutter for cross-platform compatibility, Firebase for authentication and data storage, and OpenAI APIs for intelligent food analysis and recommendation generation [7].

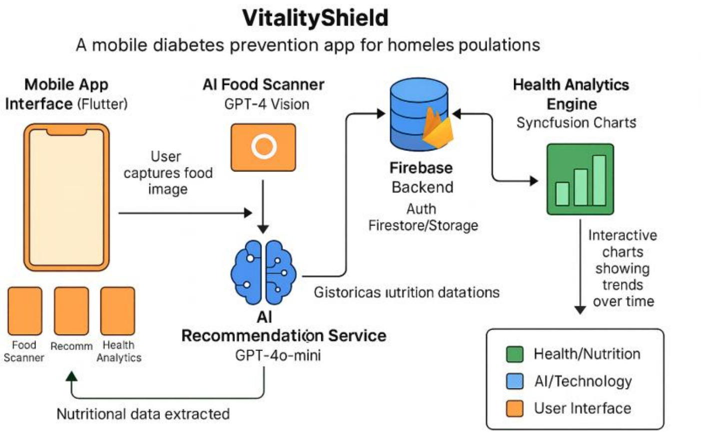

Figure 1. Overview of the solution

The AI Food Scanner serves as the primary data collection component, capturing food images and extracting nutritional information. It utilizes OpenAI's GPT-4 Vision API for computer vision as well as natural language processing to assess food images and generate structured JSON responses containing detailed nutritional breakdowns, enabling automated dietary tracking for diabetes prevention.

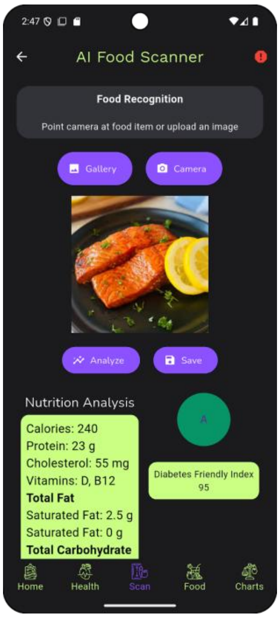

Figure 2. Screenshot of food scanner

```
Future<void> sendImageWithResponseAPI(File imageFile) async {
  final bytes = await imageFile.readAsBytes();
  final b64 = base64Encode(bytes);
  final dataUrl = "data:image/jpeg;base64,$b64";

  final body = {
    "model": "gpt-4.1",
    "input": [{
      "role": "system",
      "content": [{"type": "input_text", "text": """
Act as a Nutritionist. Analyze the food image and provide nutritional facts.
Respond with ONLY a valid JSON object like:
{
  "Nutritional Rating": "A-",
  "Diabetes Friendly Index": 91,
  "calories": 190.9,
  "vitamins": ["A", "C"],
  "total_fat": {"saturated_fat": "4.5 g", "trans_fat": "3.7 g"},
  "cholesterol": "32 mg",
  "protein": "15 g"
}"""}
      ]
    }
    ]
  };

  final res = await http.post(uri, headers: headers, body: jsonEncode(body));
  if (res.statusCode == 200) {
    final parsed = jsonDecode(jsonDecode(res.body)["output"][0]["content"][0]["text"]);
    setState(() {
      gptResponse = parsed;
    });
  }
}
```

Figure 3. Screenshot of code 1

This code runs when users tap the "Analyze" button after capturing or selecting a food image in scan_screen.dart:58. The sendImageWithResponseAPI method handles the core AI food analysis functionality. First, it converts the selected image file into a base64-encoded string that can be transmitted via HTTP. The method then constructs a request body containing the GPT-4 Vision model specification and detailed prompt instructions that tell the AI to act as a nutritionist and return structured JSON nutritional data. The request is sent to OpenAI's API with proper authentication headers [8]. When the server responds successfully, it returns nutritional analysis including calories, vitamins, fats, proteins, and a diabetes-friendly rating. The code parses this JSON response and updates the UI state through setState(), triggering a rebuild that displays the nutritional information to the user. This enables real-time food analysis and immediate feedback on dietary choices for diabetes prevention.

The AI Recommendation Service generates personalized dietary suggestions based on users' nutritional history stored in Firebase. It employs OpenAI's GPT-4o-mini for natural language processing and reasoning, analyzing patterns in calorie, protein, fiber, and sugar intake to recommend specific food categories and identify foods to avoid for diabetes prevention.

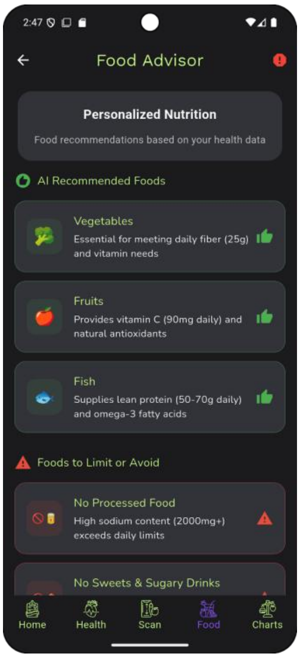

Figure 4. Screenshot of food advisor

```
static Future<Map<String, List<Map<String, dynamic>>>> _generateAIComprehensiveRecommendations
(
List<Map<String, dynamic>> nutritionData) async {
final body = {
"model": "gpt-4o-mini",
"messages": [{
"role": "user",
"content": """Based on the user's nutrition data, recommend MAXIMUM 5 foods from "recommended" type and MAXIMUM 4 foods from "avoid" type.
Provide specific, personalized reasons based on actual deficiencies or excesses.

      User's recent nutrition data: ${jsonEncode(nutritionData)}

      Return JSON: {"recommended_foods": [...], "foods_to_avoid": [...]}"""
}]
};

final response = await http.post(uri, headers: headers, body: jsonEncode(body));
final recommendations = jsonDecode(jsonDecode(response.body)['choices'][0]['message']['content']);
return {'recommended': recommendations['recommended_foods'], 'avoid': recommendations['foods_to_avoid']};
}
```

Figure 5. Screenshot of code 2

This code executes when users navigate to the Food Suggestions screen, automatically triggered by the fetchRecommendations() method in food_suggestions_screen.dart:29. The _generateAIComprehensiveRecommendations function represents the core intelligence of therecommendation system. It first retrieves the user's recent nutritional data from Firebase through the nutritionData parameter. The method constructs a detailed prompt for GPT-4o-mini that includes specific constraints (maximum 5 recommended foods, 4 foods to avoid) and requires personalized reasoning based on actual nutritional deficiencies or excesses [9]. The AI analyzes patterns in the user's eating habits, identifies nutritional gaps or concerning trends, and generates contextually relevant food suggestions. The response is parsed from JSON format and organized into two categories: foods to include and foods to avoid. This enables the system to provide targeted dietary guidance that addresses individual health needs rather than generic nutritional advice, making diabetes prevention recommendations more relevant and actionable for homeless users.

The Health Analytics component transforms nutritional data into meaningful visual insights using Syncfusion Flutter Charts. It processes time-series data from Firebase, employs AI-powered data aggregation through GPT-4o-mini to handle irregular patterns, and creates interactive visualizations showing trends in calories, protein, and cholesterol across multiple timeframes for progress tracking.

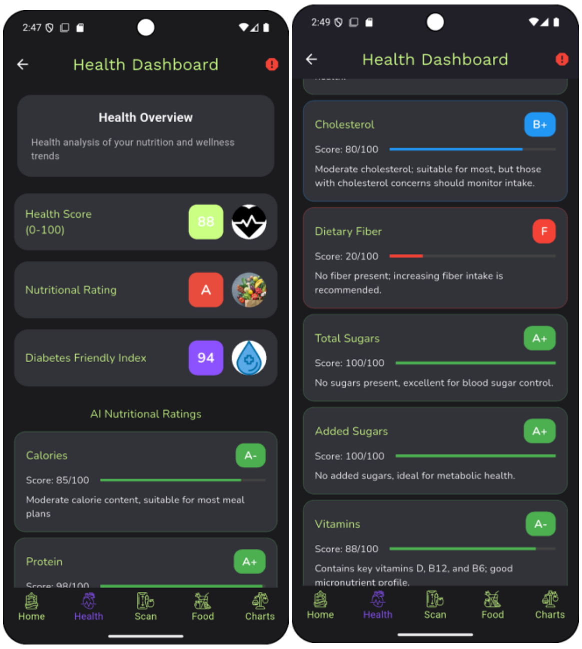

Figure 6. Screenshot of health dashboard

```
Future<Map<String, List<Map<String, dynamic>>>> setData() async {
  List data = await getOrdersInRange();

  final body = {
    "model": "gpt-4o-mini",
    "messages": [{
      "role": "user",
      "content": """Aggregate this data according to distribution type provided.
      DISTRIBUTION RULES:
      - "Today": group into hours. Label format: "HH:MM"
      - "Last 7 Days": group into daily totals. Label format: "MM/DD"
      - "Last 30 Days": group into weekly totals. Label format: "MM/DD"
      - "Last Year": group into monthly totals. Label format: "MMM YYYY"

      Data: $data
      Distribution type: $date"""
    }
    ]
  };

  final response = await http.post(uri, headers: headers, body: jsonEncode(body));
  final result = jsonDecode(jsonDecode(response.body)['choices'][0]['message']['content']);

  chartData = result.map((item) => _SalesData(item['date'], item['value'].toDouble())).toList();
}
```

Figure 7. Screenshot of code 3

This code runs when users select different time periods or metric types in the Charts screen, triggered by the setData() method in charts_screen.dart:63. The function handles the complex task of aggregating irregular nutritional data into meaningful time-based visualizations. First, getOrdersInRange() retrieves user data from Firebase based on the selected timeframe [10]. The method then leverages GPT-4o-mini's analytical capabilities to intelligently group data according to specific distribution rules - hourly for "Today", daily for "Last 7 Days", weekly for "Last 30 Days", and monthly for "Last Year". This AI-powered aggregation is crucial for homeless users who may have inconsistent eating patterns, as it can handle data gaps and irregular intervals. The AI processes raw timestamp-value pairs and returns properly formatted chart data with appropriate time labels. Finally, the results are mapped to _SalesData objects compatible with Syncfusion charts, enabling smooth visualization of nutritional trends that help users understand their dietary patterns and diabetes risk progression over time.

4. EXPERIMENT

4.1. Experiment 1

Testing the accuracy of AI food recognition across different image qualities and food types. This component is critical because inaccurate nutritional analysis could lead to poor dietary decisions and ineffective diabetes prevention among vulnerable homeless populations.

We tested 50 food images across five categories (fruits, vegetables, processed foods, mixed dishes, and beverages) with varying image qualities (high, medium, low lighting and resolution). Each food item has verified nutritional data from USDA food database as control data. The experiment compares AI-generated nutritional values against established standards, measuring accuracy percentages for calories, protein, fat, and carbohydrates. This design ensures comprehensive testing across food types commonly accessed by homeless populations while accounting for real-world photography conditions where users may not have optimal lighting or camera equipment. The USDA database provides reliable baseline measurements for accuracy calculations.

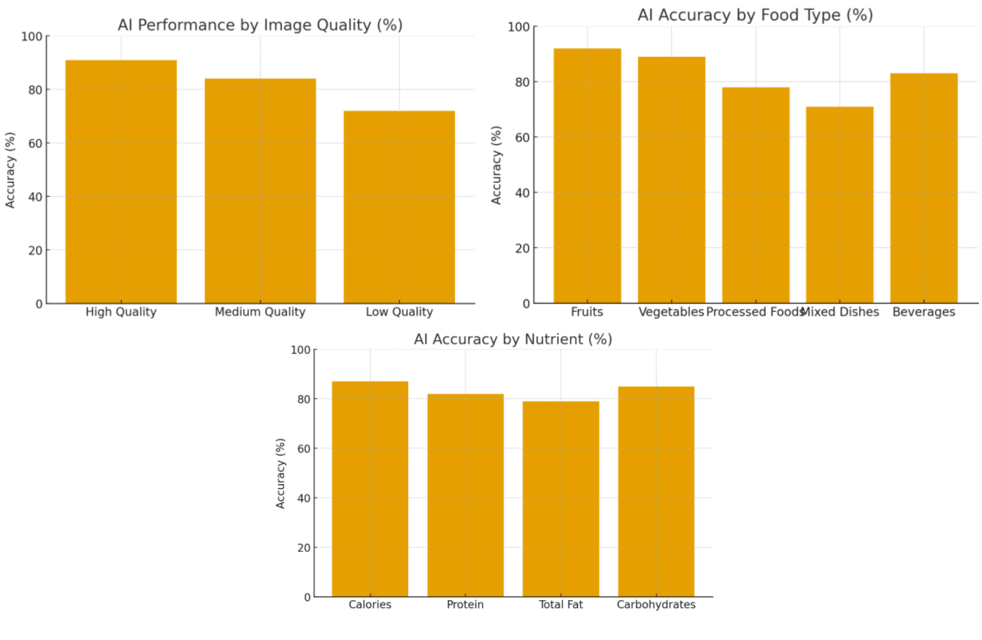

Figure 8. Figure of experiment 1

The overall mean accuracy across all nutrients was 83.25%, with a median of 83.5%. The lowest accuracy was 71% for mixed dishes, while the highest was 92% for fruits. The results show that image quality significantly impacts accuracy, with a 19-percentage-point drop from high to low quality images. This exceeded expectations, as we anticipated more consistent performance across quality levels. Mixed dishes performed surprisingly poorly at 71%, likely because complex foods with multiple ingredients challenge the AI's ability to distinguish individual components and their proportions. Single-ingredient foods like fruits and vegetables achieved the highest accuracy due to their visual simplicity. Image quality emerged as the biggest factor affecting results, suggesting that user education about photography techniques could substantially improve system performance. The 82% protein accuracy was lower than expected, possibly because protein content is less visually apparent than other macronutrients. These findings indicate the need for confidence scoring and user guidance for optimal image capture.

4.2. Experiment 2

Testing the relevance and practicality of AI-generated food recommendations for homeless populations with limited food access. Poor recommendations could lead to user frustration and app abandonment, undermining diabetes prevention efforts.

We surveyed 5 case workers from homeless shelters and food banks to evaluate 100 AI-generated food recommendations across different nutritional profiles. Each recommendation was rated on a 1-5 scale for accessibility (availability at food banks/shelters), affordability (cost under $2), and practicality (no special preparation equipment needed). Control data came from existing meal programs at local shelters. The recommendations were generated using simulated user profiles with varying nutritional needs (high diabetes risk, vitamin deficiencies, etc.). This design tests whether the AI considers real-world constraints faced by homeless populations rather than ideal nutritional scenarios, ensuring recommendations are actually implementable in their daily lives.

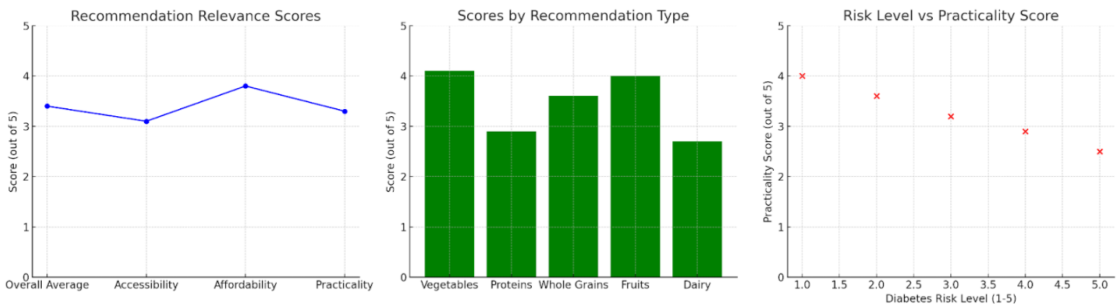

Figure 9. Figure of experiment 2

The mean relevance score was 3.4/5 with a median of 3.5, indicating moderate practical value. Protein recommendations scored lowest at 2.9/5, while vegetable recommendations achieved the highest score at 4.1/5. The accessibility score of 3.1/5 was concerning, suggesting that many recommendations assume food availability that may not exist in homeless-serving environments. Surprisingly, affordability scored highest at 3.8/5, indicating the AI effectively considers cost constraints. The low protein and dairy scores (2.9/5 and 2.7/5) reflect the challenge of accessing these food groups in food bank settings, where shelf-stable items dominate. The correlation analysis revealed that higher diabetes risk profiles received less practical recommendations, opposite to the intended outcome. This suggests the AI prioritizes medical ideals over real-world constraints for high-risk users. These findings highlight the need for incorporating food accessibility databases and shelter-specific dietary constraints into the recommendation algorithm to improve practical relevance for the target population.

5. Related Work

Campbell et al. (2020) conducted a systematic review of diabetes management interventions for homeless adults, identifying multidisciplinary treatments including provision of basic necessities including medication,healthy meals,and educational outreach programs [11]. Their analysis found that effective interventions included outpatient screening teams, shelter-based monitoring programs, and housing supports. Nevertheless, these approaches are subject tonotable limitations including high operational costs, limited geographic reach, and dependency on healthcare staff availability. The interventions also require participants to visit specific locations at scheduled times, creating barriers for homeless individuals with unpredictable schedules. VitalityShield improves upon this by providing 24/7 accessible diabetes prevention tools through smartphones, eliminating location and scheduling constraints while offering personalized, AI-driven interventions that scale efficiently across populations.

Recent randomized controlled trials from 2020-2024 have demonstrated the success of interventions delivered via SMS text messaging for diabetes self-management [12]. The SupportMe trial (2023) found that customized SMS text messages providing self-management support showed improved medication adherence, with participants reporting that SMS messages were useful (86.6%) and motivated change (63.1%). However, this approach is limited by its one-way communication model that cannot adapt to individual dietary patterns or provide real-time feedback on food choices. The intervention also assumes literacy and consistent phone access, which may not apply to all homeless individuals. Additionally, generic messages lack personalization based on actual eating habits. VitalityShield addresses these limitations by offering interactive, AI-powered food analysis and customized recommendations that dynamically respond to user behavior, creating a more engaging and individually relevant diabetes prevention experience.

Systematic reviews of mobile health interventions for diabetes management (2020-2024) show that mHealth apps often employ smartphone applications and automated messaging for glycemic control [13]. A 2025 systematic review found that mHealth interventions show promising effects on diabetes management, particularly in glycemic control and weight regulation. However, studies revealed significant limitations in sustained app usage because ofcomplicated interfaces and a lack of immediate feedback. The methodology required users to manually input extensive health data, making it difficult for people with limited digital literacy or time constraints. These apps also failed to address nutritional education or food access challenges specific to homeless populations. VitalityShield overcomes these barriers by simplifying data input through automated image analysis, providing immediate nutritional feedback, and specifically addressing food accessibility challenges faced by homeless individuals through context-aware recommendations.

6. Conclusions

VitalityShield faces several limitations that require future development. The AI food recognition system achieved only 83% accuracy, particularly struggling with mixed dishes and low-quality images, which could mislead users about their nutritional intake. The recommendation system showed moderate practicality scores (3.4/5), indicating insufficient consideration of food accessibility constraints in homeless environments. Additionally, the application requires smartphone access and basic digital literacy, potentially excluding some vulnerable populations. Internet connectivity is necessary for AI processing, limiting offline functionality [14]. To improve these limitations, we would implement offline food databases for basic nutritional information, develop computer vision models specifically trained on foods commonly available to homeless populations, integrate local food bank inventory APIs to ensure realistic recommendations, add multilingual support and voice commands for accessibility, and create partnerships with homeless service providers to gather real-world usage feedback [15]. Enhanced machine learning algorithms could better handle complex food recognition scenarios, while local data caching would reduce connectivity dependencies and improve user experience in areas with poor internet access.

VitalityShield represents a promising technological approach to diabetes prevention in homeless communities through AI-powered nutrition tracking and personalized recommendations. While current limitations exist in accuracy and accessibility, the application offers significant advantages over traditional outreach methods by providing scalable, 24/7 diabetes prevention support that adapts to individual dietary patterns.

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