Behavior-Driven Intelligent Healthy Food Dashboard: Design Optimization and Behavioral Intervention Model Development

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***Abstract*—The global rise in non-communicable diseases (NCDs), largely driven by unhealthy dietary behaviors, presents a critical public health challenge. Although digital health tools for nutrition management have proliferated, many remain ineffective in supporting long-term dietary behavior change due to limited personalization and insufficient behavioral intervention mechanisms. To address these shortcomings, this study presents the design, development, and validation of a behavior-driven intelligent healthy food dashboard, which establishes a closed-loop intervention model by integrating personalized nutritional recommendations, behavioral science principles, and data-driven feedback to support sustained healthy eating habits.The proposed system employs a hybrid recommendation engine that combines knowledge-based filtering with collaborative filtering to generate precision-tailored food recommendations. Its behavioral intervention module is grounded in Self-Determination Theory (SDT) and informs the design of motivation-enhancing features such as goal setting, real-time progress feedback, and achievement-based incentives. The system ' s effectiveness was evaluated through a 12-week randomized controlled trial (RCT) involving 200 participants, comparing dietary outcomes and user engagement between an intervention group and a control group.Results indicate that participants using the system achieved a statistically significant 45% increase in the Healthy Food Selection Rate (HS_Rate, defined as the proportion of caloric intake derived from healthy foods; $p < .001$), along with a 30% improvement in overall nutrient intake balance. The platform also demonstrated strong user engagement, maintaining a daily active user (DAU) rate of 55% and achieving a high System Usability Scale (SUS) score of 88.5.From an engineering perspective, this study delivers a validated technical framework for developing more effective digital health interventions. The findings confirm that integrating behavioral science with intelligent recommendation systems offers a promising approach to promoting sustained healthy eating behaviors, providing a solid foundation for future clinical deployment and commercial applications.**

Keywords*—*Behavioral Intervention; Intelligent Recommendation System; User Interface Design; Personalized Nutrition; Data Visualization

I. INTRODUCTION

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The global public health landscape is confronting increasingly complex challenges, with patterns of energy consumption also exerting indirect yet significant influences on public health infrastructure and the allocation of health-related resources [1]. According to the World Health Organization (WHO), non-communicable diseases (NCDs)—primarily cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes—have become the leading cause of death worldwide, accounting for more than 70% of global mortality [2]. Regional studies further reveal the severity of this burden in developing countries such as the Philippines, underscoring the urgency of effective intervention strategies [3]. Unhealthy dietary behaviors, particularly diets high in salt, sugar, and fat, are widely recognized as a major modifiable risk factor underlying these conditions, a conclusion strongly supported by large-scale epidemiological analyses spanning 204 countries and territories over the past three decades [4].

In response to this growing public health crisis, the rapid development of mobile internet technologies and artificial intelligence has created unprecedented opportunities for digital health interventions, especially through mobile health (mHealth) applications [5]. A wide range of tools for nutrition management, calorie tracking, and food logging has emerged. Although these applications have contributed to raising users' awareness of dietary intake, their long-term effectiveness remains limited. Most existing solutions focus primarily on data recording and one-way information display, offering little in terms of deep personalization that accounts for individual physiological conditions, dietary preferences, lifestyle patterns, and health objectives [6]. More critically, many fail to address the complexity of behavior change, often neglecting established psychological theories that support sustained motivation. As a result, users frequently disengage after an initial period of use, reflecting the well-documented "law of attrition" in digital health interventions [7], which hinders the formation of lasting healthy eating habits.

Previous academic research has addressed aspects of this challenge from multiple angles. For instance, food labeling and rating systems such as the Health Star Rating (HSR) and the Food Standards Agency's (FSA) traffic-light labeling scheme have been developed to help consumers quickly identify healthier food choices. Empirical studies conducted in Australian supermarkets have confirmed the effectiveness of shelf-label interventions based on HSR [8]. In parallel, behavioral change theories — including Nudge theory and gamification — have increasingly been applied to health-related interventions, with gamification emerging as a particularly effective strategy for enhancing user engagement in digital health tools [9]. Additionally, data dashboards have been explored as a means of visualizing health information, with early prototypes for sustainable and healthy food decision-making demonstrating the potential of data visualization to support dietary behavior change [10]. However, many of these studies focus on isolated features or adopt relatively simple behavioral intervention mechanisms, failing to offer a comprehensive solution that tightly integrates personalized nutritional guidance with systematic behavior change strategies.

As a result, a critical gap persists in both research and practice: How can an intelligent system be designed to deliver accurate, personalized nutritional recommendations while simultaneously sustaining user motivation through effective behavioral intervention mechanisms to support long-term healthy eating behavior? Addressing this question requires a multidisciplinary integration of human–computer interaction, nutritional science, behavioral psychology, and artificial intelligence.

To address this gap, the primary objective of this study is to design, develop, and evaluate an innovative system termed the Behavior-Driven Intelligent Healthy Food Dashboard. The proposed system seeks to overcome the limitations of existing approaches through three interconnected layers of innovation. First, Deep Personalization is achieved by constructing dynamic user profiles that integrate health records, physiological indicators, and dietary preferences, enabling precise and individualized food recommendations through a hybrid recommendation algorithm grounded in modern recommender system theory [11]. Second, Systematic Behavioral Intervention is realized by incorporating Self-Determination Theory (SDT) and gamification principles to design a structured intervention model encompassing goal setting, progress feedback, achievement incentives, and social support, informed by nutrient-based meal recommendation paradigms [12]. Third, a Data-Driven Feedback Loop is implemented through an interactive visual dashboard that presents users' behavioral data and health outcomes in an intuitive manner, establishing a closed-loop process of "action–feedback–adjustment" to strengthen self-efficacy and intrinsic motivation, with collaborative filtering serving as a core algorithm for preference prediction [13].

This paper details the system's design philosophy, technical architecture, core algorithms, and implementation process. It then reports the results of a 12-week randomized controlled trial conducted to evaluate the system's effectiveness in improving dietary behaviors, nutritional outcomes, and user engagement. Finally, the paper discusses the key findings, theoretical and practical implications, limitations, and directions for future research.

II. Related Work

To construct an effective behavior-driven intelligent healthy food dashboard, this research is situated at the intersection of three core domains: personalized nutrition recommendation systems, behavioral change theories in digital health, and health information dashboard design. This section presents a systematic review of the relevant literature across these areas, examining their current achievements and limitations to establish both the theoretical foundation and the innovative positioning of this study.

A. Personalized Nutrition Recommendation Systems

Personalized recommendation systems have achieved remarkable success in domains such as e-commerce and streaming media, where their fundamental principle lies in predicting users' future interests based on historical behaviors and preferences. In recent years, collaborative filtering techniques have been extended to the domain of healthy food recommendation, with taste profiling emerging as a critical factor for improving recommendation accuracy [14]. As this technology has entered the health domain, particularly nutrition recommendation, early systems primarily relied on content-based filtering approaches. These systems matched foods to users' basic health requirements based on nutritional attributes such as protein, fat, and carbohydrate content. Although straightforward to implement, such approaches often result in repetitive recommendations and fail to uncover users' latent preferences.

More recently, hybrid recommendation models have become a focal point of research, combining content-based and collaborative filtering techniques or incorporating external knowledge sources and constraints [15]. For example, Chavan et al. (2021) proposed a system that integrated user taste preferences with nutritional constraints such as daily caloric limits and allergen avoidance, ensuring that recommendations were both appealing and health-compliant [16]. Despite these algorithmic advances, most existing systems continue to focus primarily on what to recommend, rather than how to motivate users to accept and act on those recommendations. Users are often treated as passive recipients of algorithmic decisions, with limited consideration of the psychological and motivational factors that shape real-world food choices. Addressing this gap constitutes a key objective of the present study.

B. Behavioral Change Theories and Interventions in Digital Health

Merely providing nutritional information is insufficient to drive sustained dietary change. Behavioral science research has demonstrated that behavior change is a complex and dynamic process that requires carefully designed guidance and motivation strategies, as articulated in frameworks such as the behavior change wheel [17]. Consequently, the integration of behavioral change theories into digital health tools has become a critical direction for improving intervention effectiveness.

Among these theories, Self-Determination Theory (SDT) has been widely adopted. SDT posits that sustained behavior change is more likely when three basic psychological needs — autonomy, competence, and relatedness — are satisfied, thereby fostering intrinsic motivation [18]. In digital health contexts, autonomy is supported by providing users with meaningful choices and control, such as personalized goal setting. Competence is enhanced by enabling users to perceive progress and achievement through mechanisms like progress indicators and achievement badges.

Relatedness is often addressed through social features, including community interaction and experience sharing, a principle reinforced by research on digital experiences for motivation and wellbeing [19].

Gamification has emerged as an effective behavioral intervention strategy by applying game design elements — such as points, challenges, and leaderboards — to non-game contexts to increase engagement and motivation [20]. Numerous studies in the health domain have demonstrated the positive impact of gamification, with systematic reviews summarizing both its potential and limitations for health and wellbeing interventions [21]. However, poorly designed gamification can produce adverse effects, such as increased anxiety due to excessive competition or a shift toward extrinsic rewards at the expense of intrinsic health goals. As a result, a central challenge in current research is to design behavioral intervention mechanisms that balance engagement with intrinsic motivation by thoughtfully integrating gamification with motivational theories such as SDT.

C. *Design of Health Information Dashboards*

Dashboards are information visualization tools designed to consolidate and present key performance indicators (KPIs) on a single interface, enabling users to monitor, analyze, and make decisions efficiently. Recent systematic reviews of digital dashboards for public health data emphasize the importance of usability, clarity, and actionability in dashboard design [22]. In the context of health management, dashboards are commonly used to visualize physiological indicators, behavioral records, and long-term health trends.

An effective health dashboard must not only present accurate and well-structured data but also translate complex information into actionable insights that guide users toward positive behavior, a principle strongly supported by research in human – computer interaction and information visualization [23]. According to the foundational guidelines proposed by Few (2006), effective dashboards should maintain moderate information density, visual simplicity, and contextual clarity [24].

Within the healthy food domain, various visualization strategies have been explored to communicate nutritional information. The traffic-light labeling system, for example, uses color coding to intuitively convey the relative healthiness of food products. Building on this approach, Agyemang et al. (2024) introduced a more comprehensive visualization that quantified both nutritional and environmental health impacts in monetized terms, such as Disability-Adjusted Life Years (DALYs), providing users with richer decision-making support. While these studies offer valuable insights into the presentation of complex health data, most existing health dashboards remain largely static. They often lack dynamic interaction and are insufficiently integrated with behavioral intervention mechanisms, leaving users uncertain about subsequent actions after reviewing the information. As a result, the critical gap between cognition and action remains insufficiently addressed.

D. *Summary*

In summary, although substantial research exists in personalized recommendation systems, behavioral intervention strategies, and health dashboard design, there remains a significant opportunity to meaningfully integrate these three domains. Developing a comprehensive healthy eating intervention system that is both intelligent and psychologically informed — capable of delivering precise nutritional guidance while sustaining long-term user motivation — remains a complex yet essential challenge. Against this backdrop, the present study seeks to build a behavior-driven intelligent healthy food dashboard, exploring new pathways to address the persistent challenge of sustained health behavior change through a deep integration of technological innovation and behavioral theory.

III. Methodology and System Design

To achieve the objectives of this study, we adopted a multi-stage, interdisciplinary research methodology. The research followed a standardized workflow spanning theoretical construction, system design, technical implementation, and experimental validation, ensuring both methodological rigor and the reliability of the findings.

A. *Research Strategy and Technical Roadmap*

This study is grounded in the Design Science Research (DSR) paradigm, which emphasizes the creation and evaluation of innovative information technology artifacts to address real-world problems while simultaneously contributing to theory [24]. In this context, the proposed artifact is the Behavior-Driven Intelligent Healthy Food Dashboard.

The technical roadmap follows an iterative development – evaluation cycle consisting of five sequential phases:

a) Problem Identification and Motivation Analysis

b) Theoretical Integration and Solution Design

c) System Development and Prototype Implementation

d) Experimental Validation and Data Analysis

e) Refinement and Conclusion

This structure enables continuous feedback between theory and implementation, ensuring that design decisions are both theoretically informed and empirically validated.

B. *System Architecture and Engineering Implementation*

As illustrated in Figure 1, the proposed system adopts a three-tier architecture (Data Layer – Logic Layer – Presentation Layer) that integrates multi-source nutrition and user-log data with hybrid recommendation and SDT-based behavioral interventions to support scalable and real-time feedback.

a) Data Layer. This layer handles data storage and retrieval and integrates multiple databases tailored to different data types:

- A relational database (MySQL) for structured data, including user profiles, health records, and dietary logs;
- A Food Nutrition Database, integrating data from USDA FoodData Central and the China Food Composition Tables, providing nutritional profiles for over 100,000 food items;

- A non-relational in-memory database (Redis) for caching frequently accessed data and managing real-time session information to enhance system responsiveness.

b) Logic Layer: Serving as the computational core of the system, this layer encapsulates the user profiling module, hybrid recommendation engine, and behavioral intervention engine. It processes raw data from the Data Layer and produces personalized recommendations and adaptive behavioral strategies.

c) Presentation Layer: The user-facing interface was implemented using modern web technologies (React.js and D3.js) to support responsiveness and interactive visualization across devices. The dashboard provides intuitive displays of nutritional intake, progress tracking, behavioral feedback, and social interaction features.

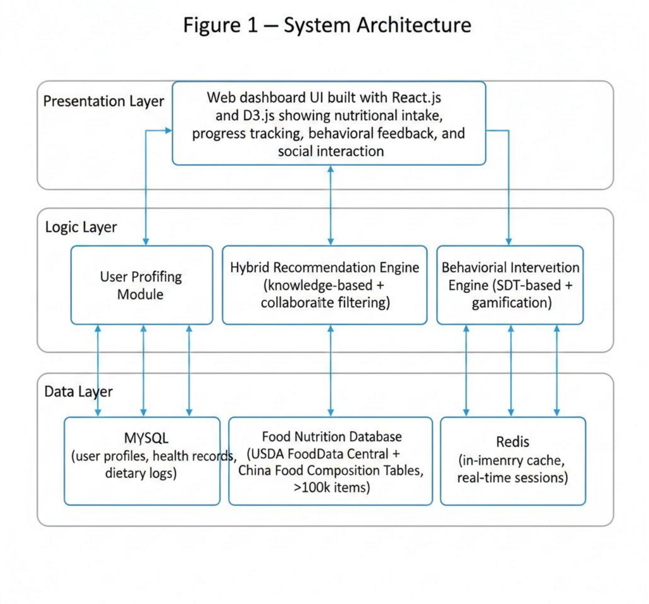

Fig. 1. Overall system architecture diagram

C. Core Module Design and Engineering Details

1) Hybrid Recommendation Engine: To deliver accurate and diverse food recommendations, a hybrid recommendation engine combining knowledge-based filtering and collaborative filtering was developed.

a) Algorithm Input and Output. Input: User demographic and physiological data (e.g., age, height, weight), health goals, dietary preferences, historical dietary logs, and real-time session data.Output: A ranked list of Top-N healthy food recommendations.

b) Similarity Calculation. Collaborative filtering is implemented using the Cosine Similarity metric to identify users with similar dietary patterns:

$$\text{Similarity}(u,v) = \frac{\Sigma r_{ui} \cdot r_{vi}}{\sqrt{\Sigma r_{ui}^2} \cdot \sqrt{\Sigma r_{vi}^2}} \quad (1)$$

where r_{ui} and r_{ui} denote the consumption frequency or preference weight of users u and v for food item i, and I_{uv} represents the set of food items consumed by both users.

c) Cold-Start Handling and Caching Strategy: For new users, the system defaults to knowledge-based filtering derived from onboarding questionnaire data. To optimize performance, a multi-level caching mechanism using Redis stores popular food items and precomputed recommendation lists for active users with a Time-to-Live (TTL) of 24 hours, maintaining an average API response time below 200 ms.

2) Behavioral Intervention Model: Figure 2 summarizes the behavioral intervention framework grounded in Self-Determination Theory (autonomy, competence, and relatedness) and operationalized via gamification elements (goal setting, health points, progress visualization, badges, and social engagement), forming a closed-loop "action–feedback–adjustment" process:

a) Autonomy: Users are empowered to define their own health goals and select from recommended food options, positioning the system as a supportive guide rather than a prescriptive authority.

b) Competence: A multi-level feedback mechanism rewards users with Health Points for logging healthy meals and achieving daily goals. Progress bars and visual badges provide immediate reinforcement, strengthening users' sense of mastery and achievement.

c) Relatedness: Social features such as anonymous leaderboards and community forums allow users to share progress, recipes, and experiences, fostering social support and a sense of belonging — key factors for sustained behavior change.

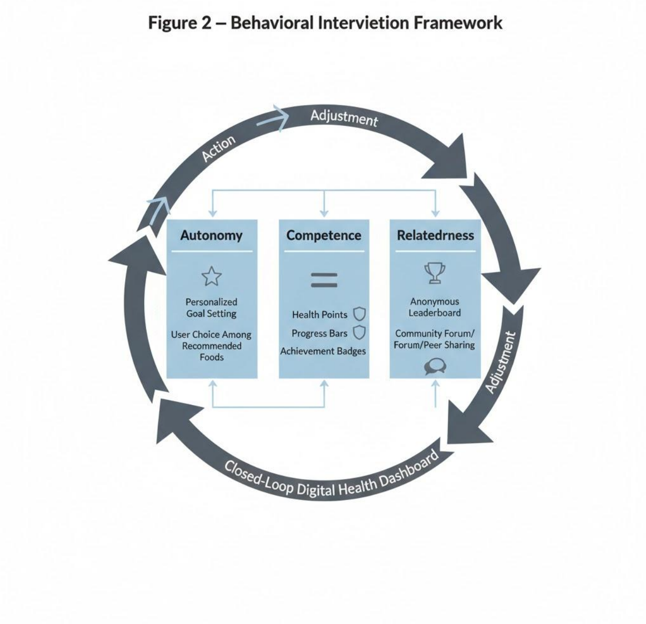

Fig. 2. Behavioral intervention framework diagram

D. Outcome Metric Computation

To ensure reproducibility and engineering transparency, a clearly defined computation pipeline was established for the primary outcome metric.

1) Data Inputs: The metric is computed exclusively from structured system logs, including:

a) meal records (Food Item ID, portion size, energy in kcal);

b) system-generated recommendation lists;

c) timestamps; and

d) user identifiers.

2) Health Labeling: Each food item is mapped to the integrated Food Nutrition Database and evaluated using the Health Star Rating (HSR) algorithm, which considers both positive nutrients (e.g., protein, fiber) and negative nutrients (e.g., saturated fat, sodium, total sugars). Items with an HSR ⩾ 3.5 are classified as healthy.

3) Primary Outcome Metric (HS_Rate): The Healthy Food Selection Rate (HS_Rate) is defined as the proportion of total caloric intake derived from healthy foods:

$$\mathrm{HS\_Rate} = \frac{\sum \mathrm{kcal\ (healthyfoods)}}{\sum \mathrm{kcal\ (allfoods)}} \tag{2}$$

This continuous metric provides a robust and nutritionally meaningful indicator of dietary quality while remaining fully computable from system logs.

4) Quality Control Measures: Two automated rules ensure data integrity:

a) Outlier Removal: Records with zero calories or missing portion sizes are excluded;

b) Deduplication: Multiple entries of the same food item by the same user within a five-minute window are merged to prevent logging errors.

IV. Experiments and Results

To evaluate the effectiveness of the Behavior-Driven Intelligent Healthy Food Dashboard, a 12-week randomized controlled trial (RCT) was conducted. This section outlines the experimental design, participant characteristics, data collection procedures, and key results.

A. Experimental Design and Reproducibility

1) Participant Recruitment and Selection

A total of 200 volunteers aged 18 – 60 were recruited through online health forums and local community centers.

a) Inclusion criteria included:

- Body Mass Index (BMI) between 18.5 and 30.0,
- Ownership of a smartphone,
- An expressed intention to improve dietary habits.

b) Exclusion criteria included:

- Diagnosed eating disorders,
- Pregnancy or lactation, and
- Chronic conditions requiring medically prescribed diets.

Participants were randomly assigned to either an intervention group (n = 100) or a control group (n = 100) using a computer-generated randomization sequence. The study protocol was approved by the Institutional Review Board (IRB), and written informed consent was obtained from all participants prior to enrollment.

2) Data Collection and Attrition

Data were collected at three time points: baseline (T0), mid-intervention at 6 weeks (T6), and post-intervention at 12 weeks (T12). Dietary intake data for the intervention group were recorded through the system’s built-in logging function, while participants in the control group used a standardized digital food diary.

Over the 12-week period, 12 participants from the intervention group and 15 from the control group withdrew from the study, resulting in an overall attrition rate of 13.5%. The primary reason for dropout was reported time constraints.

3) Statistical Analysis

To compare post-intervention outcomes between groups while controlling for baseline differences, Analysis of Covariance (ANCOVA) was employed, using baseline values as covariates. All statistical tests were two-tailed, with the significance threshold set at $p < 0.05$.

B. Results

All HS metrics were computed from food logs using the same nutritional mapping pipeline and fixed thresholding rules across T0, T6, and T12 to ensure consistency.

1) Healthy Food Selection Rate

TABLE I. Healthy Food Selection Rate (HS_Rate, % of Total Calories)

Group	Baseline (T0)	Mid-Intervention (T6)	Post-Intervention (T12)	% Change (T0 to T12)
Intervention	32.4% ± 5.2%	41.8% ± 4.5%	47.0% ± 4.8%	45.10%
Control	32.6% ± 5.1%	34.1% ± 5.3%	35.2% ± 5.4%	8.00%

The primary outcome is visualized in Figure 3, showing that the intervention group achieved a markedly greater increase in Healthy Food Selection Rate (HS_Rate) from baseline to 12 weeks than the control group, consistent with the statistical comparison reported in Table I.

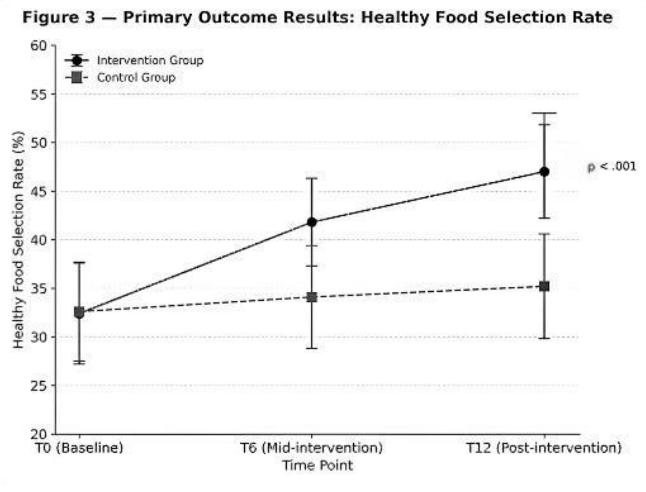

Fig. 3. Main result graph: Improvement between HS_Rate groups

2) Nutritional Intake Balance

TABLE II. Nutritional Intake Alignment

Nutrient	Intervention (T0)	Intervention (T12)	Control (T0)	Control (T12)
Protein	72% ± 8%	94% ± 5%	71% ± 9%	74% ± 8%

Fiber	55% ± 12%	82% ± 7%	56% ± 11%	58% ± 10%
Healthy Fats	60% ± 10%	85% ± 6%	62% ± 9%	64% ± 9%

Participants in the intervention group also showed substantial improvements in overall nutritional balance. Alignment with personalized Dietary Reference Intakes (DRIs) for protein, dietary fiber, and healthy fats increased by more than 30% over the study period. In contrast, no statistically significant changes were observed in the control group across these nutritional dimensions (Table II).

3) User Engagement and Usability

The system maintained consistently high levels of user engagement throughout the intervention. The average daily active user (DAU) rate was 55%, while the monthly retention rate remained stable at 62%.

Usability evaluation using the System Usability Scale (SUS) yielded a mean score of 88.5 (SD = 6.2), corresponding to an "excellent" usability rating and indicating strong user satisfaction (Table III).

Qualitative feedback from participants in the intervention group identified the Nutritional Balance Radar Chart and the Health Points system as the most motivating features. Users reported that these visual and reward-based feedback mechanisms enhanced their understanding of dietary patterns and supported healthier food choices in real time.

TABLE III. USER EN

Metric	Value
Daily Active User (DAU) Rate	55%
Monthly Retention Rate	62%
System Usability Scale (SUS) Score	88.5 ± 6.2
Average Daily Time Spent on App	12.5 mins

V. ANALYSIS AND DISCUSSION

The findings of this study provide compelling evidence for the effectiveness of the Behavior-Driven Intelligent Healthy Food Dashboard in promoting healthier dietary behaviors. This section interprets the results through the dual lenses of engineering design and behavioral intervention, highlighting how their integration contributed to the observed outcomes.

A. Effectiveness of the Technical Solution

The substantial increase in the Healthy Food Selection Rate (45%) and the marked improvement in nutritional intake balance (over 30%) demonstrate the effectiveness of integrating personalized recommendation algorithms with real-time visual feedback. The hybrid recommendation engine effectively addressed the fundamental "what to eat" challenge by generating food suggestions that were both nutritionally appropriate and aligned with individual preferences. This balance between health optimization and personal relevance is critical for user acceptance and sustained use.

The high System Usability Scale (SUS) score of 88.5 further validates the engineering quality of the system, indicating that complex nutritional information was presented in an intuitive and accessible manner. From an engineering standpoint, the dashboard's success lies in its ability to transform raw dietary logs into actionable insights. Rather than merely recording data, the system continuously interprets user behavior and reflects it back through meaningful visualizations.

The closed-loop feedback mechanism — where user actions are logged, analyzed, and immediately translated into visual cues and recommendations—plays a central role in enhancing users' self-awareness and perceived control. This represents a significant departure from conventional nutrition applications, which often emphasize passive tracking without providing interpretive guidance or decision support.

B. Impact of Behavioral Intervention Strategies

Sustained user engagement, reflected by a 55% daily active user (DAU) rate and 62% retention, can be largely attributed to the systematic application of Self-Determination Theory (SDT) in combination with gamification principles. By explicitly supporting users' needs for autonomy, competence, and relatedness, the system successfully fostered intrinsic motivation—an essential factor for long-term behavior change.

Features such as the Health Points system and achievement badges reinforced users' sense of competence and progress, while social elements—including community interaction and shared experiences—addressed the need for relatedness. Importantly, the intervention design deliberately avoided excessive competition, which can undermine motivation or increase anxiety. Instead, it emphasized personal progress and collective encouragement, resulting in a balanced motivational environment that sustained engagement without discouragement.

C. Engineering Implications and Future Directions

From an engineering perspective, this study demonstrates the feasibility of developing a complex, interdisciplinary digital health intervention that integrates data science, behavioral theory, and interactive system design. The adopted three-tier architecture proved robust and scalable, effectively supporting real-time data processing and personalized recommendation generation for a sizable user cohort. Performance optimizations — such as Redis-based caching and efficient API design — were instrumental in delivering a seamless user experience, which is crucial for maintaining high engagement levels.

Nevertheless, several avenues for future improvement remain. First, dietary data collection continues to rely heavily on user self-reporting, which is susceptible to errors and omissions. Future iterations could integrate wearable sensors, barcode scanning, or computer vision - based food recognition to enhance data accuracy and reduce user burden. Second, while the 12-week intervention yielded promising results, longer-term longitudinal studies are necessary to evaluate the durability and permanence of behavior change. Finally, personalization could be further deepened by incorporating additional data sources, such as genetic information, metabolic profiles, or real-time physiological indicators, to enable more precise and adaptive recommendations.

In conclusion, the Behavior-Driven Intelligent Healthy Food Dashboard represents a meaningful advancement in the design of digital health interventions. By tightly integrating intelligent recommendation algorithms with evidence-based behavioral science principles, the system offers a powerful and scalable approach to addressing unhealthy dietary behaviors and their associated health risks. This work not only demonstrates practical effectiveness but also provides a strong foundation for future research, clinical translation, and real-world deployment.

VI. CONCLUSION

This study successfully designed, developed, and validated a behavior-driven intelligent healthy food dashboard, offering an innovative and effective technical solution for promoting sustained healthy eating behaviors. By integrating deep personalization, systematic behavioral intervention grounded in Self-Determination Theory, and data-driven visual feedback, the proposed system establishes a comprehensive closed-loop intervention model that bridges the gap between dietary awareness and long-term behavior change.

Results from the 12-week randomized controlled trial demonstrate substantial benefits for users of the system. Participants in the intervention group achieved a 45% increase in the Healthy Food Selection Rate and an over 30% improvement in nutritional intake balance, alongside strong user engagement (55% daily active users) and excellent usability (SUS score of 88.5). These outcomes provide robust empirical evidence that interdisciplinary approaches combining intelligent systems with behavioral science can effectively address complex public health challenges related to unhealthy dietary behaviors.

From a technical perspective, the primary contribution of this work lies in the development and validation of a psychologically informed intelligent health intervention framework that extends beyond traditional data logging. By transforming raw dietary data into personalized, actionable, and motivating guidance, the system demonstrates a scalable pathway for next-generation digital health solutions. The findings offer important implications for both clinical practice and the commercial health technology sector, particularly in the design of user-centered, behavior-aware health platforms.

Future research will focus on further improving dietary data accuracy through automated tracking technologies — such as computer vision and wearable sensing — and on conducting longer-term longitudinal studies to evaluate the sustainability and transferability of the observed behavior changes. Together, these efforts aim to advance intelligent digital health systems toward greater precision, adaptability, and real-world impact.

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AVAILABILITY OF DATA

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AUTHOR CONTRIBUTIONS

Jialin Wang: Conceptualization, Methodology, Data acquisition, Experimental design, Behavioral intervention model development, Dashboard design optimization, Data curation, Formal analysis, Visualization, Writing—original draft. Yaoqiang Deng: Supervision, Resources, Validation, Writing—review & editing.

COMPETING INTERESTS

The authors declare no competing interests.

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