Balancing Goals, Health, and Cost: A Food Information System for Managing Complex Choices and Fostering Sustained Food Agency

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ABSTRACT

Technology offers new opportunities to support healthier food choices, particularly for individuals in low-income communities who face systemic barriers to obtaining nutritious, affordable groceries. We introduce a novel conceptual model of grocery planning that frames food purchasing as a multi-objective optimization problem that considers cost, nutrition components, and a consumer's personal dietary goals. Guided by Zimmerman's model of Self-Regulated Learning and prior research on food agency, we designed the Food Information System, a planning tool that provides optimized product recommendations aligned with users' goals by integrating store inventory, prices, and nutritional data. We evaluated our system in an eight-week within-subjects intervention with 55 participants from a food-insecure community, followed by focus group sessions. While overall Healthy Eating Index scores remained largely stable, participants reported improved nutritional awareness and greater perceived agency in planning and purchasing groceries. We discuss design implications to support food agency by promoting long-term food literacy and by enhancing autonomy in making food choices.

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CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

Food Information Systems, Food Agency, Optimization, Food Recommendations

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1 INTRODUCTION

Technology is changing the way consumers obtain food, with one in five individuals reporting an online grocery purchase in the last month [81]. These shifts offer opportunities to address pressing issues such as transportation access to healthy foods [28], food insecurity [66], and nutrition disparities [65, 76]. However, developing effective interventions that improve eating behaviors and providing consumers with the necessary information to make informed food choices remains challenging. This is particularly the case for individuals living in low socio-economic conditions where access to affordable, healthful foods may be limited [84]. For populations facing transportation challenges, time constraints, or limited access to affordable, nutritious food, well-designed technological interventions could play a key role in mitigating health disparities.

While many consumers express a desire to eat healthfully, their food choices are shaped by a wide array of interrelated factors such as health goals, cultural and personal preferences, food cost, nutritional knowledge, and access to reliable information [54, 73, 109]. In the United States, adult obesity rates have exceeded 40% [2, 3], with dietary quality remaining a persistent concern [25]. For instance, grocery baskets continue to be low in fruits and vegetables and high in added sugars, sodium, and saturated fats [74, 75]. These problems are even more acute for individuals living in low socioeconomic conditions, who may face compounded constraints such as limited budgets, time constraints, and fewer resources to interpret and act on nutrition guidance [25, 30]. Simply providing people with more information does not always translate into better food choices, especially when the broader food environment makes those choices difficult to implement.

To address these challenges, we develop and evaluate a new conceptual model for food planning and recommendation that aims to improve healthy food choice behaviors. The novel conceptual model was based on the prior literature on food agency [30] and Zimmerman's Self-Regulated Learning theory [113] for sustained behavioral change. To implement this conceptual model, we present the Food Information System that holistically supports healthy food choice behaviors throughout a grocery shopping cycle. Within the system, users can input dietary goals and plan grocery shopping lists. The system then provides users with an optimal collection of products aligned with their dietary goals, balancing current sales, store inventory, and nutritional data, with a multi-linear optimization strategy. Reflection on their final food choices is promoted with a comprehensive feedback report on their purchases. Our work is guided by the following research question: *How might we design to encourage sustained food agency behaviors for healthy food choice?*

We conduct an eight-week within-subjects intervention study with 55 participants from a food-insecure community to evaluate the Food Information System, measuring the differences in dietary quality of grocery purchases compared to a baseline. Through a series of focus groups with 20 participants, we also collect user experiences and feedback. Although the average HEI score post-intervention increased compared to pre-intervention, this change was not statistically significant. However, participants reported increased nutritional awareness, strengthened food literacy, and more intentional grocery choices. In addition, the study revealed implications for future grocery technologies, including the need for greater personalization, user control, and transparency for informed decision-making to better support behavior change. Our findings contribute insights for the development of tools that empower individuals to exercise food agency within complex shopping environments. We contribute the following:

- We present and implement a novel conceptual model for sustained, goal-aligned food choice that supports strategic grocery list planning, balances cost and nutritional factors, and supports reflection on grocery outcomes, guided by food agency principles [30] and a behavioral change theory [113].
- We conduct an eight-week within-subjects intervention study to evaluate the impact of the Food Information System on grocery planning and shopping behavior of low-income households, showing improvements in perceived food agency and nutritional awareness.
- We discuss design implications to support food agency by promoting long-term food literacy and by enhancing autonomy in making food choices.

2 RELATED WORK

We begin by examining the concept of food agency and how design principles can extend this capacity across the holistic food procurement cycle. We then discuss personal informatics, highlighting the specific challenges of self-tracking focused on food contexts. Finally, we review existing approaches in recommendation and optimization to identify the technical gaps our system addresses in balancing nutritional goals with real-world constraints.

2.1 The Role of Food Agency in Supporting Healthy Grocery Shopping

To address the challenges food insecure individuals face in making healthy food choices, our work is grounded in the concept of **food agency**, defined as an individual's capacity to actively and independently make decisions to achieve their food-related goals [30]. This concept builds on Bandura [9]'s concept of *human agency,* which posits that "people are contributors to their life circumstances, not just products of them," with "the capacity to exercise control over the nature and quality of one's life" [8]. While food agency has previously been explored in the context of food preparation [58, 61, 94, 103], within the field of human–food interaction, Dillahunt et al. [30] recently expanded this concept to the food procurement context. This expanded view is salient as it reflects that individuals must navigate and exercise control over a complex interplay of *person-related* (e.g., preferences, dietary goals), *environmental* (e.g., the access to and cost of healthy food), and *food property* factors (e.g., nutritional composition) when making food choices [64].

Drawing from the lived experiences of food insecure individuals, Dillahunt et al. [30] derived a set of key design principles for technologies aiming to enhance food agency: (1) **amplify optimization behaviors,** supporting users' efforts to maximize nutritional value within a budget, aligned with their dietary goals, reducing the time and cognitive load required to balance multiple personal, environmental, and food-related factors; (2) **leverage substitutions,** suggesting alternatives to items individuals chose to meet their health and financial goals; (3) **design for nutritional awareness,** supporting individuals to understand health implications of their choices.

2.2 Extending Food Agency Across the Holistic Food Procurement Cycle

While Dillahunt et al. [30]'s work provides principles to enhance agency in the food procurement context, its primary focus was on the planning phase of grocery shopping. However, food procurement is not a single event but a complex, multi-stage process in real life. To truly enhance food agency and foster lasting behavior change towards healthier grocery shopping, we argue that these design principles must be extended to support the entire grocery shopping journey, from initial list planning, on-site or online shopping, to the stage of post-purchase reflection. For instance, reflecting upon the outcomes of past choices, such as goal attainment, budget, and nutrition, can inform future planning and create a continuous feedback loop.

Previous research has developed technologies that support shoppers at various stages of their grocery shopping journey, aligning with the above-mentioned design principles for food agency. Technologies for **grocery planning** have focused on helping users prepare for their shopping trips. For instance, COOKNOOK [50] aims to reduce the cognitive load of grocery shopping by offering personalized recipes and shopping lists tailored to users' time, budget, and existing inventory, amplifying optimization behaviors.

During the **shopping** phase, technologies have aimed to provide real-time, in-the-moment support. For example, Bedi et al. [11] and Wimer et al. [107] developed an interactive nutritional label system to help shoppers understand and compare nutritional values of different products to enhance their nutritional awareness. Ahn et al. [5]'s augmented reality (AR)-assisted mobile grocery-shopping application, designed for in-store shopping, helps shoppers to quickly and easily find healthy food items, highlighting all recommended products in an aisle with a color-code, which also informs shoppers on which products to avoid based on their health concerns. This application can help users amplify optimization behaviors and leverage substitutions. Another study developed heuristics to guide the design of food-related technologies that can empower individuals to make informed food choices [13]. The suggested heuristics directly fall into the discussed design implications to uphold food agency, such as clear statements about how nutrients affect health, summarization of nutrition information, support for budgeting while balancing health and cost, and optimization of search results based on dietary goals.

Finally, tools that support **reflection** on purchased groceries focus on helping users review the outcomes of past grocery shopping decisions to inform future ones. For instance, Nutriflect [80] uses receipts to create a visualization that compares food products purchased in each category of the Austrian food pyramid (e.g., vegetables, milk) against the pyramid's recommendations or users' own goals, increasing nutritional awareness. Another example is Foodle [105], designed to make users aware of their nutritional patterns by visualizing their grocery purchase data over time. Foodle recommends foods that can fill the gaps between a user's current state of nutrition and a target state based on their receipt data analysis, partially supporting optimization behaviors. In contrast, an analysis of existing food tracking apps criticizes that these apps fail to recognize the financial, locational, and time barriers to access to healthy food [72], which is another emphasis on the importance of balancing personal, environmental, and food-related factors to help users' efforts to make optimal food choices.

While prior works have made valuable contributions to supporting each stage of food procurement, these interventions are often fragmented, focusing on single phases in isolation. However, treating planning, shopping, and reflection as disconnected events fails to support the continuous, cyclical nature of behavioral change. One exception is the system proposed in Bomfim et al. [15] that bridges these stages; before shopping, users create a grocery list and receive personalized, gamified challenges. In the store, users can scan products to see color-coded visualizations of nutritional content. At checkout, the app provides a summary of completed goals to encourage reflection. However, the authors acknowledge that their system does not directly address the issue of budgeting or food insecurity and calling for future research to consider this critical area. This leaves a significant gap, especially for low-income populations. To foster long-term, sustainable, and healthy grocery shopping habits, a holistic approach is needed, seamlessly connecting these phases that are currently treated disparately into a single, cohesive loop, while also integrating real-world constraints.

2.3 Personal Informatics and Food Tracking

Our work intersects with the field of personal informatics, which studies how systems help individuals collect and reflect on personal data to gain self-knowledge [62]. Li et al. [62] conceptualize this process as deciding what to track, selecting tools, tracking data, integrating data, reflecting, and acting. Failures in the early stages of personal informatics often create cascading barriers [62]. For example, the high burden of manual food logging for data collection can limit reflection and often leads to abandonment [26]. Our work aims to mitigate this burden, by asking participants to submit only receipts and photos of their purchased groceries, rather than manually logging them. Beyond usability challenges, many personal informatics systems currently fail to leverage theoretical foundations or apply specific strategies from theory they could benefit from [10, 36, 56]. Furthermore, systematic reviews in self-tracking for mHealth note that current research often fail to engage with distinct user subgroups, particularly those from disadvantaged population segments [110]. We address these gaps by grounding our intervention in Zimmerman's Self-Regulated Learning model [113] and designing for the constraints and needs of low-income populations.

In the field of HCI, technologies to support healthier food purchasing have often been evaluated using proximal measures derived from shopping behavior and food literacy constructs. For instance, Reitberger et al. [80] computed the difference between the optimal ratios of seven food types (e.g., "Fatty food, sweets and savory products"; "Cereals and potatoes") and the ratios observed in users' actual purchases. Similarly, Bomfim et al. [15] compared planned versus purchased counts of fruits and vegetables and ultra-processed foods, measured food literacy using the General Nutrition Knowledge Questionnaire (GNKQ) [59], and captured health-related beliefs through the Health Belief Model Survey (HBMS) [85].

For effective reflection, systems must balance numeric metrics with qualitative feedback. Merely quantitative goals are often hard for users to relate to their well-being [67]. For instance, Purpura et al. [77] note that providing only quantified metrics for weight management can discard personal experiences. To complement such quantified feedback with qualitative insights, Silva et al. [89] explored conversational food journaling, finding that participants desired honest, goal-oriented feedback with a positive and encouraging tone. Similarly, people often want more feedback on how well they achieved their nutrition goals for food logging [44]. Without careful design, individuals may fall into cycles of negative rumination rather than insightful self-refection, leading to tracking abandonment [32].

While LLMs offer new possibilities for generating such positive, qualitative feedback, recent research highlights challenges in its implementation. Users often struggled to formulate effective prompts or find the process of manually integrating personal tracking data tedious [24]. They also found generic LLM responses lacking personalization and empathy and failing to perform accurate math [24]. Moreover, personal informatics literature notes that users often struggle to determine how to act after reflecting on their data [62] and that systems often lack the multidisciplinary expertise, such as that of dietitians, required to ensure efficacy [36].

To address these challenges, we designed our self-reflection intervention to bridge the gap between rigorous data analysis and empathetic, expert-driven feedback. We programmatically calculated numerical feedback, including numerical dietary quality indices and the identification of specific positive food choices (e.g., the product with the most protein) to ensure accuracy and avoid the risk of hallucinations. We then utilized an LLM strictly for generating natural language explanations. Responding to calls to incorporate experts into self-tracking tools, we developed our system prompt in collaboration with nutrition scientists and embedded official sources to ensure the feedback was empathetic, goal-aligned, and provided specific, actionable suggestions to guide future behavior.

2.4 Limitations of Current Food Recommendation Approaches

Previous research on food recommendations has primarily relied on traditional approaches such as content-based [46, 69], collaborative-based [33, 60], and hybrid methods [82, 93]. These systems typically employ user ratings or item descriptions to recommend products that align with existing preferences or suggest similar items [34, 42, 93]. Similarly, in commercial settings, online grocery platforms use personalization and substitution algorithms to suggest comparable or complementary products [63]. While these systems are effective for personalization, brand loyalty, or user engagement, they often reinforce established habits rather than encourage dietary change, limiting their potential to support healthier outcomes.

Building on this foundation, subsequent work has integrated health considerations into recommendation systems. Recipe and product recommendation tools, for instance, incorporate nutritional constraints alongside consumer preferences [34, 42]. More recent studies leverage LLMs to generate recipe suggestions that meet dietary guidelines, such as macronutrient distributions or sodium targets [52], or to propose healthier alternatives to meals while maintaining user preferences [29]. These systems mark an important step toward nutrition-aware personalization. However, most operate at the level of recipes or meals rather than at the level of product choices that shape real-world grocery purchases.

In parallel, optimization techniques have been widely applied to diet planning and analysis. Prior work has established using linear programming models for diet and recipe optimization [17, 35, 35, 101]. Many-objective optimization frameworks have also been proposed to balance multiple nutritional and practical factors simultaneously [111]. While these approaches incorporate nutrition information, they often overlook critical considerations such as household budgets and existing food inventories, which are especially relevant in food-insecure communities. For example, Germino et al. [47] applied linear programming to test whether diets consistent with the Dietary Guidelines for Americans (DGA) could be achieved within the Supplemental Nutrition Assistance Program (SNAP) monthly allotment [47], showing the opportunity to optimize around cost. Although such tools are powerful for modeling trade-offs across complex needs, they have not yet been applied at the product level to support real-time grocery decisions.

3 FOOD INFORMATION SYSTEM: DESIGN AND FUNCTIONALITY

In this section, we discuss the design of the Food Information System. We begin by outlining the conceptual model that guided the app's development and explain how Zimmerman's model of Self-Regulated Learning (SRL) provides a framework for translating this conceptual model into features that support planning, decision-making, and reflection. Finally, we detail the app's system implementation including data sources, optimization approach, and Food Hierarchy used to recommend food items to users. Interwoven throughout this section are specific design decisions made to both communicate our conceptual model and implement Zimmerman's model.

3.1 Conceptual Model

In this section, we outline the conceptual model, or a high-level idea of how a system is organized and operates [68], that guided the design of the Food Information System. Our model views grocery shopping as **an optimization problem in which the consumer's task is to assemble a basket of items that balances affordability, nutritional quality, and personal dietary goals.** The Food Information System operationalizes this model by collecting a user's goals and shopping list items, then applying an optimization strategy that identifies specific products based on current sales, store inventory, and nutritional data.

3.1.1 Design Principles Toward Food Agency. We drew on food agency design principles introduced by Dillahunt et al. [30], that provide guidance for designing around the food planning and purchasing strategies of low-income shoppers. Their work surfaced three recurring behaviors that shaped the design goals of our conceptual model:

- **Amplify Optimization Behaviors:** Shoppers carry out complex optimizations across cost, nutrition, and dietary preferences when making food purchasing decisions.
- **Leverage Substitutions:** Shoppers are open to substitutions in their grocery lists and will often make substitutions to support their optimization.
- **Design for Nutritional Awareness:** Shoppers express a desire to eat healthy and benefit from nutritional awareness.

The Food Information System is designed to support these behaviors across all phases of the shopping process: during *planning* (e.g., by setting dietary goals and building a balanced list), while *shopping* (e.g., by providing product recommendations and substitutions that reduce cognitive load), and in *reflection* (e.g., through personalized reports that highlight successes and suggest improvements).

3.1.2 Optimizing Over a Collection. Our approach differs from the conceptual models of common apps that provide recommendations, such as music or movie recommendations, where systems suggest single items independently of one another. In contrast, the Food Information System recommends a collection of products that together form a grocery basket. As users build their list, the optimization dynamically updates recommendations so that each new item is evaluated in relation to the whole basket. This means the composition of the basket is continuously re-assessed, and previously suggested items may change as the system balances cost, nutrition variables, and user goals across the items in the shopping list. This basket-level approach represents a fundamentally different conceptual model for recommendation and captures the complexity involved in grocery shopping.

3.1.3 Aligning with Standard Nutrition Guidelines. We grounded our design in the Dietary Guidelines for Americans (DGA) [91] and the United States Department of Agriculture's (USDA) MyPlate framework[97]. The DGA recommends dietary patterns that promote health and help prevent the major chronic diseases prevalent in the U.S. [25]. The DGA includes reducing nutrients of concern such as sodium, saturated fats, and added sugars, and encouraging a greater consumption of fruits, vegetables, whole grains, low-fat dairy, and a variety of protein sources. We designed our dietary goals and recommendations to address these factors. By incorporating these concepts into the design, we support the conceptual model by communicating and educating users about healthy shopping decisions. We also reinforce the concepts of nutrition education programs that many of our intended users are already exposed to (e.g., Supplemental Nutrition Assistance Program-Education (SNAP-Ed), the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) [12, 20, 78, 83]).

The MyPlate food guide provides a visual image promoting the dietary guidance of the DGA [97] and uses a color-coding approach, assigning a unique color to each food group, e.g., red for fruits, green for vegetables. Prior studies show that MyPlate familiarity has a positive correlation with health behaviors and may be an effective nutrition educational tool to promote healthful dietary patterns [6, 18, 96]. Similar color-coded nutrient profiling systems that categorize foods based on their nutritional composition have been shown to improve the quality of food choices made during online grocery shopping [39].

To complement the DGA and MyPlate frameworks, our app also incorporates the Healthy Eating Index (HEI), a standardized measure developed by the USDA and the National Cancer Institute to evaluate how closely a set of foods aligns with the DGA [91]. The HEI provides an overall score (0–100) and component scores capturing adequacy (e.g., fruit, vegetable, and whole grain intake) and moderation (e.g., limits on sodium, added sugars, and saturated fats). Although originally designed for individual intake, the HEI has been widely applied to food purchases and distributions at the household and community level, including supermarket baskets and food pantry offerings [7, 49, 87, 108]. These applications support its use as a proxy for the healthfulness of a household's food basket. In our design, we use the HEI to provide feedback on the nutritional quality of users' shopping purchases and track weekly behavior change.

3.1.4 Self-Regulated Learning for Sustained Healthy Grocery Shopping Behaviors. To theoretically ground our interventions, we adopt Zimmerman's model of Self-Regulated Learning (SRL) [112]. While the food agency principles guided what to design for, SRL provides the psychological framework for *how* to design in order to help shoppers sustain these behaviors over the long term. This framework is particularly well-suited for our context.

First, the grocery store environment, both physical and online, poses challenges that demand active self-regulation, including resisting marketing tactics that aim to promote impulse purchases over more nutritious options [76, 106] and overcoming ingrained purchasing habits. Second, Zimmerman's framework is rooted in Bandura [9]'s human agency; self-regulation is the source of personal agency to achieve one's goals [112], which aligns with our ultimate design goal to build food agency—the capacity to set and achieve food-related goals.

Lastly, modifying grocery shopping behavior requires a holistic, cyclical process. Zimmerman's three-phase cyclical model provides a structured lens to holistically support this process, encompassing *forethought* (planning a grocery list), *performance* (making food product choices), and *self-reflection* (reviewing shopping feedback to inform future trips). In the context of healthier grocery shopping, self-regulation encompasses setting dietary goals, making purchasing decisions aligned with those goals, and reflecting on whether the choices made support them. This lens positions our interventions as a technological scaffold for behavioral changes that help users adapt their shopping habits over time, increasing their food agency.

In the next section, we describe how our design choices implement our conceptual model, align with the three phases in Zimmerman's SRL framework, and incorporate Dillahunt et al. [30]'s design principles.

3.2 Translating Self-Regulated Learning Theory into Design Features

In this section, we describe how the Food Information System features operationalize into each SRL phase to promote sustained, goal-aligned food purchasing behaviors. Table 1 summarizes these mappings.

3.2.1 ***Forethought: Goal Setting and Strategic Planning.*** In Zimmerman's model, the forethought phase includes processes that precede efforts to act [112]. The Food Information System supports this phase by allowing users to set dietary goals, build a grocery list, and view the nutritional distribution of their planned purchases.

Setting Dietary Goals. When using the app for the first time, users are prompted to set their dietary goals (Figure 1a). These goals may include reducing sodium, saturated fats, added sugars, or animal meats; increasing intake of fruits, vegetables, whole grains, fish, or plant proteins; and avoiding allergens or other unwanted ingredients. By prompting users to engage in setting dietary goals, the app initiates a self-regulated cycle. This also sets a ground for amplifying optimization behaviors, as the app later leverages these defined goals to provide tailored recommendations.

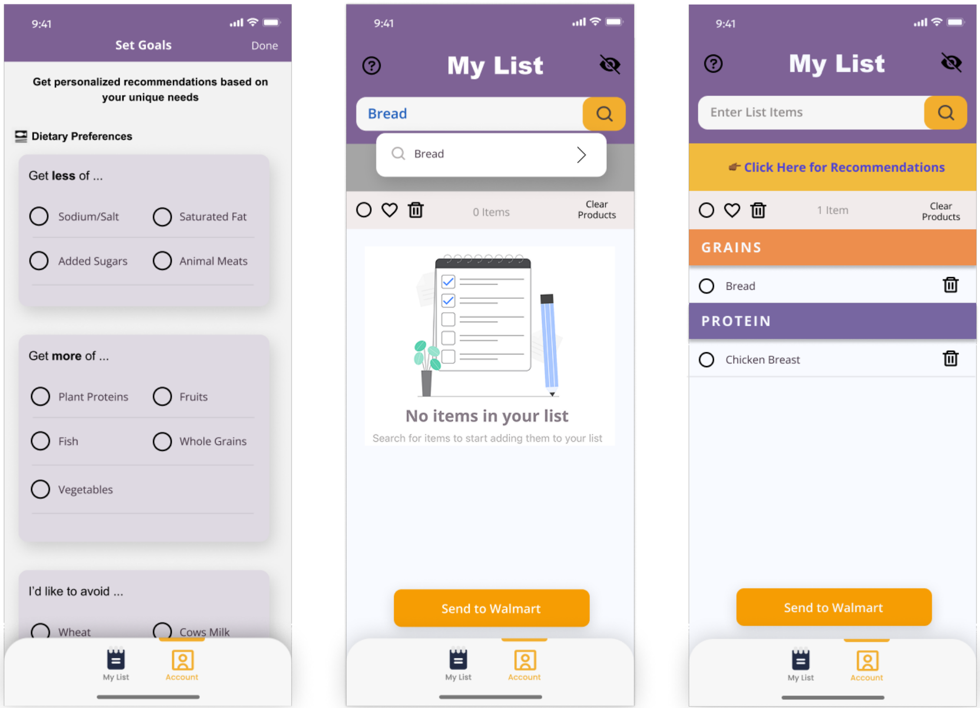
SELF-REGULATED LEARNING		FOOD INFORMATION SYSTEM	FOOD AGENCY BEHAVIOR
FORETHOUGHT PHASE–*Food Information App*			
Task Analysis: Interpreting and breaking down a learning task	**Goal Setting:** Deciding upon specific learning/performance outcomes	Figure 1a: Set Dietary Goals	Amplify Optimization Behaviors
	Strategic Planning: Strategically planning resource use to achieve goals	Figure 1c: Items are Categorized	Design for Nutritional Awareness
PERFORMANCE PHASE–*Food Information App*			
Self-Control: Focusing on the task and optimizing effort	**Task strategies:** Methods and tactics to carry out the goals/plans **Attention Focusing:** Improving one's concentration and screening out other external factors	Figure 2a: Retrieve Recommendations Figure 2b: : View Alternative Options	Amplify Optimization Behaviors Leverage Substitutions
	Self-instruction: Guiding and directing one's own behavior toward the goal	Figure 2c: Learn More About Products	Design for Nutritional Awareness
Self-Observation: Monitoring one's own behaviors to become aware of their progress	**Self-Recording:** Tracking and documenting one's own behaviors and progress	Figure 3a: Mark Items as Complete Figure 3b: Heart Items for Purchase	Amplify Optimization Behaviors
SELF-REFLECTION PHASE–*Grocery Feedback Report*			
Self-Reaction: The feelings and inferences after judging one's own performance	**Self-Satisfaction:** Positive affect regarding one's performance, enhancing motivation	Figure 4a: View Positive Food Choices	Design for Nutritional Awareness
	Adaptive Inference: Conclusions about how one needs to alter one's strategy for future attempts	Figure 4b: See Suggestions	Design for Nutritional Awareness, Leverage Substitutions
Self-Judgment: Comparing performances against a standard and attributing causes to the results	**Self-Evaluation:** Comparing one's performance against a standard or goal **Causal Attribution:** Understanding the cause of one's errors or successes	Figure 5b: Goal Progress Figure 5c: View Alternative Options	Design for Nutritional Awareness

Table 1: An overview of how the Food Information System operationalizes the phases, processes, and methods of Zimmerman's Self-Regulated Learning [112, 112, 113] and Food Agency design principles guided by Dillahunt et al. [30]

Planning a Shopping List Strategically. Within the main page in the app, users can build a shopping list by entering grocery items in free text (Figure 1b). As shown in Figure 6, when a user enters an item, the backend system interprets the text and maps it to a standardized keyword representing a type of food item in our Food Hierarchy —a structured taxonomy that organizes products into multi-level categories for later use in the optimization (detailed in Section 3.3.5). Each list entry is also automatically categorized into one of the MyPlate food groups (Fruits, Vegetables, Grains, Protein Foods, and Dairy)[1] and color-coded for immediate visual feedback, as shown in Figure 1c. This categorization enables users to identify imbalances or gaps in their planned purchases and supports the strategic refinement of the list. By visualizing the distribution of food groups, users can make adjustments that better align with both national dietary guidelines and their personal goals. Detailed information about keyword matching and MyPlate categorization appears in Appendix A.3.

[1]https://www.myplate.gov/

3.2.2 ***Performance: Executing and Adjusting Plans.*** The performance phase in the Self-regulated Learning model emphasizes the execution of strategies and the monitoring of progress during a task. It includes (1) self-control processes to help performers to focus and optimize effort and (2) self-observation mechanisms like recording one's own progress and behavior [112]. The Food Information System supports these with features that help users act on their grocery planning intentions, maintain focus on dietary goals, and reflect on their actions during the shopping process.



(a) (b) (c)

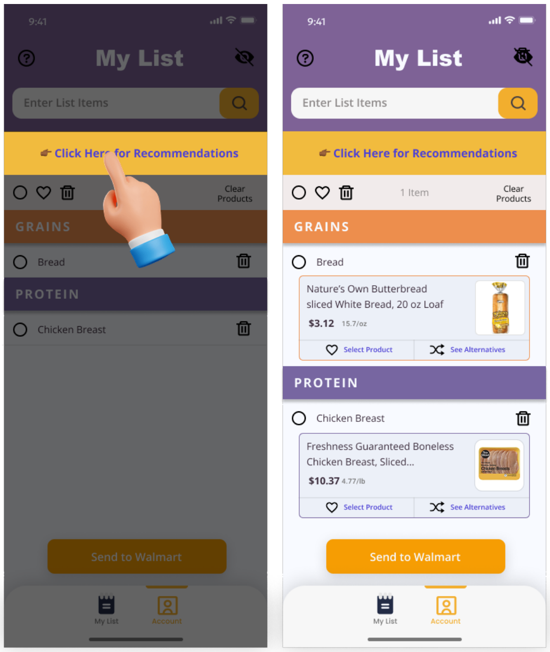
Figure 1: The Food Information System features for *Task Analysis* in the Forethought phase. (a) The user *sets dietary goals*, which are later considered in the optimization; (b) The user then builds their shopping list by using free text; (c) The system categorizes text entries into MyPlate groups, allowing users to review the food group distribution and *strategically plan* their list.

Self-controlled, Strategic Food Choice with Focused Attention. To help users make an optimal food choice, the *Food Information App* facilitates self-control by providing actionable task strategies and supporting attention focusing. As a user builds their list, they can select the "Get Recommendations" button, which triggers an optimization algorithm (detailed in Section 3.3.3) to generate a set of product recommendations tailored to their dietary goals, store availability, and pricing (Figure 2a). This curated list functions as a concrete task strategy. Externalizing a set of goal-aligned choices can help users implement their goals and amplify optimization behaviors, factoring in multiple constraints, including sales and nutrition with less cognitive effort.

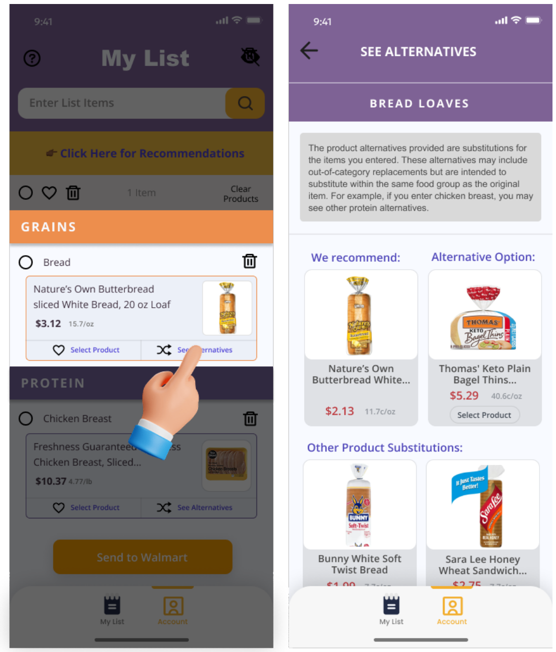
For added flexibility, users can explore alternative substitutions for any recommended food item that maintain nutritional alignment while allowing for preference and variety (Figure 2b). These alternatives encourage users to leverage substitutions, including lower-cost options within the same food category (e.g. ground turkey for beef as protein), similar products from different brands, different package sizes such as bulk options, and alternatives from related categories that offer similar nutritional or culinary functions (e.g., lentils for beef). These substitutions help users stretch their budgets while still meeting dietary and nutritional needs, expanding their options in resource-constrained situations.

Self-controlled Food Choice with Self-instruction. For each recommended item, users can view its price, product image, and nutrition label, alongside a natural-language explanation of why the product was selected (Figure 2c). These LLM-generated (OpenAI's Assistants API) explanations, based on a system prompt developed with nutrition scientists and dietitians, help users interpret nutrition facts in relation to their goals and understand potential health impacts (see Appendix A.3.4). By reading these explanations, users engage in a form of self-instruction, internalizing the personalized nutritional reasoning. This feature not only fosters nutrition awareness but a deeper understanding that can be be applied to future choices.

Self-observation of Grocery Shopping via Self-recording. Our app design encourages self-observation, the process of monitoring one's own actions, by inviting users to engage in self-recording through explicit actions that require them to track and finalize their choices. If a user has already purchased a list item elsewhere and no longer needs a recommendation for it, a user can mark it as "complete," as shown in Figure 3a, removing it from subsequent optimization runs. Similarly, as users "heart" a recommended item, they save that product selection indicating they would like to purchase it (Figure 3b). Hearted items remain part of the optimization but are treated as fixed product selections, meaning no new recommendations



(a)



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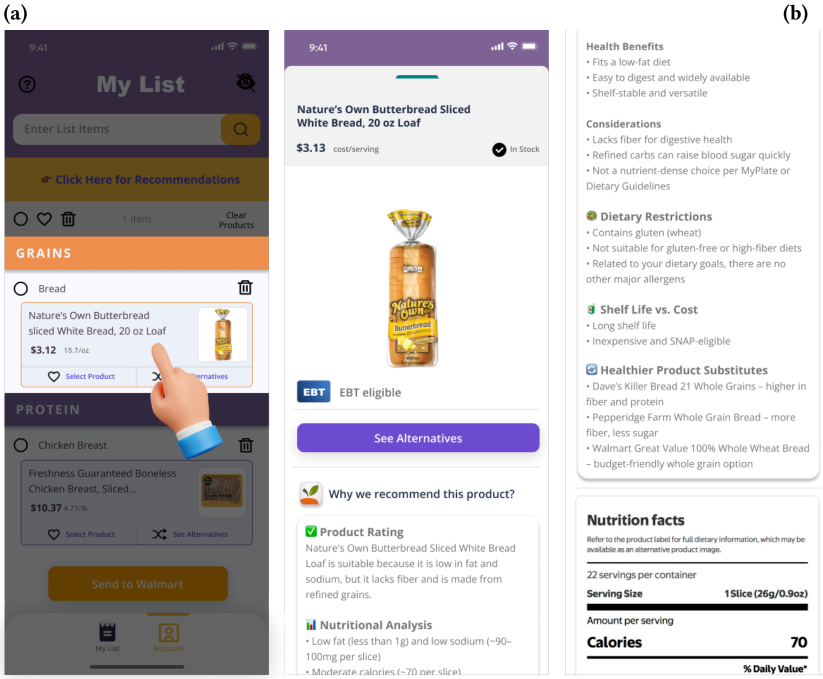
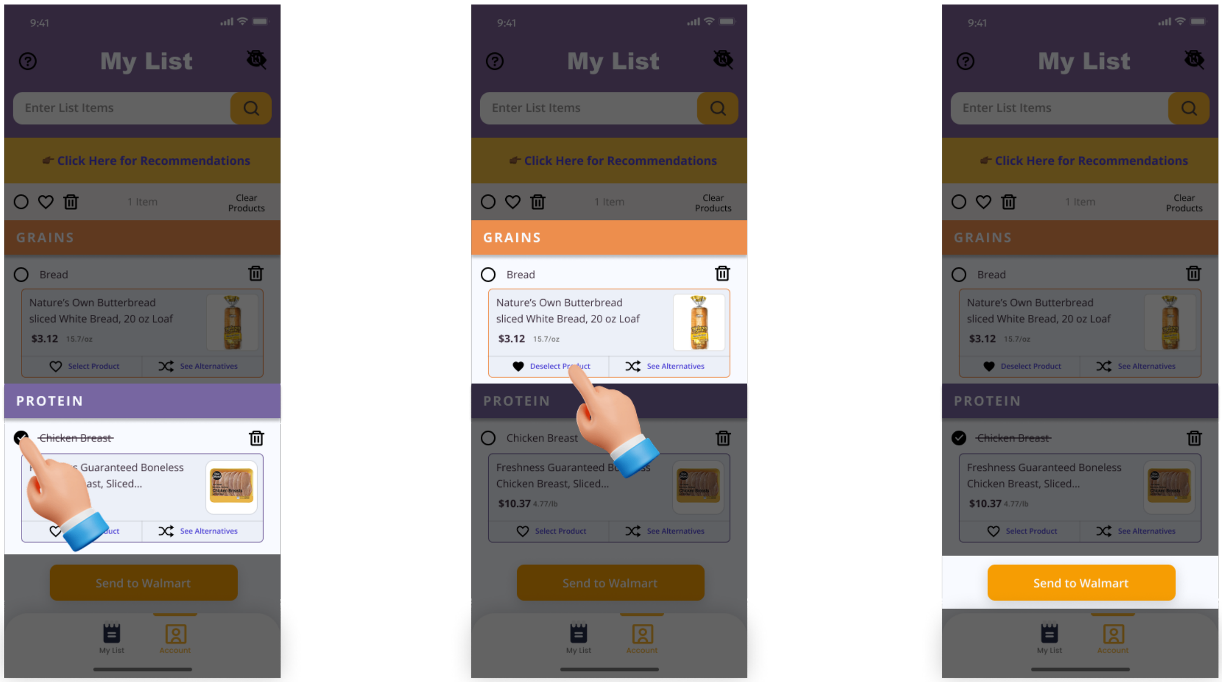


(c)

Figure 2: The Food Information System features for *Self-Control* in the Performance phase. (a) Once the user clicks the Get Recommendations button, the optimization model is triggered and the app presents the optimal product for each text entry that balances users' dietary goals with store availability and pricing, serving as a *task strategy* for making optimal choices and supporting *attention focusing* by preventing distractions from less optimal options; (b) Once the user clicks the See Alternatives button, they can view substitutions (Alternative Options) which are optimal choices from broader food categories; (c) Once the user clicks on the selected product, they can view its price, image, nutrition label, and a LLM-generated explanation justifying the recommendation, which supports *self-instruction*.



(a) (b) (c)

Figure 3: The Food Information System features for *Self-Observation* in the Performance phase. (a) When the user purchases a product, they can mark it as "complete", *self-recording* purchased products, and this removes the constraint from the optimization model; (b) Users can "heart" recommended items to lock them into their cart, which will later be sent to Walmart, thereby *self-recording* their selections. This locks the optimization variable for that item, ensuring it remains in the cart during future optimization runs; (c) After hearting all the products they like, users can click the Send to Walmart button to transfer their cart to the Walmart app.

will be generated for them. Items not hearted remain dynamic and may be re-optimized if the user adds more items or updates their goals. These mechanisms prompt users to consciously reflect on and finalize their food choices. This reinforces their awareness of how their selections align with their dietary intentions, enabling them to monitor their adherence to their goals. When ready, users can proceed to the checkout, sending their selected products to Walmart for pickup or delivery (Figure 3c).

3.2.3 *Self-reflection: Reviewing and Learning from Choices.*

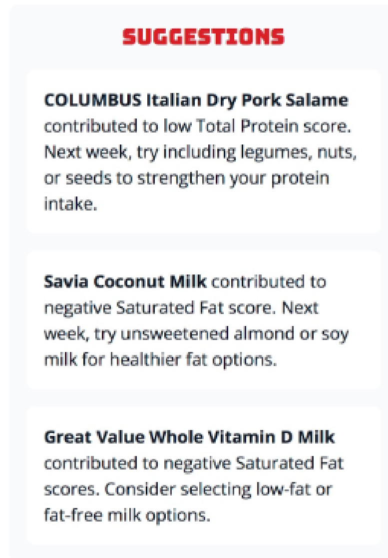
The self-reflection phase of Zimmerman's Self-Regulated Learning centers on learning from past actions to guide future behavior via self-reaction and self-judgment [112]. In the context of grocery shopping, self-reflection would focus on understanding how well one's own shopping behavior aligns with their dietary goals and what adjustments might improve outcomes in the future. To support users in this phase, we provided a personalized *Grocery Shopping Feedback Report* [2] (Figures 4, 5), which is accessible via a secure weblink after users complete their purchases and is delivered on a bi-weekly basis. To enable self-judgment, the report aggregates a user's grocery purchases in the past two weeks and assesses the overall dietary quality against their stated nutrition goals. To foster self-reaction, the report offers tailored feedback and suggestions with encouraging language. This feedback is dynamically generated by an LLM (OpenAI's Assistants API) prompt engineered with a nutrition scientist to provide goal-aware and advice grounded on the DGA based on the user's shopping basket. To prevent the LLM from making unsupported nutritional inferences, the model is supplied with all relevant precomputed data, including the user's HEI score, top nutrient contributors for each HEI nutrition component, and a cleaned, merged dataset linking Walmart products to USDA nutrient profiles (See more details in Appendix B).

Self-reaction via Highlighting Positive Choices. In support of self-reaction, the report promotes a positive motivational response by highlighting successes. The "Positive Choices" section (Figure 4a) affirms healthy purchases with encouraging language, enhancing self-satisfaction about one's performance, which can sustain motivation and strengthen a user's self-efficacy in making positive changes [88].

Self-judgment with Choices Linked to Outcomes. The feedback report is designed to facilitate self-judgment by enabling structured self-evaluation and causal attribution. For self-evaluation, the report compares a user's past two-week shopping decisions against their stated dietary goals (Figure 5a) and the DGA, using

[2]https://grocery-feedback.vercel.app/sNVkwuqr0s/week3-4

(a)



(b)

Figure 4: The Grocery Shopping Feedback Report features for *Self-Reaction* in the Self-reflection phase of the Self-regulated Learning model. (a) The report highlights positive food choices made, promoting *self-satisfaction*; (b) The report helps users make *adaptive inferences* by offering concrete recommendations for future shopping, grounded in past food choices.

the HEI Score to numerically quantify compliance [91] (Figures 5b, 5c). The HEI score is calculated from adequacy components[3] and moderation components[4]. To simplify interpretation, scores are also categorized as, "Great," "Moderate," and "Needs Improvement," allowing users to easily assess the quality of their choices. The report also supports causal attribution by explaining how specific items contributed positively or negatively to each HEI component score, linking outcomes to controllable choices, helping users attribute results to their choices rather than a fixed ability, which is critical for sustained motivation [113].

Self-reaction via Adaptive Inference on Future Food Choices. Finally, the report facilitates adaptive inferences by helping users form an actionable plan for their next shopping trip. When improvements are needed, it provides concrete recommendations, such as choosing lower-sodium options or selecting more fiber-rich foods. By suggesting specific changes, the report helps users modify their shopping strategies based on past behavior, turning self-reflection into a preparatory step for the next cycle of self-regulation.

3.3 System Implementation

Figure 6 illustrates the system implementation workflow, which includes pre-processing activites such as data cleaning and run-time processes that occur during app use. In this section, we describe our implementation, including the data sources used, the optimization approach, and how the Food Hierarchy supports generating relevant substitutions.

3.3.1 Data Sources. We designed the system around real product data from a single Walmart store located in the census tract where our low-income target users regularly shop. Walmart is one of the largest low-cost grocery retailers in the United States [102], and national data show that it often serves as a primary retailer for low-income families and is widely used by households participating in federal nutrition assistance programs (e.g., SNAP, WIC) [21]. We accessed Walmart inventory data through the Bluecart API, with data refreshed twice weekly to align with Walmart's inventory-update schedule, and obtained nutritional information for each product by linking Walmart items to USDA nutritional databases. Full details about Walmart integration, data cleaning, and USDA data sources are provided in Appendix A.1.

3.3.2 Development of the Food Hierarchy. To organize and classify the Walmart products, we developed a multi-level food hierarchy as shown in Figure 6. The hierarchy follows a tree-like structure, with the *MyPlate* food groups as the top-level parent nodes, the What We Eat in America (WWEIA) food classification system as intermediate categories, followed by item-specific keywords, and finally the Walmart products as the leaf nodes. We mapped each Walmart item into a keyword and category to build the hierarchy. For more details on the development of the Food Hierarchy see Appendix A.2.

[3] total fruits, whole fruits, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins
[4] fatty acids, refined grains, sodium, added sugars and fatty acids

(a) (b) (c)

Figure 5: The Grocery Shopping Feedback Report features for *Self-Judgment* in the Self-reflection phase of the Self-regulated Learning model. The report supports *self-evaluation* by assessing recent shopping decisions against (a) users' dietary goals and (b), (c) the established Healthy Eating Index standard; it aids *causal attribution* by clarifying how particular items affected each dietary goal and HEI scores

3.3.3 Optimization Approach. The Food Information System uses a multi-objective optimization strategy that considers a user's shopping list and dietary goals to generate product recommendations. The objective is to minimize the total cost of the shopping list while selecting items that fulfill dietary goals depending on a user's selection. This is a novel approach to recommending items that considers the current food landscape, including inventory, cost, and sales of products, as well as specific nutritional factors to make recommendations. This limits the user's burden of identifying and integrating all of the required information to make an optimal choice.

3.3.4 Model Formulation. To generate a set of recommended products, we formulate a linear programming model that minimizes a multi-objective cost function based on user-defined preferences. To account for package size, the optimization uses the cost per serving of each item rather than total price.

To provide flexibility, users can also optionally select dietary goals in the app (discussed in Section 3.2.1) to reduce sodium, saturated fat, and/or added sugars [98], three nutrients that are emphasized for reduction in the DGA [31, 48]. When selected, these goals are weighted equally with cost per serving in the optimization objective such that all active objectives sum to 1. A detailed description of the model is provided in Appendix A.3.3.

The model is defined as follows:

$$\text{Minimize } Z = w_1 \sum_i C_i X_i + w_2 \sum_i S_i X_i + w_3 \sum_i F_i X_i + w_4 \sum_i A_i X_i$$

Here, Z is the objective function representing the overall cost of the entire shopping cart. The variable X_i represents the quantity or selection of item i. C_i is the cost per serving of item i, while S_i, F_i, and A_i represent the amount of sodium, saturated fat, and added sugars in item i, respectively. The weights w_1, w_2, w_3, and w_4 reflect user preferences for minimizing each respective component. To ensure that user intent is respected, we introduce constraints that require the inclusion of exactly one product for each user-entered list item. For each list item j, this is expressed as:

$$\sum_{i \in j} X_i = 1$$

with each category bounded by a minimum and maximum of one unit, ensuring a single item from each category is chosen.

3.3.5 Using the Food Hierarchy for Substitutions. To leverage substitutions, our optimization algorithm must identify reasonable potential substitutions for any food item. As shown in Figure 6, when a user enters an item for initial recommendations, the search is constrained to products within the keyword's corresponding WWEIA *Specific Food Category*. This ensures the top recommendation remains close to the user's intended selection.

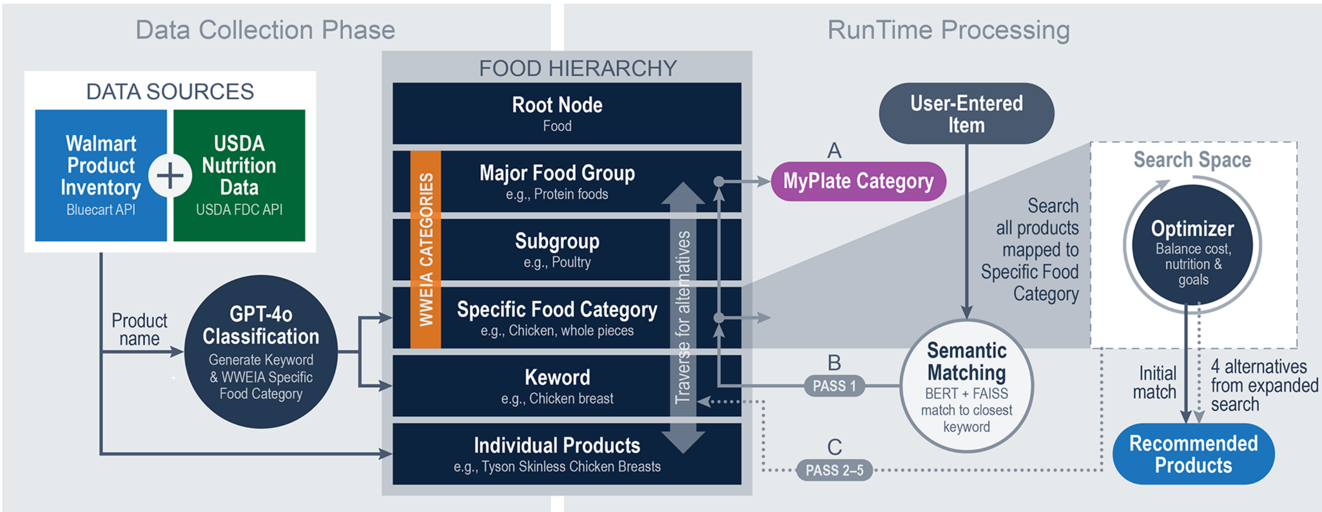


Figure 6: System implementation workflow depicting the processes involved in both the data collection phase and the run-time processing phase. Section A illustrates how a user-entered item is categorized into a MyPlate category (as shown in Figure 1C). Section B shows how the item is mapped to a keyword that defines the optimization search space (as shown in Figure 2A). Section C shows how alternative recommendations are generated through optimization (as shown in Figure 2B).

The hierarchy also supports controlled expansion of the search space to generate alternative recommendations. In the *See Alternatives* view, the system expands outward from the initial category by first considering items within the same *WWEIA Subgroup* and then progressing to broader parent groups, based on the user's dietary goals. This flexible structure ensures substitutions remain relevant while providing opportunities for cost savings and dietary alignment. Specific details on the controlled expansion of the search space are provided in Appendix A.3.3.

4 INTERVENTION STUDY

This intervention study examined the impact of the Food Information System on participants' grocery planning and shopping behaviors. In this section, we describe the study design, participant recruitment, procedures, data collection methods, and analysis approach.

4.1 Study Design

We conducted an eight-week within-subjects intervention study to evaluate the Food Information System. However, to capture participants' natural shopping habits before the introduction of study supports, we included a preliminary baseline week. The study therefore consisted of three phases:

- **Baseline (Week 0):** Participants shopped without access to the Food Information System and without the weekly financial stipend. This allowed for a comparison between unassisted baseline behavior and behavior under the stipend-only condition (Pre-Intervention).
- **Pre-Intervention (Weeks 1–4):** Participants received the $100 weekly grocery stipend but shopped without access to the Food Information System. This phase served to isolate the effect of financial resource relief on shopping behaviors.
- **Food Information System (Weeks 5–8):** Participants were introduced to the Food Information System (described in Section 3) and instructed to use the app for grocery planning and list-building prior to shopping, as well as to review the biweekly grocery feedback report after shopping, while continuing to receive the $100 weekly stipend.

Across all phases, participants submitted grocery receipts and photos to the research team. Receipt collection is a common and widely accepted method for measuring household food purchasing behavior and is considered one of the most comprehensive and detailed approaches [40]. This level of detail comes with the known tradeoff that sharing receipts may influence purchasing behaviors due to increased mindfulness about spending or nutrition, and/or social desirability pressures. We therefore treat receipts as an informative data source that may shape purchasing behavior, as discussed more in Section 7.

Households were recruited through a variety of local organizations, including healthcare organizations, neighborhood associations and community service organizational partners through their social media and direct word-of-mouth referrals. We also distributed recruitment flyers to client-facing staff at these sites which included a link or QR code to an interest form; this contained 15 screening questions covering basic demographic information, shopping routines, and preferred method of contact. Research team members reviewed each form to screen for eligibility and ensure representation from the targeted census tracts. Eligible participants were adults (18+) residing in the local community who owned a smartphone or agreed to use one provided. Only one participant per household was eligible to enroll and receive study incentives.

To address potential financial barriers to nutritional choice changes, each participating household received $100 per week in a grocery stipend, totaling up to $800 over the course of the eight-week study. These funds were distributed through digital Walmart gift cards and served both to support participation and to simulate a consistent weekly grocery budget across all households. To address potential transportation barriers to nutritional choice changes, households additionally received an extra $12.95 per month to cover the cost of a Walmart+ membership, which allowed for free grocery delivery and pickup during the intervention period.

4.2 Study Procedures

4.2.1 Pre-study Intake and Preparations. For those selected, participants completed a 15–30 minute intake survey administered via Qualtrics. The survey included questions about household demographics, food security (e.g., *"In the last 6 months, did you ever cut the size of your meals or skip meals because there wasn't enough money for food?"*), ranked grocery store preferences, and access to or use of technology. We also surveyed participants' prior experience with grocery technologies. Researchers informed participants of the study expectations, including the requirement of documenting their grocery purchases each week throughout the study.

Before the study began, we reviewed the weekly data collection protocol and obtained verbal consent with participants to collect grocery purchase data. Researchers also asked participants about their personal goals for the intervention, shopping priorities, and gave them an opportunity to ask questions before the study began. Participants were informed about eligibility for weekly gift card stipends, which required submitting receipts and completing a 3–5 minute check-in survey. While receipt submission was required, we allowed flexibility due to varying shopping habits (e.g., shopping every two weeks instead of weekly). Participants submitted photos of receipts through their preferred method of text or email.

To assess proximal changes in participants' perceived ability to use mobile grocery apps for key shopping tasks, we administered four items pre- and post-intervention. The items capture key tasks targeted by our system's workflow: (1) planning grocery shopping using a mobile app; (2) searching/selecting products aligned with dietary needs or preferences; (3) quickly finding information needed to compare products; (4) sticking to a grocery budget. The items were developed collaboratively by a nutrition scientist and a social scientist, drawing on prior self-efficacy measures and adapted to reflect the system's target behaviors [95]. Responses were collected on a slider 0-100 scale (0 = strongly disagree, 100 = strongly agree). Because our goal was to measure task-specific perceived comfort in the precise behaviors the system supports, rather than general usability, we used this targeted item set rather than a broader standardized usability instrument.

4.2.2 Food Information System Intervention. During weeks 5-8 the research team introduced the *Food Information System App* to all participants. At the end of Week 4, participants received a Qualtrics survey with download instructions (iPhone or Android) and an orientation video covering account setup and core features such as list-building, goal setting, product recommendations, and sending selected items to their Walmart cart for checkout. A brief tutorial was also available upon logging in for the first time.

To remain eligible for weekly gift cards, participants were instructed to use the app each week to build their grocery lists. The research team monitored usage, following up with non-users to ensure engagement and resolve issues. During the first week of app usage, nightly office hours were offered both in person at community centers and virtually via Zoom to answer questions or solve technical problems. Thereafter, office hours were held once per week for the remainder of the intervention.

In Weeks 5-8, we collected all participants' interactions with the app. This included basic metrics such as the login frequency, time spent per session, and pages visited. We also recorded users' selected dietary goals, shopping lists, recommended products, and how often users selected the recommended product or suggested alternative.

Additionally, at the end of Week 5 and Week 7, participants received a personalized *Grocery Feedback Report* (detailed in Section 3.2.3) via text message and email. This report summarized their Walmart grocery transactions from the previous two weeks to support reflection on their shopping habits. We captured interaction data from the reports, including how often participants viewed the report, time spent reviewing it, and which features had interaction.

4.2.3 Post-study Survey, Interviews, and Focus Groups. We distributed an exit survey to all participants which asked them to rank the app features they found most important, share their thoughts on the recommendations and suggested alternatives, provide feedback, and offer overall reflections on their experience with the study. The survey also included four items to measure perceived ability to use mobile grocery apps for key shopping tasks described in Section 4.2.1.

In addition, we recruited 20 participants to participate in 90-minute focus groups. Participants were selected based on their availability and represented a range of both low and high engagement with the app. Two focus group sessions were held in person at a local community center, and two were conducted virtually via Zoom. The discussions explored participants' experiences with online grocery shopping and their use of the Food Information System. Topics included their comfort with online ordering, initial impressions of the planning app, and how the app influenced their product choices and shopping routines. Participants also reflected on whether the app impacted their health-related behaviors, how they approached budgeting and tracking throughout the study, and which features they found most helpful, challenging, or could be redesigned. To capture a range of perspectives, we separated participants into low, medium, and high user groups based on app engagement. Engagement was measured by the total number of sessions completed during the intervention, and percentile cutoffs were applied (e.g., low users fell within the bottom 33rd percentile).

4.3 Participants

We recruited 55 households from specific census tracts near our university that were classified as food insecure by the local Food Access Council. Recruitment focused on purposive sampling within the census tracts for general representation, with particular emphasis on ensuring representation from target groups (e.g., female-headed households). Participant demographics are summarized in Table 2. Participants ranged in age from 23 to 65, with a mean age of

Characteristic	Category	N (%)
Age	18 to 24	2 (3.64)
	25 to 34	18 (32.73)
	35 to 44	14 (25.45)
	45 to 54	11 (20)
	55 to 64	9 (16.36)
	65 to 74	1 (1.82)
Gender	Female	48 (87.27)
	Male	7 (12.73)
Race/Ethnicity	White	25 (45.45)
	Black or African American	18 (32.73)
	Hispanic/Latino	4 (7.27)
	Asian	1 (1.82)
	Other	7 (12.73)
Participating Food Programs	No	28 (50.91)
	Yes	27 (49.09)

Table 2: Participant demographics

approximately 41. The majority were female ($N = 48$), and most identified as either White ($N = 25$) or Black ($N = 18$). Around half of our participants ($N = 27$) indicated that they participate in food assistance programs, such as the SNAP and WIC. 83.6% ($N = 46$) of participants utilized general grocery apps and 56.36% ($N = 31$) participants had experience using the Walmart app. In terms of frequency of grocery *app* usage, 10.9% ($N = 6$) used weekly or multiple times a week; 18.18% ($N = 10$) used monthly or multiple times a month; and 14.54% ($N = 8$) used yearly or multiple times a year. In terms of grocery *websites* usage, 10.9% ($N = 6$) used weekly or multiple times a week; 10.9% ($N = 16$) used monthly or multiple times a month; and 20% ($N = 11$) used store apps yearly or multiple times a year.

4.4 Data Analysis

4.4.1 Evaluating the Dietary Quality of Groceries Purchased. To evaluate the dietary quality of each participant's grocery basket, we calculated HEI scores, a USDA-developed, density-based measure that assesses how well food intake aligns with the Dietary Guidelines for Americans [91]. This scoring system (see Section 3.2.3) has been applied in the DGA and prior studies examining the dietary quality of purchased groceries (e.g., [41, 100]). See Appendix C for further description on how the HEI Score was calculated.

4.4.2 Impact on Grocery Shopping Behaviors. To assess whether the weekly $100 stipend was associated with changes prior to introducing the Food Information System, we compared HEI scores between Week 0 and the Pre-Intervention (Weeks 1–4) phase. Paired t-tests were conducted to assess if the provided financial resources alone resulted in significant changes in dietary quality prior to the introduction of the Food Information System. To evaluate the impact of the Food Information System, we compared HEI scores between Pre-Intervention phase (Weeks 1–4) and Food Information System phase (Weeks 5–8), using paired t-tests. Because we tested 14 components, we applied a Bonferroni correction to our significance threshold, reducing it to $\frac{.05}{14} = .004$.

To examine how engagement in the Food Information System influenced behavior change, we calculated a difference score ($\Delta\text{Score} = \text{Average Score}_{\text{Weeks5-8}} - \text{Average Score}_{\text{Weeks1-4}}$) for each HEI component. We utilized Ordinary Least Squares (OLS) regression that predicted these score differences between the Pre-Intervention and Post-Intervention period. Control variables included the average scores of the corresponding HEI dietary component in the Pre-Intervention period and self-identified food insecurity score. Independent variables captured engagement behaviors categorized into (1) **App Engagement** measured by *Average Session Time* and *the Number of Cart Submissions* and (2) ***Grocery Feedback Report* Engagement** measured by *Average Session Time* and *the Number of Report Views*. We applied Bonferroni correction across the set of component-by-engagement tests (14 HEI components × 4 engagement predictors), reducing our significance threshold to $\frac{.05}{56} = .0009$. The final model specification was:

$$\begin{aligned}\Delta_{\text{Score}_i} = {} & \beta_0 + \beta_1(\text{PreInterventionScore}_i) + \beta_2(\text{FoodInsecurity}_i) + \\ & \beta_3(\text{AppSessionTime}_i) + \beta_4(\text{CartSubmissionNumber}_i) + \\ & \beta_5(\text{ReportSessionTime}_i) + \beta_6(\text{ReportViewNumber}_i) + \epsilon_i\end{aligned}$$

To analyze changes in user's perceived ability to use mobile grocery apps for key shopping tasks, we conducted a two-sided paired-samples t-test comparing pre- vs. post-intervention responses and applied a Holm correction. We report the t statistic with degrees of freedom and within-subject effect size, Cohen's d_z.

4.4.3 Qualitative Analysis. We conducted a thematic analysis [16] of transcripts from focus group sessions. Three members of the research team independently reviewed all transcripts and extracted key quotes that captured meaningful participant reactions, interpretations, or feedback about specific app features. Each researcher then independently applied codes to the extracted quotes to capture patterns and recurring ideas. The three members held two collaborative meetings to compare initial codes, reconcile differences, and refine the coding scheme where we organized their codes into higher-level thematic categories. Through several rounds of discussion, we refined and reorganized the clusters until we agreed on a coherent set of themes.

Once the themes were finalized, we mapped them onto the phases of Zimmerman's Self-Regulated Learning model. Within each phase, we aligned themes with specific app features or design decisions they referenced.

5 RESULTS

5.1 Quantitative Results

To understand how often people took the app's advice, we calculated the ratio of purchased recommended items to the total number of recommended items. The average purchase rate was 11.29% (SD=10.55%), and the median purchase rate was 10.53%, suggesting consistent uptake across participants. The most frequently purchased recommended items were staple goods from the following food groups: Vegetables (23.85%), Milk and Dairy (22.31%), Protein Foods (20.77%), and Fruits (11.54%). Conversely, the low uptake of recommendations for food categories like Snacks and Sweets (2.31%) and Mixed Dishes (e.g., ramen) (1.53%) suggests that these categories may be more influenced by established preferences, making users more resistant to substitutions.

	Pre-Interv. Mean (SD)	Post-Interv. Mean (SD)	ΔM (Post-Pre)	t(46)	p_{Holm}	Cohen's d_z
I feel comfortable planning my grocery shopping using a mobile phone app	63.59 (26.02)	79.45 (23.31)	15.85	4.06	< .001	.59
I feel comfortable searching for and selecting products within a mobile phone app based on my dietary needs and preferences	61.17 (27.22)	78.62 (23.61)	17.45	4.56	< .001	.66
I am able to quickly find the information I need to decide between two or more products that a mobile phone app might recommend for me to buy	56.98 (24.74)	76.28 (22.95)	19.30	4.25	< .001	.62
I feel comfortable with using a mobile phone app to help me stick to my grocery budget	57.28 (27.20)	73.98 (26.69)	16.70	4.19	< .001	.61

Table 3: Pre- and post-intervention user attitudes toward mobile grocery tools (paired responses, n = 47). p-values are Holm-corrected across the four comparisons.

5.1.1 Changes in the Average Healthy Eating Index Scores Across Three Phases. To analyze possible effects of the financial stipend, we compared HEI scores from the baseline (Week 0) to the Pre-Intervention phase (Weeks 1–4). Because not all participants submitted receipts for Week 0 or submitted blurry ones, this analysis was restricted to the subset of participants who provided data for Week 0 (N = 43). Among the 43 participants, the stipend alone did not result in statistically significant dietary improvements. The `TotalHEI` score, along with all the HEI components, remained virtually unchanged moving from a mean of 51.99 to 52.21 (Δ=0.21, p=.903) (See Table 4 in Appendix D). This suggests that participants largely used the additional funds to continue existing shopping patterns.

We then compared average HEI scores from the Pre-Intervention phase to the Food Information System phase for all participants (N = 55). The average of total HEI score increased slightly from the Pre-Intervention phase to the Food Information System phase, but this difference was not statistically significant (Δ = 1.22, p = .358). Component-level scores showed mixed directions and did not remain significant after correcting for multiple comparisons across HEI components (See Table 5 in Appendix D). We therefore interpret these component patterns as inconclusive.

5.1.2 Effects of Intervention Engagement on Healthy Eating Index Scores. OLS models examined whether engagement metrics were associated with pre-to-post changes in HEI components. While several engagement coefficients had relatively small uncorrected p-values (e.g., the number of cart submissions for fruits), none remained significant after correction (See Table 6 in Appendix D).

5.1.3 Changes in User Attitudes Towards Mobile Grocery Tools. As shown in Table 3, among the 47 participants who completed both the pre- and post-intervention surveys, their comfort with using mobile grocery tools increased significantly (adjusted p < .001). Participants reported greater comfort with using a mobile app to plan grocery shopping (M=63.59 vs. M=79.45), searching for and selecting products aligned with dietary needs (M=61.17 vs. M=78.62), quickly access information to compare products (M=56.98 vs. M=76.28), and adhere to a budget (M=57.28 vs. M=73.98). The 4-item set showed good internal consistency at both timepoints (Cronbach's α_{pre}=0.85, α_{pre} =0.86). Contextualizing these findings within the participants' existing digital literacy, as detailed in Section 4.3, 83.6% of participants were prior users of general grocery apps, with 29.08% utilizing them on a weekly or monthly basis and 14.54% on a yearly basis. 56.36% were prior Walmart app users. This suggests that improvements in self-reported, task-specific comfort with mobile grocery tools over time using the Food Information System.

5.2 Qualitative Results

We present the themes related to each stage of Zimmerman's self-regulation cycle (e.g. forethought, performance, and self-reflection Phases) [113] as identified in the focus groups. Participant quotes are labeled by participant ID and level of app usage (Participant ID, Low/Medium/High).

5.2.1 Forethought Phase: Goal Setting and Strategic Planning.

Goal Setting Increased Accountability. Participants described how setting dietary goals at the outset of using the app anchored their decision-making throughout the planning process. Entering in dietary goals served as a reminder of the participants intentions. One reflected, *"You set the goal, and the goal was always there to remind you when you were doing the shopping list." (P5, Low)*. For others, stating goals increased accountability and supported dietary commitment: *"I'm gonna buy more fruits and vegetables since I told the app that...I'm gonna be intentional to do that." (P4, Medium)*.

List Planning Activity Supported Disciplined Purchases. Strategic planning for shopping was further supported through the app's list building feature, which functioned as the central place where participants both tracked what they needed and managed the specific products associated with each list item.. Participants described using the list throughout the week to capture items they needed: *"I kind of go through the week building a list and add as I think of things like...'[My daughter] has school...and I'm going to need snacks for this'." (P10, High)*. Others stated that having both the item and its associated product options in one place helped reduce distractions and unnecessary purchases and reinforced disciplined planning: *"I like the list because it keeps me from buying stuff that I don't need...I know I'm gonna get exactly what's on that list." (P1, High)*.

Due to the list being directly connected to the Walmart cart participants said it helped reduce impulse purchases and supported budget-conscious decision making. Per one participant, *"I spent less on groceries...during this study...when I go [to grocery stores]...everything's right there in front of you...doing it online...was easier to...adhere to a list" (P15, Low).* The app's feature to save previous lists across weeks further supported planning and reinforced shopping routines: *"Week to week it was basically the same items that I was purchasing." (P18, High).*

Visual Categorization Promoted Nutritional Balance. Visual categorization of list items by MyPlate food groups also enhanced strategic planning by helping participants assess the nutritional balance of their carts. This prompted users to make more deliberate choices to fill gaps in key food groups. As one participant noted: *"I didn't have enough protein one week...so I added some beef and chicken" (P9, Medium).* Another explained that the color-coded categories supported balanced planning: *"It was also helpful to me to see an overall view...like, 'Oh, I don't have enough veggies'." (P12, High).*

For some participants, the MyPlate organization mirrored existing in-store shopping habits. One shared, *"I'm a list person and on my list I have...every section of the store." (P14, High).* Participants also expressed interest in features that would help prompt consistent planning, such as integrating time-based reminders: *"If it sent you a reminder like, 'It's Thursday. You want to make your grocery list. You like to shop on Friday'...I think that would be real helpful." (P5, Low).*

Desire for Goal Customization. Participants found the app's goal-setting and nutritional customization features useful and engaging, while also suggesting goals that expand traditional definitions of healthy eating. One participant emphasized the need for options to filter by *"sugar free, but also anything free" (P12, High)*, while another wanted a way to prioritize, *"more whole foods...less processed" (P7, High).* These requests reveal a desire for identifying products along expanded dimensions of nutritional wellness beyond more conventional metrics.

5.2.2 Performance Phase: Informed Choices with Recommendations/ Alternatives.

Recommendations Promote Discovery and Exploration. Making food choices while grocery shopping involves a dynamic negotiation between person-related, environmental, and food property factors [64]. Our food product recommendation model provides alternatives designed to ease this complex process, mitigate the cognitive load and guide users towards their goals. Most participants demonstrated an accurate understanding of the app's conceptual model that inputting dietary goals would tailor suggestions for individual list items: *"You can input your goals...and it would help curate [recommendations on list items]...help you get towards those goals." (P13, Low).*

The app's recommendations served as a tool for discovery, expanding users' consideration sets beyond their habitual choices. Some participants welcomed this disruption to their routine and appreciated how it nudged them to new possibilities: *"I saw a lot of different brand recommendations...I was able to explore a little bit more...than I would in the store [where] I know what I'm looking for." (P7, High).* This exploration also helped some participants better understand the interchangeability of product substitutes for recipes. One participant noted, *"Yogurt, sour cream and ricotta cheese are all very interchangeable in a lot of different recipes." (P14, High).* Importantly, we noticed that participants' openness to this exploration was amplified by the financial stipend provided, which reduced the economic risk of trying unfamiliar products: *"I felt more comfortable taking a risk, and I was able to try a product...I don't know that much about this one but it doesn't hurt as much" (P7, High)*).

Some Suggestions were Non-Negotiable. The effectiveness of these suggestions was mediated by the shopper's priorities, which proved to be highly context-dependent. For certain meal components, **personal factors**, such as using products for intended recipes were non-negotiable, rendering substitutions irrelevant. Participants noted frustration particularly when receiving recommendations from different food categories, reflecting on the app's failure to consider the purchase context: *"If I'm cooking the meals that requires chicken breast, I'm not gonna switch that up for turkey...pork chops or anything else" (P3, Medium).* Similarly, others emphasized that cheaper alternatives did not always meet their needs: *"It didn't give me a better option for a chicken breast...It just gave me...the cheaper version, legs, which would be harder to cook for what I was going to use it for" (P16, Low).*

This priority shifted based on the shopping occasion, such as shopping for specific recipes versus general stocking-up: *"It would depend on...whether I was buying for a particular meal or just grocery shopping." (P8, High).* At times, deeply ingrained personal preferences outweighed any other factor; *"I wanted Pepsi and...it recommended coke...that did make me angry" (P7, High).* Others noted that while health considerations were important, they could be overridden if the recommended item clashed with their desired eating experience: *"Food experiences I'm looking to get...outweighs...[my] reduced sugar goal...I'm interested...if they also align with the eating experience that I'm trying to get to" (P13, Low).*

Price and Nutrition Shaped Trade-offs. Conversely, some purchases invited openness to substitutes, with participants prioritizing **environmental factors** such as price or **food property factors** such as nutrition. For some, price was the dominant factor: *"I've got to get the most out of every dollar...second priority is...what's healthy for us." (P14, High).* Others emphasized value over brand loyalty: *"I'm not a brand person. If something is better for me and it's cheaper, sign me up for that." (P10, High).* However, this balancing act often varied by food category, as shoppers might be willing to spend more on certain items than others, e.g., *"some things you can go higher for, and then some things you just choose not to" (P20, Low).* Another also described this shifting logic, noting that price was the primary driver for staple items, while for produce, quality was more valued over cost: *"If I wanted a can of beans, I'm going to look at the prices...when it goes to vegetables...it's the fresher, the way they look, and the better quality." (P16, Low).*

Desire for Meal Building. Some participants emphasized a need for the app to move beyond item-level substitutions toward guidance that supported meal planning. They wanted help combining ingredients into balanced meals. One participant suggested: *"This vegetable would go perfect with your chicken" (P18, High)* or flag an overall imbalance such as, *"There's way too much starch...have an alternative suggestion." (P18, High).* Others envisioned the app recommending complete meal ideas drawn from their list, suggesting it would be *"cool if [the user] made the list and the alternatives showed [them]...meals that could be put together" (P15, Low).*

Desire for Increased Agency. Participants' feedback reflected a desire for technology that supports, rather than supplants, the user's food agency in two dimensions: control over how recommendations are generated and autonomy in final product selection. On one hand, several participants expressed a desire for customizable weights in the algorithm based on personal priorities such as budget, nutrition, and intended use through features such as sliders: *"balancing budget with nutrition...If there were sliders...[you could set] how is budget more important or less important than nutrition." (P13, Low).* Others wanted transparency and choice in the data sources used for financial calculations, including *"comparing [items] across store brands, and including whatever digital coupons may be available" (P15, Low).*

On the other hand, some feedback focused on empowering the user to make the final, informed choice from a set of well-presented options with the app serving as a deliberative tool, rather than a prescriptive one. They requested transparent trade-offs between budget and health, for instance, *"breaking down the nutritional value of [a recommended product] versus the cheaper choice" (P20, Low).* Another participant wanted the app to lay out a spectrum of options from which the user can exercise their own judgment, showing *"here's the healthiest choice, and here's the cheapest choice...and maybe here's some in between...and people can decide" (P19, Medium).*

Participants suggested personalizing the display of nutritional information so that it aids deliberation while reducing cognitive loads. This personalization equips the user with the most relevant details to make their own choices. For instance, by *"[tailoring] it to each person's goals...focus on a few...nutritional values" (P17, High).* Some desired proactive real-time feedback that helps them self-monitor their choices while leaving the final decision in their hands: *"If there was something we were choosing that didn't align with...my health goals...an alert [could say], 'This doesn't go with the goals that you said you were trying to meet.'" (P15, Low).*

5.2.3 Self-Reflection Phase: Self-Awareness and Continuous Behavioral Change.

Feedback Revealed Habits and Drove Change. We designed the biweekly grocery feedback reports to facilitate the self-reflection phase in Zimmerman's self-regulation cycle, where individuals evaluate their performance to inform future actions. This reflection made participants *"more conscious of what [they were] buying...to make some improvements" (P17, High)*, increasing awareness and motivating tangible behavior change. P18 explained that she now pays closer attention to nutrition facts while shopping, *"So now I...look at those labels...the ingredients and calories, and saturated fats and sugars." (P18, High).*

Purchase breakdowns into visualized food groups surfaced hidden habits, revealed otherwise invisible patterns, and provided concrete evidence for what participants had only sensed intuitively about their dietary habits. For instance, *"I've always known we need more veggies [and] fruits. We eat too much of protein and rice...it was helpful to...confirm something that I've known, and...get me motivated to change" (P12, High).* Beyond confirming what they had already known, the reports also delivered unexpected nutrition insights that offered learning opportunities. For instance, one participant was taken aback by feedback on a drink she believed was a healthy choice: *"I thought... 'V8 Splash...says 25% less sugar...that's good...I'll try it.' But then [the report] shows...it only has 5% juice in it...I was really surprised...I wouldn't have paid attention to that." (P16, Low).* This new awareness was also valuable for products where nutritional information was not readily available: *"With produce, I don't think you normally see the nutritional information, especially if it's not packaged." (P17, High).*

These *"eye-opener"* moments were not passive realizations; they prompted future action with specific suggestions from the reports. One participant's experience illustrates this link from insight to behavior, *"I never thought that yellow potatoes are worse than red potatoes. I did not even look at the nutritional value of that" (P19, High)*, which led her to grab red potatoes on subsequent shopping trips. Similarly, another participant highlighted an example where the feedback directly affected their next purchase: *"I liked at the very end where it gives suggestions...'You bought this...it wasn't good for you but try this instead next week like...a low-sodium turkey breast or chicken breast.'" (P9, Medium).* These examples show the self-regulation cycle in action, where self-reflection directly informed the forethought and performance phases of the next shopping trip.

Affirmation Encouraged Motivation. The reports' affirming, rather than punitive tone, a design choice purposefully made to foster self-satisfaction, was highly valued. Participants appreciated being acknowledged for positive decisions: *"I enjoyed when I did make good decisions that it acknowledged that." (P8, High).* Others noted the value of seeing both strengths and weaknesses in their purchases: *"I liked how...it broke it down for the good stuff that you bought and the not-so-good stuff," (P15, Low).* At the same time, participants envisioned more dynamic tools to understand the balance of their purchases. One suggested a dynamic "gauge" tool showing how healthy items could counterbalance less healthy ones, and how substitutions might shift the balance: *"You buy some healthy things, and you don't realize how much the unhealthy counterbalances that...Maybe you could make even some of those substitutions to see how...it would balance it back out." (P15, Low).* This suggestion reflects a desire for more sophisticated forms of self-reflection, actively modeling the impact of future choices.

Household Reports Limited Personal Relevance. Participants envisioned several improvements to make reports more personalized and reflective of their own dietary behaviors. First, they noted that the reports reflected household purchases, not individual consumption, which could lead to inaccurate feedback on personal goals: *"Some of the stuff that I ordered...wasn't for me. It was for my daughter." (P1, High).* This led to suggestions for multi-profile features to cater to varying dietary goals and needs within a household: *"It would be nice if you could have multiple profiles...for instance, my husband was diabetic, and he needed different things than what I needed." (P5, Low).*

Furthermore, participants pointed out that the reports, by focusing on a single shopping trip, failed to capture their complete consumption patterns over time. As one participant noted, *"I buy like a 20lb bag of rice and it lasts me two months...it's not going to take into consideration that I have a bunch of rice at home." (P12,* *High)*. To address these gaps, participants suggested options for manual input of food products to create a more holistic dietary picture. For instance, *"If you...were low in grains, [it could ask] 'Have you met this [recommended amount of nutrient] outside of the app?'" (P10, High)*. Another participant suggested letting the users select the products they want to include in reports to have them more attuned to their context: *"You select your options...and it gives you a report based on your selection." (P3, Medium)*.

Desire for Long-Term and Holistic Tracking. Participants wanted to see their progress over time, transforming the weekly reports into a tool for longitudinal tracking rather than a snapshot. With a desire to review history and see trends in grocery purchases, one participant suggested a *"progress calculator...that's really effective over time. Like...'Over the last 6 months you've did a great job reducing your sugar...Still eating that ice cream over 6 months.'" (P13, Low)*. This desire for historical perspective reflects the cyclical nature of self-regulation, where reflecting on long-term patterns is key to sustaining positive behavior change.

While the reports were valuable for post-purchase reflection, participants expressed a desire to integrate these insights more seamlessly into their subsequent grocery shopping cycles. They wanted the lessons from a prior week's report to proactively inform the food choices of the next, creating a continuous feedback loop: *"If I saw it in the app and now I've seen it again on the report, that's gonna stick because I've seen it twice now...it reinforces the behavior of change." (P14, High)*.

5.2.4 Integration across phases. Although we present these findings separately, participants themselves stressed the value of connecting planning, shopping, and reflection. Several explicitly described envisioning the three as a cycle: *"The coolest thing would be if the three things work together...You create your list, you go through, you see your alternatives, and then [see the report]." (P15, Low)*. When these phases were linked, participants felt they could better track progress, identify strategies that worked, and close the loop between intention and outcome. As one participant noted, *"If you could see all that stuff up front before you go shopping... you have it all right there before you buy it." (P19, Medium)*. Integration across phases was described as amplifying optimization, reinforcing good habits, and providing continuity across otherwise fragmented shopping episodes. Providing more immediate rational and explanation as people as assembling their lists makes recommendations understandable and actionable. One participant noted their report suggesting that *"this choice probably wasn't the best one for you.. I like that kind of feedback...if I had that up front, then I would have never purchased that...I could have made a different choice." (P19, Medium)*.

6 DISCUSSION

Despite financial support, a planning tool, and reflection reports, we did not detect statistically conclusive changes in overall HEI. This highlights the difficulty of shifting basket-level dietary quality in real world, resource-constrained contexts. Household purchases reflecting multiple individuals' preferences, eating habits, and stockpiling may have dampened measurable HEI change. However, quantitative results on mobile grocery tool attitudes and qualitative evidence indicate that participants' perceived food agency and nutritional awareness improved. This suggests that our system successfully impacted the proximal antecedents of behavior change [58], necessary precursors to the long-term dietary shifts.

Participants understood the app's conceptual model as supporting the cyclical process outlined in Zimmerman's Self-Regulated Learning framework, enabling them to optimize choices, select substitutions, and build nutritional awareness in alignment with their goals. They recognized how recommendations were generated from these goals and reported positive changes in grocery shopping behaviors through features such as list planning, visual cues, tailored product suggestions, and feedback reports. However, participants also expressed a desire for greater transparency and a sense of agency in the recommendation logic, suggesting opportunities to improve the app's recommendation features.

Drawing from our findings, we discuss how food agency can be supported across two dimensions that reflect the core tenets of human agency: (1) *building the capabilities* by fostering foundational food literacy through long-term learning and cyclical reflection; (2) *supporting the exercise of control* by enhancing in-the-moment agency through increased user control over the optimization algorithm and informational transparency for informed choice.

6.1 Building Capabilities: Fostering Foundational Food Literacy

Drawing from Bandura [8]'s definition of human agency, one dimension of supporting food agency involves building the user's *capabilities* to make independent decisions. Our findings show that both the app and the grocery report served as an effective educational tool for nutritional awareness. The Food Information System strengthened users' food literacy, the ability to understand, evaluate, and apply nutritional information in daily food decisions [27]. Participants described gaining a deeper understanding of how their food choices aligned with their nutritional goals and being encouraged to evaluate and apply nutrition information more thoughtfully in their everyday contexts. This reflects prior research findings that digital tools supporting nutrition knowledge can act as catalysts for long-term behavior change [14, 51, 86].

6.1.1 Understanding a Balanced Diet through Visual Learning. Our participants reported that seeing a visual balance of items across MyPlate food groups during list planning increased their awareness of nutritional variety in their shopping cart. This **visual organization helped them assess their own plans and identify nutritional gaps**, echoing prior work linking familiarity with MyPlate to patterns of applying nutrition information in everyday food choices [92]. Participants also noted that these visuals supported in-store navigation and made it easier to follow through on their plans. Yet awareness and familiarity with MyPlate remain low in many food-insecure populations [57], which reinforces the importance of embedding accessible educational aids within grocery planning tools.

Organizing shopping lists around MyPlate categories may also influence how users think about their choices. The app's structure may promote additive thinking by helping consumers focus on including certain food groups (e.g., fruits, vegetables, whole grains), rather than subtractive thinking, which involves limiting foods high in sodium, saturated fat, or added sugars. As prior work highlights, moderation components remain top dietary concerns for Americans [74, 75], but are often harder to address due to the hidden nature of these nutrients in many processed foods. In contrast, adequacy components may be more actionable, as they involve increasing the intake of more easily identifiable whole foods.

To address this gap, future systems could make moderation components more visually salient during the planning phase. Shopping lists could categorize processed foods based on their contribution to moderation components such as sodium and saturated fat, **helping users better assess the overall nutritional balance**. Since many of these nutrients are not easily identifiable, design strategies might also include visual overlays on nutrition facts labels or icons that flag high levels of concern [53]. For instance, a front-of-package warning symbol is required on products that are high in saturated fat, sugars, or sodium in Canada [71]. Prior research has also shown that highlighting specific areas of the nutrition label improves user understanding, particularly when emphasizing nutrients that exceed recommended amounts [107].

6.1.2 Sustaining Behavioral Change through Cyclical Reflection. Our findings indicate that the *Grocery Shopping Feedback Report* served as a meaningful prompt for self-reflection, encouraging users to **reconsider their food choices and pursue healthier alternatives in future shopping trips**. Rather than functioning only as a post-hoc evaluation tool, participants described the report as a meaningful intervention that increased their nutritional awareness, supported goal-setting, and reinforced behavior change over time. Several participants expressed satisfaction when improvements in their shopping behavior led to a higher score. This aligns with prior research suggesting that such reflective tools can function as a form of gamification and provide ongoing motivation to improve dietary habits [15].

Participants desired reports to be better aligned with their actual behaviors, including the ability to manually select or input items acquired outside the app's scope (e.g., food pantries) or exclude purchases made for others, such as family members or pets. This echoes findings from prior personal health informatics literature that emphasize providing users with direct control over their data, as rigid tracking systems that lack editability can lead to frustration and inaccurate goal monitoring [45, 89]. To address this, feedback reports could **incorporate semi-automated tracking**, combining automated inputs from receipts with user-driven controls (e.g., manual item selection). This approach allows users to determine what is included or excluded, fostering the awareness and engagement that can be lost in fully automated reports [23].

Participants suggested integrating feedback across the entire shopping cycle, transforming the post-purchase report into actionable suggestions for future shopping trips as a pre-purchase tool. This serves as a forward-looking reflection aid, **allowing users to anticipate the nutritional composition of their cart and make real-time adjustments**. For instance, the system could offer proactive suggestions, like recommending whole-grain bread when white bread is added to the list, based on insights from the user's previous reports. Furthermore, participants envisioned a more dynamic form of feedback where they could experiment with basket combinations to immediately see nutritional impacts. These approaches embody the *integration* and *action* stages of the foundational stage-based model of personal informatics systems [62], where data should not be just reviewed but actively scaffolds future decisions. By tightly linking reflection with planning, such systems can close the loop between insight and behavior.

6.2 Exercising Control: Enhancing In-the-Moment Food Agency

Another aspect of human agency is that people are active contributors to their life circumstances [8, 9]. Supporting food agency requires empowering users to *exercise control* over their immediate choices. While our app's optimization algorithm was designed to simplify decision-making, participants did not want a prescriptive system that optimized in isolation; they wanted a tool that they could work with together. This reflects a need for agency in the performance phase, where individuals actively execute and adjust their food choices in real-time. Participants expressed this need across two areas: control over the optimization process and the informational transparency required to make a final, informed choice themselves.

6.2.1 User Control over Real-Time Optimization. Our participants revealed implications for *amplifying optimization behaviors*, demonstrating that **optimization is a dynamic negotiation that shifts based on context, category, and individual priorities**, rather than a static, one-size-fits-all process. This variability in how users balance personal, environmental, and food-related factors challenges traditional food recommendation approaches that apply uniform criteria across all choices. The complexity of these trade-offs emerged at multiple levels: *individuals* prioritized such factors differently–e.g, price being the dominant factor for some, while others prioritized food experience over dietary goals–these priorities also varied by *food category*–e.g., prioritizing price for staple items while prioritizing freshness for produce. This echoes prior research noting that the heterogeneity of user goals and contexts often exceeds what most tools provide [22, 36–38, 67].

These multi-dimensional variations in decision criteria indicate that fixed optimization weights fail to capture nuanced, real-world decision-making. Future systems could address this through **adaptive optimization profiles**, functioning as "adaptable" systems that tailor behavior to user characteristics [19, 79]. Rather than applying universal weights, systems could allow users to specify distinct optimization parameters for different food categories, instructing systems with user-informed guidelines and logic [89]. For example, this might manifest as preference profiles or category-specific sliders, enabling users to prioritize factors (e.g, price, quality) differently across items.

Participants also expressed **needs for context-aware substitution logic**. Their openness to alternatives varied by intended use of an item; they were more open to out-of-category substitutions when building general inventory, but less for recipe-specific purchases, where particular ingredients were non-negotiable. Cross-category substitutions, regardless of nutritional or economic benefits, disrupted meal planning when applied without considering purchase context. This highlights that to encourage users to *leverage substitutions*, systems must evolve beyond item-to-item swaps toward more context-aware recommendations.

Embedding context awareness can be realized through explicit mode selection, allowing users to **toggle between substitution logic for each item**. For instance, one mode would constrain alternatives within narrow food categories (e.g., chicken breast options), while another mode would suggest alternatives from broader categories (e.g., across chicken or protein sources). The system might also infer a use context of each item from list composition, identifying when items cluster into recipes versus general pantry stocking. Respecting these contextual boundaries would reduce friction between algorithmic suggestions and purchase intentions, possibly making it more likely for users to accept and benefit from recommended alternatives.

6.2.2 Empowering Informed Choice through Informational Transparency. Beyond controlling the optimization process, participants desired to make final, informed choices themselves, echoing the findings from a recent study employing automated, AI-driven health recommendations [89, 104]. We respond to recent calls for identifying (1) *what information* users want (2) *at what levels of detail* to make empowered health decisions [104], within the context of healthy grocery shopping.

Rather than single optimal recommendations or limited alternatives, participants desired **a broader spectrum of options with clear trade-offs**, e.g., sorting by health vs. affordability or comparisons explaining nutritional differences. This transparency can support *designing for nutritional awareness*, equipping users to exercise informed judgment, echoing recent findings that users demand reasoning and interpretation behind GenAI health insights [24]. To balance information this richness against cognitive overload, participants suggested **personalizing displays** to focus attention on user goals, similar to users in Silva et al. [89] with specific conditions requesting flags for condition-specific parameters. This could be implemented via progressive disclosure, using at-a-glance cues like color coding (e.g., [15, 107]) or badges (e.g., "Low Sodium") to scaffold immediate decisions, while keeping detailed explanations available on demand for gradual food literacy building.

Participants also wanted to grasp **a complete picture of their food environment**, demanding an expanded data ecosystem integrating information across multiple stores and coupons. This could also include assistance programs eligibility, which is particularly urgent given a recent policy change that restricts SNAP spending on certain items[5], significantly affecting how food-insecure households navigate their choices. By showing which products qualify for assistance programs or when digital coupons become available for nutritious options at which stores, the system can empower users to optimize within their resource constraints.

7 LIMITATIONS AND FUTURE WORK

While this study demonstrates the promise of integrating nutrition feedback and optimization into grocery planning, several limitations warrant consideration and provide direction for future work. First, our optimization relied on data from a single store, Walmart, selected for its data availability and prevalence in the local area. However, as prior research has shown, many individuals source food from multiple locations, including different grocery stores, discount retailers, and food pantries [30]. Focusing on one major vendor neglects the importance of food sovereignty movements, which are particularly vital in low-resource settings [4, 55]. Future systems should explore ways to integrate diverse food sources into the optimization process to better reflect the real food environments of users and support multi-store planning.

Second, the accuracy of real-time inventory and nutritional data posed a challenge. Some recommended products were out of stock or had incomplete nutritional information, which limited the app's reliability. Improving data quality and incorporating more robust databases of up-to-date nutrition and inventory information will be essential to increase user trust and ensure the relevance of recommendations.

Third, although our team conducted extensive informal testing of the app's recommendations, we did not conduct a formal expert evaluation of recommendation quality. Informal testing guided several refinements to the recommendation logic, and the intervention used the final revised model; however, our findings revealed opportunities to further refine the relevance of the recommendations. Future work should include a more rigorous evaluation of the recommendation engine to incorporate structured testing and expert review. Similarly, in the *Grocery Shopping Feedback Report*, while we collaborated with a nutrition scientist to design the report and programmatically computed the HEI score and nutrient contributors provided to the LLM, our evaluation of the reports was also informal and based primarily on manual review. Future work should therefore explore alternative prompting strategies, model selection, and formal expert validation.

Importantly, participants submitted grocery receipts and photos and interacted with the research team throughout the study, which could affect purchasing behavior by increasing mindfulness and self-monitoring or introducing social-desirability pressures. Because receipt submission occurred across the baseline, pre-intervention, and app phases, these effects were present throughout the study. Additionally, the weekly stipend may have introduced potential carryover effects across weeks, particularly for shelf-stable foods purchased in earlier weeks and consumed over longer periods. Because the HEI score aggregates purchases within discrete weeks, it does not explicitly account for such carryover. Future work could address these limitations through more passive purchase data collection (e.g., automated transaction logs, purchase reimbursement instead of pre-purchase gift cards) and by incorporating measurement strategies that better account for multi-week consumption of shelf-stable foods. Longer-term study deployments could further mitigate these effects by allowing purchasing and consumption patterns to stabilize over time, making it easier to distinguish short-term reactivity from sustained changes in food purchasing behavior.

Moreover, the 8-week intervention period may have been insufficient to capture the full trajectory of behavioral change. Given our findings that proximal outcomes such as food literacy and self-efficacy improved, a longer longitudinal deployment would be necessary to observe whether these precursors eventually translate into measurable shifts in purchasing patterns and overall diet quality. The HEI is a distal metric that aggregates across many

[5]https://www.hhs.gov/press-room/maha-monday-snap-waivers.html

dietary components and may be slow to shift conclusively within short deployments, especially in low-resource contexts where food decisions are constrained (e.g., lacking kitchen appliances). Future work could complement HEI with more proximal indicators (e.g., nutrition knowledge with GNKQ [59]), targeted purchase shifts (e.g., more fruits/ vegetable items, reduced ultra-processed food counts as in [15]), or deviations from recommended food-group proportions over time [80]. These measures can provide a more diagnostic signal of improvements in food choices even when overall HEI remains stable.

Finally, participants' attitudes toward mobile grocery tools may have been positively shaped by the multiple layers of support provided during the study. All participants received hands-on onboarding, and many attended weekly office hours where they could ask questions and troubleshoot issues. While this support likely reduced barriers to adoption, it also introduces uncertainty about whether similar attitudes would persist in contexts without such guidance. However, our findings suggest that providing sustained support can play an important role in helping users overcome barriers to adoption. Future work should therefore investigate scalable strategies for onboarding and continued engagement, examining how different levels of support influence both adoption and long-term use of mobile grocery technologies.

8 CONCLUSION

We present the Food Information System, which introduces a novel conceptual model for grocery planning that collects a user's goals and shopping list items, then applies an optimization strategy to identify specific products based on current sales, store inventory, and nutritional data. The design draws on principles of food agency and focuses on the planning and purchasing strategies of low-income shoppers. To theoretically frame our interventions, we draw on Zimmerman's model of Self-Regulated Learning to support sustained behavior change across the phases of planning, shopping, and reflection.

Findings from our eight-week intervention show that the system was associated with fostering perceived food agency. Participants reported increased nutritional awareness, strengthened food literacy, and more intentional grocery choices. At the same time, the study revealed important implications for future grocery technologies, including the need for greater transparency, personalization, and user control to better support behavior change. This research marks a first step toward designing grocery technologies that not only promote healthier purchases but also promote food literacy and self-regulated learning. Our findings contribute insights for the development of tools that empower individuals to exercise food agency within complex shopping environments.

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A SYSTEM DESIGN AND IMPLEMENTATION OVERVIEW

A.1 Data Sources and Integration

A.1.1 Walmart Inventory. We obtained Walmart product inventory and pricing information via the Bluecart API [1]. The API returned data fields including product names, Universal Product Code (UPC) codes, brand, package size, price, and image URLs. We filtered this inventory to include only products available at a single Walmart store located within the census tract corresponding to the majority of our participant population. Products that did not contain a valid price field were excluded from the dataset, as price information was required for optimization. The Bluecart data were refreshed twice weekly, overnight on Monday and overnight on Friday, based on confirmation from the store that Walmart's primary inventory and pricing updates occurred on those days.

A.1.2 USDA Nutritional Data Sources. Because the Bluecart API did not include nutritional information, we supplemented product-level data using official government databases maintained by the United States Department of Agriculture (USDA). The USDA's Food-Data Central (FDC) [6] is an integrated data system that provides detailed information on the nutrient composition of foods available in the U.S. market, combining data from multiple USDA-supported databases to support dietary research [43].

Specifically, we used the USDA Global Branded Foods Products Database (GBFPD)[7], which contains nutrient information for commercially packaged and brand-name foods sold in the United States. This database is updated twice per year in partnership with food manufacturers and retailers to reflect changes in product formulations and new entries [99]. We accessed this dataset via the publicly available CSV file released by the USDA, and for each Walmart product, we matched the product's UPC to the corresponding entry in the dataset to extract its full nutrient profile. For Walmart products that could not be directly matched to a branded entry, we used the Food and Nutrient Database for Dietary Studies (FNDDS)[8], which provides representative nutrient profiles for commonly consumed foods in the United States and is updated every two years in coordination with national dietary surveys. To retrieve these data, we used the USDA FDC API [70], which allowed product keyword-based searches using the full Walmart product name to identify the closest corresponding FNDDS food code match. Products for which no corresponding nutritional information could be identified were excluded from the dataset, as nutrient values were required for the optimization process.

[6] https://fdc.nal.usda.gov/
[7] https://fdc.nal.usda.gov/food-search?type=Branded
[8] https://fdc.nal.usda.gov/food-search?type=Survey%20(FNDDS)

A.2 Walmart Food Product Categorization and Food Hierarchy

We organized Walmart products using a multi-level Food Hierarchy grounded in the USDA's *What We Eat in America (WWEIA)* [9] classification system. WWEIA was selected to align system behavior with established U.S. dietary monitoring standards and to constrain recommendations to nutritionally comparable foods.

During early testing, we found that mapping products directly to WWEIA *Specific Food Categories* was too coarse-grained to reliably match free-text grocery items (e.g., broad categories such as *Cheese* or *Other vegetables*). To address this limitation, we introduced an intermediate *keyword* layer that captures item-specific food types (e.g., *cheddar cheese*, *chicken breast*), enabling more precise alignment between user-entered items and structured food categories while preserving WWEIA as the underlying nutritional framework.

Keywords and category mappings were generated at scale using a GPT-based large language model (`gpt-4o-2024-08-06`). Given a Walmart product name, the model produced both a concise keyword and an associated WWEIA *Specific Food Category*, allowing products to be placed consistently within the hierarchy without manual labeling.

Complete details on hierarchy construction, category refinements, keyword generation prompts, cleanup procedures, and mapping examples are provided in the Supplementary Materials.

A.3 Backend Workflow and Recommendation Pipeline

This section summarizes the run-time pipeline executed when a user enters list items and requests recommendations (Figure 6). Full implementation details, model formulation, and configuration files are provided in the Supplementary Materials.

A.3.1 Mapping User List Items. To interpret free-text list entries, the system semantically matches each user-entered item to the closest *keyword* node in the Food Hierarchy using a SentenceTransformer embedding model (`all-MiniLM-L6-v2`) with FAISS-based nearest-neighbor retrieval. The matched keyword determines the candidate product set used in optimization and enables upward traversal to broader categories when generating alternatives.

A.3.2 MyPlate Categorization. Each list entry is also assigned to a MyPlate food group by inheriting the keyword's parent WWEIA *Major Food Group* (mapped to MyPlate categories); items that do not align cleanly with MyPlate are labeled *Other*.

A.3.3 Recommendation and Alternatives Generation. Recommendations are produced with a mixed-integer optimization model implemented in **Python-MIP**. The objective minimizes *cost per serving* and, when selected by the user, also reduces nutrients of concern (sodium, saturated fat, added sugars) via an equally weighted weighted-sum objective. The solver selects exactly one product per list item from a hierarchy-informed candidate set and respects user *hearted* (locked) items as fixed choices across re-optimizations.

To generate alternatives, the system expands the candidate set in a controlled manner by traversing upward in the Food Hierarchy

[9] https://www.ars.usda.gov/ARSUserFiles/80400530/pdf/2123/Food_Category_List_2021-2023.pdf

(e.g., from the keyword's WWEIA *Specific Food Category* to broader parent groups), excluding previously selected items to promote diversity. When users select "get more of" or "get less of" goals, the system applies rule-based category substitutions (encoded as a JSON mapping) so that alternatives are more likely to come from goal-aligned categories.

Overall, the pipeline returns five options per list item: one primary recommendation and four alternatives spanning progressively broader or goal-aligned search spaces. Complete optimization details (objective, constraints), hierarchy traversal logic, and goal-substitution rules are provided in the Supplementary Materials.

A.3.4 Generating a Food Explanation. For each recommended food product, we generate a brief explanation describing why that item was selected. These explanations are produced by a large language model and are tailored to the user's chosen dietary goals and the nutrition profile of the product. We use GPT-4o to generate each explanation, providing the model with the relevant nutrient values and the user's selected goals. We used the same prompting strategy and design guidelines provided by previous literature on generating food product explanations [90]. The full prompt used to generate these explanations is included in the Supplementary Materials.

B DEVELOPMENT OF THE GROCERY SHOPPING FEEDBACK REPORT

The *Grocery Shopping Feedback Report* is delivered via a secure weblink and summarizes participants' recent purchases using the USDA Healthy Eating Index (HEI) and their stated dietary goals. The report combines (1) a web-based interface that renders structured feedback and (2) an LLM-driven generation step that produces goal-aware narrative text grounded in precomputed nutrition data.

B.1 LLM-Based Feedback Generation and Guardrails

We generated the report text using OpenAI's Assistants API (model: `gpt-4o-2024-08-06`). To support accurate interpretation and reduce unsupported inferences, the model was provided with all relevant computed inputs rather than asked to estimate nutrition values. For each participant, inputs included: (i) a summary of HEI total and component scores for the reporting period, (ii) a structured list of "top contributor" items for each HEI component, and (iii) a cleaned merged dataset linking purchased Walmart products to USDA nutrient profiles. The assistant was also configured with reference materials (e.g., DGA and HEI/FPED documentation) to support consistent dietary language.

The full assistant definition (system instructions, retrieval configuration, reference files), the strict JSON output schema, and the Python generation script used to produce report content are provided in the Supplementary Materials.

C HEI SCORE CALCULATION

To calculate HEI scores, we manually reviewed each item listed on participants' grocery receipts, referring to photos, and assigned the appropriate Food and Nutrient Database for Dietary Studies (FNDDS) food code[10] (e.g., "bettergoods Chocolate Indulgence Chocolate Sea Salt Granola, 11 oz" was mapped to `53714200`, whose food description is "Cereal or granola bar, chocolate coated"), similar to [108]. To compute HEI scores, we leveraged nutrient composition information of each food code from FNDDS and the Food Patterns Equivalents Database (FPED)[11]. HEI scores were calculated for each week using participants' weekly grocery receipts.

[10] Available at https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fndds-download-databases/

[11] Available at https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fped-databases/

D QUANTITATIVE ANALYSIS

Metric (Maximum Score)	Baseline Mean (SD) (N = 43)	Pre-Intervention Mean (SD) (N = 43)	t(42)	p-val	Cohen's d_z
Total HEI Score (100)	51.99 (11.25)	52.21 (11.38)	0.12	.903	.019
Total Fruits (5)	3.15 (2.05)	3.08 (1.52)	-0.21	.837	-.032
Whole Fruits (5)	3.55 (2.12)	3.34 (1.38)	-0.60	.551	-.092
Total Vegetables (5)	3.49 (1.75)	3.71 (1.08)	0.83	.411	.127
Greens and Beans (5)	2.06 (2.22)	2.47 (1.65)	1.23	.227	.187
Whole Grains (10)	2.61 (3.56)	1.69 (1.75)	-1.53	.134	-.233
Dairy (10)	4.74 (3.59)	5.58 (2.35)	1.45	.155	.221
Total Protein (5)	3.89 (1.88)	3.97 (0.92)	0.28	.783	.042
Seafood and Plant Proteins (5)	2.20 (2.21)	2.21 (1.56)	0.02	.988	.002
Fatty Acids (10)	2.83 (3.59)	2.74 (2.94)	-0.13	.898	-.020
Refined Grains (10)	7.48 (3.39)	6.94 (2.42)	-0.90	.375	-.137
Sodium (10)	4.67 (3.83)	5.52 (2.7)	1.54	.131	.235
Added Sugars (10)	7.87 (3.12)	7.95 (1.92)	0.17	.866	.026
Saturated Fat (10)	3.47 (3.89)	2.99 (2.82)	-0.75	.456	-.115

Table 4: Comparative analysis of HEI scores for baseline and pre-Intervention; p-values shown are uncorrected; significance evaluated at Bonferroni-adjusted α=0.004

Metric (Maximum Score)	Pre-Intervention Mean (SD) (N = 55)	Post-Intervention Mean (SD) (N = 55)	t(54)	p-val	Cohen's d_z
Total HEI Score (100)	51.91 (10.62)	53.13 (11.56)	0.93	.358	.125
Total Fruits (5)	2.95 (1.55)	3.39 (1.54)	2.10	.04	.283
Whole Fruits (5)	3.19 (1.47)	3.43 (1.55)	1.02	.312	.137
Total Vegetables (5)	3.69 (1.14)	3.81 (1.21)	0.63	.528	.086
Greens and Beans (5)	2.48 (1.69)	2.49 (1.58)	0.03	.976	.004
Whole Grains (10)	1.45 (1.66)	1.9 (1.97)	1.62	.111	.219
Dairy (10)	5.22 (2.38)	5.06 (2.39)	-0.44	.659	-.060
Total Protein (5)	4.03 (1.03)	3.71 (1.29)	-1.90	.063	-.256
Seafood and Plant Proteins (5)	2.30 (1.59)	2.15 (1.41)	-0.65	.517	-.088
Fatty Acids (10)	2.89 (2.87)	2.69 (2.33)	-0.55	.587	-.074
Refined Grains (10)	7.19 (2.29)	7.50 (2.47)	0.77	.446	.104
Sodium (10)	5.33 (2.6)	6.07 (2.63)	2.07	.044	.279
Added Sugars (10)	8.00 (1.87)	7.41 (2.15)	-1.85	.07	-.249
Saturated Fat (10)	3.15 (2.84)	3.54 (2.95)	0.91	.365	.123

Table 5: Comparative analysis of HEI scores for pre- and Post-Intervention; p-values shown are uncorrected; significance evaluated at Bonferroni-adjusted α=0.0009

	Adequacy Component										Moderation Component			
	Total HEI Score	**Total Fruits**	**Whole Fruits**	**Total Vege-tables**	**Greens, Beans**	**Whole Grains**	**Dairy**	**Total Protein**	**Seafood Plant Protein**	**Fatty Acids**	**Refined Grains**	**Sodi-um**	**Added Sugars**	**Satu-rated Fats**
Control Variables														
Pre Score	-.342	-.423	-.459	-.765	-.683	-.449	-.617	-.403	-.823	-.637	-.774	-.475	-.634	-.509
	(.007)	(.001)	(.002)	(.000)	(.000)	(.015)	(.000)	(.009)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
	[-.585,-.098]	[-.666,-.180]	[-.738,-.181]	[-1.071,-.458]	[-.929,-.437]	[-.805,-.093]	[-.910,-.325]	[-.700,-.105]	[-1.084,-.562]	[-.855,-.419]	[-1.087,-.460]	[-.726,-.225]	[-.890,-.378]	[-.778,-.240]
Food Insecurity	-.845	-.084	-.048	.133	.145	-.320	-.293	.036	.098	.143	-.432	-.235	.151	.090
	(.204)	(.399)	(.654)	(.127)	(.176)	(.038)	(.092)	(.662)	(.379)	(.386)	(.016)	(.172)	(.255)	(.649)
	[-2.167,.477]	[-.281,.114]	[-.261,.165]	[-.039,.305]	[-.067,.357]	[-.620,-.019]	[-.636,.050]	[-.127,.198]	[-.124,.320]	[-.186,.472]	[-.780,-.083]	[-.576,.106]	[-.113,.416]	[-.305,.484]
App Engagement Variables														
App Avg. Sess. Time	.001	-.000	-.000	.000	.001	.000	.001	.000	.001	-.001	.000	-.001	.000	-.001
	(.840)	(.874)	(.925)	(.292)	(.270)	(.868)	(.461)	(.682)	(.309)	(.230)	(.848)	(.225)	(.670)	(.331)
	[-.005,.007]	[-.001,.001]	[-.001,.001]	[.000,.001]	[.000,.001]	[-.001,.001]	[-.001,.002]	[-.001,.001]	[.000,.001]	[-.002,.001]	[-.001,.002]	[-.002,.001]	[-.001,.001]	[-.003,.001]
# Cart Submits	.278	.188	.194	.096	.168	.043	-.132	-.039	-.019	-.030	-.061	-.110	.041	.043
	(.528)	(.008)	(.012)	(.102)	(.023)	(.667)	(.257)	(.480)	(.783)	(.788)	(.605)	(.341)	(.636)	(.752)
	[-.604,1.160]	[.052,.325]	[.045,.344]	[-.020,.212]	[.024,.311]	[-.159,.246]	[-.363,.099]	[-.149,.071]	[-.160,.121]	[-.257,.196]	[-.296,.175]	[-.340,.120]	[-.132,.214]	[-.228,.314]
HEI Report Engagement Variables														
Report Avg. Sess. Time	-.023	-.000	.001	-.002	-.002	-.004	.020	-.002	-.006	-.011	.006	.001	-.002	-.015
	(.585)	(.963)	(.898)	(.683)	(.800)	(.642)	(.074)	(.710)	(.397)	(.302)	(.634)	(.903)	(.858)	(.234)
	[-.108,.061]	[-.013,.012]	[-.013,.015]	[-.013,.009]	[-.016,.012]	[-.023,.015]	[-.002,.042]	[-.012,.008]	[-.019,.008]	[-.032,.010]	[-.017,.028]	[-.021,.023]	[-.018,.015]	[-.041,.010]
Report # of Views	-.120	.058	.093	-.088	-.146	-.062	-.107	-.109	-.142	.109	-.182	.063	-.215	.194
	(.879)	(.612)	(.452)	(.384)	(.251)	(.713)	(.590)	(.245)	(.243)	(.576)	(.388)	(.753)	(.156)	(.419)
	[-1.705,1.464]	[-.171,.288]	[-.155,.342]	[-.288,.113]	[-.399,.107]	[-.401,.277]	[-.506,.291]	[-.295,.077]	[-.382,.099]	[-.282,.500]	[-.603,.239]	[-.340,.467]	[-.516,.085]	[-.285,.672]
Observations	50	50	50	50	50	50	50	50	50	50	50	50	50	50
R^2	.23	.42	.40	.41	.48	.30	.38	.22	.54	.50	.44	.31	.40	.32
Adjusted R^2	.12	.34	.32	.33	.41	.21	.29	.11	.47	.42	.36	.21	.32	.23

Table 6: Estimated coefficients, (p-value), and [95% confidence intervals] of the variables in the OLS regression models predicting change in each HEI component from Pre to Post