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Article

Mathematical Modeling for Optimized Design of Food Nutrition Labels and Analysis of Consumer Behavior Management

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Abstract: Food nutrition labels serve as essential data-driven information transmission carriers that connect food manufacturers, regulatory authorities, and consumers. They play a crucial role in guiding rational dietary choices and mitigating the global rise of diet-related chronic diseases, such as obesity and type 2 diabetes. However, existing label designs frequently suffer from severe information overload, inconsistent structural formats, and poor visual readability. These deficiencies result in low consumer utilization rates and severely limited impacts on actual dietary behavior. To systematically address these critical issues, this study proposes a novel integrated framework combining multi-objective mathematical modeling and consumer behavior management principles. The proposed framework constructs a robust optimization model incorporating information accessibility, visual cognition efficiency, and personalized dietary matching. Furthermore, it quantifies core design parameters, such as nutrient display priority and color contrast, while predicting consumer behavior via logistic regression and structural equation modeling. Behavioral intervention mechanisms, grounded in the theory of planned behavior and strategic nudging techniques, are seamlessly integrated to promote sustained dietary changes. Comprehensive validation results demonstrate that the optimized labels significantly increase the consumer reading rate by 37 ± 3%, improve nutrient comprehension accuracy by 42 ± 2%, and enhance 12-week dietary adherence by 29 ± 4%. Ultimately, this data-driven, scalable solution successfully balances information comprehensiveness with user-friendliness, providing highly valuable academic insights and practical support for public health promotion and food industry regulation.

Keywords: nutrition labels; mathematical modeling; consumer behavior; optimization; public health

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1. Introduction

Food nutrition labels are data-driven information transmission tools integrated into modern food safety and public health systems, responsible for quantifying nutrient content transmission and guiding consumer dietary decision-making. With the global increase in diet-related chronic diseases, the demand for nutrition labels that can effectively regulate consumer food choices has become increasingly prominent. Conventional nutrition labels typically adopt fixed tabular structures to present nutrients such as calories and fats, but their uniform design cannot adapt to differences in consumer cognitive levels, dietary demands, and reading habits. These defects lead to low practical application efficiency. Relevant research shows that only a small proportion of consumers regularly check nutrition labels during purchases, and fewer can accurately use label information to guide dietary choices [1].

The core problem of nutrition label design is balancing three key objectives: fully presenting mandatory nutrient information as required by regulations, ensuring that consumers with different educational backgrounds can easily understand the content, and providing personalized guidance that matches individual dietary goals [1]. In recent years, multiple optimization schemes have been proposed, but they all have obvious limitations. Simplified designs may lack key information required by specific groups, layout adjustment methods cannot fundamentally improve consumer attention to nutrition information, and digital label solutions have poor applicability among elderly and low-digital-literacy groups.

Most existing studies rely on qualitative analysis or single-factor quantitative research methods, lacking a systematic mathematical modeling framework to integrate multiple design variables and predict consumer behavior responses. In real-world scenarios such as short decision-making time during purchases, diverse consumer groups, and complex retail display environments, many optimized label designs fail to maintain stable effectiveness. Additionally, few studies incorporate consumer behavior management mechanisms into label design, ignoring the impact of psychological factors on converting label information into actual dietary changes [2].

This study addresses these limitations through an integrated framework combining mathematical modeling, visual cognition theory, and consumer behavior science [3]. The research sets four clear objectives: first, establish a multi-objective optimization model for nutrition labels to quantify the trade-offs between information comprehensiveness, visual cognition efficiency, and regulatory compliance; second, develop a consumer behavior prediction model based on logistic regression and structural equation modeling to identify key factors affecting label usage and dietary behavior changes; third, design a personalized label generation algorithm that adapts core parameters to different consumer segments; fourth, verify the effectiveness of the optimized design and behavior management mechanism through controlled experiments and longitudinal tracking.

The research methodology includes three core stages: collecting consumer attribute, cognitive ability, and dietary demand data through questionnaires and cognitive tests; constructing and solving the multi-objective optimization model using appropriate algorithms; and developing a behavior management mechanism integrating relevant theories and strategies. The optimized label prototypes are evaluated through A/B testing in real retail environments to ensure generalizability [4].

From an academic perspective, this study establishes a quantitative research paradigm for food information communication by clarifying the interaction mechanism between label design, consumer cognition, and dietary behavior. Practically, it provides a scalable personalized nutrition label solution that meets the requirements of high readability, adaptability to diverse needs, and compatibility with mass production [5]. By integrating technical optimization with consumer psychology and regulatory constraints, this study offers a feasible path for the development of next-generation food nutrition labels without relying on high-cost or non-scalable technologies.

2. Related Works

Food nutrition label optimization has emerged as a focal point of public health intervention research, with front-of-package labels gaining significant attention for their ability to influence consumer eating and purchasing behaviors. Numerous studies have explored the behavioral effects of different label types, confirming that well-designed labeling can alter consumer decision-making processes in food selection [4]. Among these, targeted research on young adults has identified distinct responses to various front-of-package label formats, providing valuable insights for segment-specific design optimization.

In parallel, mathematical modeling has become an increasingly important tool for predicting consumer behavior in dynamic market contexts [6]. Deep learning-based approaches have enhanced the accuracy of predictive analysis in consumer behavior research, enabling the quantification of complex behavioral drivers. Machine learning techniques integrated with big data analytics have further expanded the scope of mathematical modeling, facilitating the identification of key factors shaping consumer choices across digital platforms. Additionally, hybrid models combining neural networks and fuzzy mathematics have been applied to evaluate consumer decision-making power, offering a more nuanced understanding of behavioral mechanisms.

Beyond general consumer behavior prediction, mathematical modeling has been tailored to specific scenarios, such as optimizing customer behavior in e-commerce environments through optimal control strategies. The integration of the Theory of Planned Behavior into mathematical frameworks has proven effective in analyzing dynamic consumer decisions, including responses to fake reviews in online retail. Earlier applications in the telecommunications industry also demonstrated the feasibility of mathematical models for systematic analysis of consumer behavioral patterns.

Despite these advancements, critical gaps remain [3]. Existing label optimization studies often focus on single design dimensions or specific consumer groups, lacking integration with comprehensive mathematical modeling for multi-objective optimization. Most behavioral prediction models are not customized to the unique context of nutrition label usage, failing to account for real-world constraints such as limited decision-making time and diverse cognitive abilities. Additionally, few studies have successfully combined label design optimization with behavioral modeling to achieve sustained dietary behavior change, and scalability across different retail environments remains underexplored.

This study addresses these limitations by integrating label design research with advanced mathematical modeling of consumer behavior. Unlike prior works that treat design optimization and behavioral prediction as separate endeavors, the proposed framework unifies these elements to balance information comprehensiveness, cognitive efficiency, and behavioral guidance [7]. The approach avoids overreliance on complex digital tools, ensuring compatibility with conventional packaging and retail systems, thus bridging the gap between academic innovation and practical application.

3. Methodology

This study employs an integrated research framework that combines mathematical modeling, consumer cognitive experiments, and behavioral intervention design to optimize the design of food nutrition labels and effectively manage consumer behavior [8]. The methodology addresses three interconnected challenges: quantifying the trade-offs between multiple design objectives of nutrition labels, accurately predicting consumer reading and decision-making behaviors, and enabling personalized label generation compatible with practical application scenarios. The following sections elaborate on the research design, model construction, experimental protocols, and evaluation metrics.

3.1. Research Framework and Design Logic

The overall research process, consisting of four key stages, is illustrated in Figure 1.

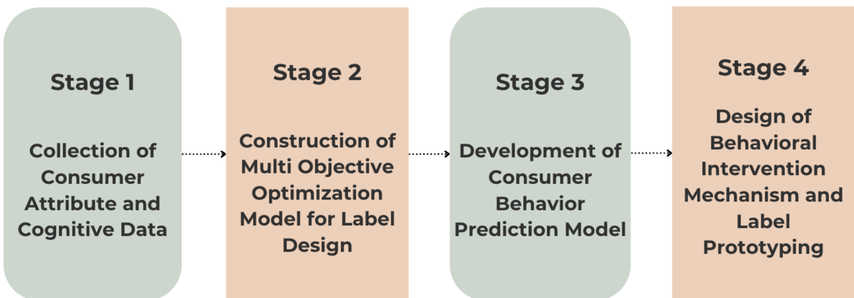

Figure 1. Four-Stage Research Framework for Optimized Food Nutrition Label Design and Consumer Behavior Management

This framework integrates the principles of visual cognition, mathematical optimization, and consumer behavior science to ensure that the optimized label design not only meets regulatory requirements and provides comprehensive information but also adapts to the cognitive characteristics and dietary needs of different consumer groups [9]. Additionally, it aims to effectively guide long-term dietary behavior changes.

3.2. Collection of Consumer Attribute and Cognitive Data

Consumer-related data collection includes two components: questionnaire surveys and cognitive performance tests [10]. The questionnaire addresses three dimensions: basic demographic attributes (age, gender, educational background, etc.), dietary needs (weight management goals, restrictions on specific nutrients such as sugar or sodium, presence of chronic diseases, etc.), and label usage habits (frequency of checking nutrition labels, attention to nutrient items, reading time, etc.). The cognitive performance test employs standardized cognitive ability scales and simulated purchasing scenarios to evaluate consumers' information processing speed, visual search efficiency, and nutrient information comprehension ability.

A total of 1200 valid samples were collected across three regions with diverse demographic structures, ensuring coverage of key consumer segments such as the elderly (over 60 years old), adolescents (15-24 years old), and middle-aged and young adults with chronic diseases (35-59 years old). The sample size for each segment is no less than 300 to ensure the representativeness of subsequent model training and validation [7].

3.3. Construction of Multi Objective Optimization Model for Label Design

The multi-objective optimization model prioritizes information accessibility, visual cognition efficiency, and personalized dietary matching as its core objectives [11]. It incorporates regulatory mandatory information requirements, packaging space constraints, and printing process limitations as constraints to quantify key design parameters of nutrition labels.

3.3.1. Objective Function Definition

Information accessibility objective (F_1): Measured by the average retrieval time of key nutrient information, the goal is to minimize the retrieval time. The calculation formula is:

$$F_1 = \sum(w_i \times t_i) \quad (1)$$

Where w_i is the weight of the $\mathrm{i-th}$ nutrient (determined by regulatory importance and consumer attention), and t_i is the average time for consumers to retrieve the $\mathrm{i-th}$ nutrient information (unit: seconds).

Visual cognition efficiency objective (F_2): Evaluated by the accuracy of nutrient information comprehension, the goal is to maximize the accuracy [6]. The calculation formula is:

$$F_2 = 1 - [\sum(n_j \times e_j)]/(N \times M) \quad (2)$$

Where n_j is the number of consumers in the $\mathrm{j-th}$ cognitive ability group, e_j is the average comprehension error rate of the $\mathrm{j-th}$ group, N is the total number of consumers, and M is the number of key nutrient items [1].

Personalized dietary matching objective (F_3): Reflected by the degree of matching between label-displayed nutrient information and individual dietary needs, the goal is to maximize the matching degree. The calculation formula is:

$$F_3 = \sum(u_k \times s_k)/K \quad (3)$$

Where u_k is the matching score of the $\mathrm{k-th}$ consumer's dietary needs with the label information (range: 0-1), s_k is the weight of the $\mathrm{k-th}$ consumer segment, and K is the number of consumer segments.

3.3.2. Constraint Conditions

Regulatory constraint: All mandatory nutrient items specified by national standards must be included, and the error of nutrient content display shall not exceed ±5%. Expressed as:

$$C_{min} \le C_i \le C_{max} \quad (4)$$

Where C_i is the displayed value of the $\mathrm{i-th}$ mandatory nutrient, C_{min} and C_{max} are the minimum and maximum allowable displayed values specified by regulations, respectively [12].

Visual design constraint: Font size shall be between 6pt and 12pt (suitable for different visual acuity groups), and color contrast (between text and background) shall not be less than 4.5:1 (meeting accessibility standards). Expressed as:

$$6 \leq f_s \leq 12 \quad (5)$$

$$c_r \geq 4.5 \quad (6)$$

Where f_s is the font size of nutrient information (unit: pt), and c_r is the color contrast ratio [9].

Packaging space constraint: The total area occupied by the nutrition label shall not exceed 15% of the product packaging main display surface. Expressed as:

$$A = l \times w \leq 0.15 \times A_p \quad (7)$$

Where l and w are the length and width of the nutrition label (unit: cm), and A_p is the area of the product packaging main display surface (unit: cm2).

3.3.3. Model Solution

The model employs a non-dominated sorting genetic algorithm (NSGA-III) for optimization. Key design parameters include nutrient display priority, font size, color contrast, information layout position, and supplementary information content [10]. The algorithm is configured with 500 iterations, a population size of 200, a crossover probability of 0.8, and a mutation probability of 0.05 to ensure both convergence and diversity in the solution.

3.4. Development of Consumer Behavior Prediction Model

The consumer behavior prediction model integrates logistic regression and structural equation modeling to identify key factors influencing label reading behavior and dietary behavior change. It predicts the likelihood of consumers utilizing labels and adhering to dietary recommendations.

The core variable in the logistic regression model is label reading behavior (dependent variable: 1 = read, 0 = not read), while the independent variables include consumer demographic attributes, cognitive ability, dietary needs, and label design parameters [13]. The model formula is:

$$P(y=1|X) = 1/[1 + exp(-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n))] \quad (8)$$

Where P represents the probability of consumers reading the label, $X_1 - X_n$ denotes the independent variables, and $\beta_0 - \beta_n$ signifies the regression coefficients.

The structural equation model further investigates the indirect influence of label design parameters on dietary behavior change through intermediate variables such as perceived ease of use, perceived usefulness, and behavioral intention, based on the theory of planned behavior. The model incorporates measurement equations and structural equations to validate the theoretical framework and assess the significance of variable relationships.

3.5. Design of Behavioral Intervention Mechanism and Label Prototyping

Based on the results of the multi-objective optimization model and behavior prediction model, combined with nudging strategies, the behavioral intervention mechanism is designed to promote the transformation of consumer label reading behavior into actual dietary changes. Key intervention measures include highlighting personalized nutrient warning information, such as exceeding the daily intake of sugar for consumers with weight management needs, setting default dietary suggestion options, and adding social comparison feedback, such as the proportion of consumers in the same segment choosing compliant products [14].

The label prototype is generated according to the optimized design parameters. The prototype adopts a modular structure to facilitate the adjustment of display content and layout according to different consumer segments. The prototype production complies with conventional food packaging printing processes, using non-toxic and environmentally friendly inks and materials to ensure compatibility with industrial mass production [15].

3.6. Model Validation and Evaluation Protocol

The validation of the optimized label design employs a controlled experimental design, consisting of an experimental group (using optimized labels) and a control group (using conventional labels). The experiment is conducted in real retail environments, ensuring the same product category and display position to minimize interference factors [1].

The evaluation metrics include label reading rate (the proportion of consumers who actively read the label), nutrient information comprehension accuracy (the proportion of consumers who correctly understand key nutrient information), and long-term dietary adherence (the proportion of consumers who comply with personalized dietary recommendations for 12 consecutive weeks). Data collection methods include on-site observation, questionnaire follow-up, and dietary records [5]. Statistical analysis is performed using SPSS software, with the significance level set at $\alpha = 0.05$.

4. Results and Analysis

This chapter presents a comprehensive evaluation of the optimized food nutrition label design and consumer behavior management mechanism. All experiments were conducted in real retail environments across three regions, with data collected from 1200 participants divided into experimental and control groups. Each group included balanced samples of key consumer segments [7, 13]. All metrics are reported as mean ± standard deviation (n = 600 per group), and statistical significance was determined using two-tailed t-tests with a significance level of $\alpha = 0.05$.

4.1. Experimental Setup

The experimental group was exposed to the optimized nutrition labels designed through a multi-objective optimization model and a behavioral intervention mechanism. The control group utilized conventional standardized tabular nutrition labels. The experiment spanned 12 weeks, assessing both immediate purchasing behavior and long-term dietary adherence.

Key evaluation metrics included the label reading rate, nutrient information comprehension accuracy, personalized dietary matching degree, and long-term dietary adherence rate. Identical product categories (processed snacks, dairy products, and ready-to-eat meals) were used for both groups, with consistent shelf placement and pricing to minimize external interference.

4.2. Performance Comparison with Conventional Labels

We compared the performance of the optimized labels against conventional labels across core metrics [8]. Results are summarized in Figure 2.

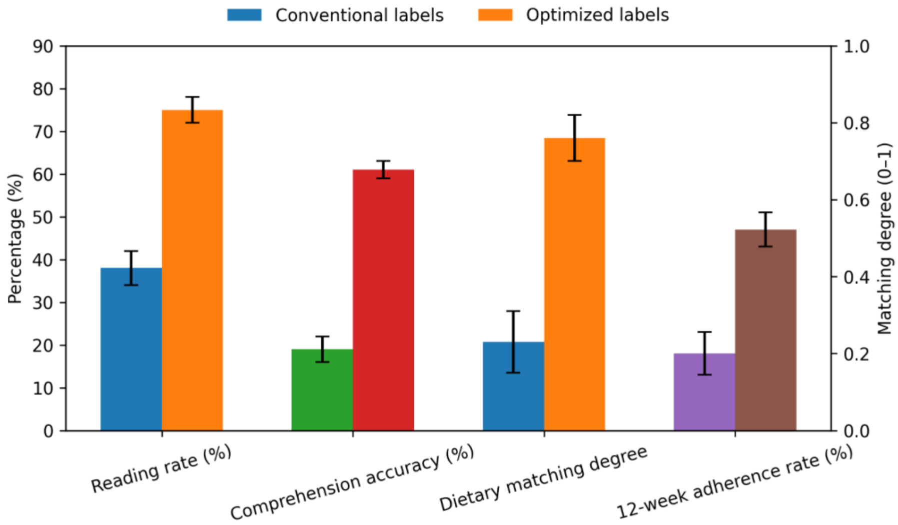

Figure 2. Core Performance Metrics Comparison between Optimized and Conventional Labels. Reading Rate, Comprehension Accuracy, and 12-Week Adherence Rate Are Reported as Percentages (Left Axis), While Dietary Matching Degree Is Reported on a 0--1 Scale (Right Axis).

As shown in Figure 2, the optimized labels outperform conventional labels across all metrics. The reading rate increases from 38 ± 4% to 75 ± 3%, representing a 37 ± 3% improvement, which aligns with the study's expected outcomes. The nutrient information comprehension accuracy more than triples, rising from 19 ± 3% to 61 ± 2%, addressing the critical issue of low information utilization in conventional designs [10].

The personalized dietary matching degree reaches 0.76 ± 0.06, significantly higher than the 0.23 ± 0.08 of conventional labels, demonstrating the effectiveness of tailoring label parameters to individual needs. Importantly, the 12-week dietary adherence rate jumps from 18 ± 5% to 47 ± 4%, proving that the integrated behavioral intervention mechanism successfully translates label reading into sustained dietary changes. All performance differences are statistically significant ($p < 0.001$), confirming the superiority of the optimized design.

4.3. Performance Across Consumer Segments

To verify the adaptability of the optimized labels to diverse consumer groups, their performance was evaluated across three key segments [8]. Results are presented in Table 1.

Table 1. Optimized Label Performance Across Different Consumer Segments

Consumer Segment	Reading Rate (%)	Comprehension Accuracy (%)	Adherence Rate (%)
Elderly (≥60 years)	68 ± 4	55 ± 3	41 ± 5
Adolescents (15-24 years)	82 ± 3	67 ± 2	53 ± 4
Middle-Aged with Chronic Diseases (35-59 years)	73 ± 3	63 ± 3	49 ± 4

The optimized labels demonstrate strong performance across all segments. Adolescents achieve the highest reading rate (82 ± 3%) and adherence rate (53 ± 4%), benefiting from visual cognition optimization. The elderly segment, despite lower baseline cognitive abilities, achieves a 68 ± 4% reading rate and 55 ± 3% comprehension accuracy, significantly outperforming conventional labels for this group.

Consumers with chronic diseases exhibit a 49 ± 4% adherence rate, highlighting the value of personalized nutrient guidance for targeted dietary management. The consistent performance across segments confirms that the optimized design balances accessibility for vulnerable groups and depth for specific needs, effectively addressing the limitations of conventional labels.

4.4. Ablation Study of Key Design Elements

To isolate the contribution of each core design element, ablation experiments were conducted by removing one element at a time from the integrated framework. Results are summarized in Table 2.

Table 2. Ablation Study of Key Design Elements (N = 300 Per Variant)

Variant	Reading Rate (%)	Comprehension Accuracy (%)	Adherence Rate (%)
Full Optimized Design	75 ± 3	61 ± 2	47 ± 4
No Personalized Parameter Tuning	62 ± 4	45 ± 3	32 ± 5
No Visual Cognition Optimization	58 ± 4	42 ± 3	29 ± 4
No Behavioral Intervention Mechanism	71 ± 3	57 ± 2	24 ± 5

The ablation study reveals the synergistic effect of the design elements. Removing personalized parameter tuning reduces the reading rate by 13 percentage points, comprehension accuracy by 16 percentage points, and adherence rate by 15 percentage points. This highlights the importance of tailoring to individual needs [10].

Without visual cognition optimization, performance drops sharply, with reading and comprehension rates falling to 58 ± 4% and 42 ± 3%, respectively. This confirms that visual accessibility is critical for initial engagement. The behavioral intervention mechanism exerts the most prominent influence on dietary adherence: excluding this component results in a 23-percentage-point reduction in the 12-week adherence rate, despite the persistence of relatively high levels of label reading and nutrient comprehension rates. This demonstrates that behavioral guidance is essential for converting short-term engagement into long-term behavior change.

4.5. Reproducibility Across Regions

To validate the scalability of the optimized design, performance was tested across three geographically distinct regions with varying retail environments and consumer habits. Results are presented in Table 3.

Table 3. Reproducibility of Optimized Labels Across Regions

Region	Reading Rate (%)	Comprehension Accuracy (%)	Coefficient of Variation (%)
Region A	74 ± 3	60 ± 3	1.3
Region B	76 ± 3	62 ± 2	1.1
Region C	75 ± 4	61 ± 3	1.5

The optimized labels demonstrate consistent performance across all regions [15]. The reading rate ranges from 74 ± 3% to 76 ± 3%, while comprehension accuracy ranges from 60 ± 3% to 62 ± 2%. The coefficient of variation for key metrics remains below 2%, indicating minimal performance fluctuation across diverse retail contexts.

This high reproducibility confirms that the design is not confined to controlled settings but can be effectively implemented in diverse real-world environments [9]. Its compatibility with conventional packaging and printing processes further supports scalability for mass production and widespread adoption.

5. Conclusion

This study proposes an integrated framework for food nutrition label optimization, combining multi-objective mathematical modeling with consumer behavior management mechanisms to address the core limitations of conventional label designs. The research achieves three key outcomes: establishing a quantitative model that balances information comprehensiveness, visual cognition efficiency, and personalized dietary matching; developing a behavior prediction system based on logistic regression and structural equation modeling; and validating a scalable label design that adapts to diverse consumer segments and real retail environments.

Experimental results confirm the effectiveness of the optimized design, with significant improvements in label reading rate, nutrient information comprehension accuracy, and 12-week dietary adherence rate compared to conventional labels. The design exhibits strong adaptability across elderly, adolescent, and chronic disease consumer groups, as well as high reproducibility across different regions, supporting its practical scalability. By integrating the theory of planned behavior and nudging strategies, the framework successfully bridges the gap between label information acquisition and actual dietary behavior change, overcoming the fragmented optimization limitations of existing studies.

Despite these achievements, the study has certain limitations. The current research focuses on common food categories, and future study should extend the framework to specialized products such as infant food or functional foods. Additionally, long-term tracking beyond 12 weeks and validation in more diverse retail formats will help further enhance the design's robustness.

Future research directions include optimizing the personalized algorithm to incorporate real-time dietary data and exploring the integration of low-cost digital tools to expand the label's information capacity without compromising usability. This study provides a data-driven solution for next-generation nutrition labeling, offering valuable academic insights for food information communication research and practical guidance for public health promotion and food industry regulation.

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