Explainable AI for Nutrition: A Research Proposal on Enhancing Trust and Health Outcomes in Food Recommendation Systems

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I Introduction

Food recommender systems (RS) significantly influence dietary behaviors, yet face major challenges of balancing interpretability, health-awareness, and user preferences. The opacity of conventional systems discourages users' trust, which necessitates explainable articial intelligence (XAI) methods[1]. This proposal aims to examine the integration of XAI in food recommenders to enhance dietary compliance and user satisfaction. The refined research question is: *What are the effects of integrating nutritional expertise and user-centered explainability into hybrid food recommender systems on dietary compliance and user satisfaction compared to non-explainable systems?*

II Literature Review

Recent work highlights systemic limitations in aligning taste, nutrition, and explainability in food recommenders [1]. Analysis of fifteen studies [1],[2],[3],[4],[5],[6],[7],[8],[9],[10],[11],[12],[13],[14],[15] reveals three persistent gaps: failure to jointly optimize health and preference, static or inaccessible explanations, and limited scalability across populations.

A. Tensions Between Personalization and Health

Post-hoc models show black-box systems often misalign with dietary goals [1]. Grocery recommenders reinforce poor habits [2], and even hypergraph models prioritize flavor over nutrition [3]. Group-based and attention-driven systems add constraints [4], [5], but do not resolve trade-offs. Context-aware engines like HANA lack generalizability [6], and educational cold-start filters improve onboarding [7], yet fall short on cross-context performance.

B. Explainability and User Trust

XAI techniques such as image clustering and symbolic rule extraction support saliency and expert readability [8], [9]. Rule-driven substitutions improve compliance [10], while conversational agents offer interactive reasoning [11]. Ensemble models signal industry demand for transparency [12]. Still, real-time multi-objective models are too complex [13], and large-scale personalization remains theoretical [14]. Studies with older adults stress context- and literacy-sensitive design [15].

C. Research goal

Across all studies, a consistent picture emerges: existing systems struggle to reconcile personal taste with nutritional rigor, lack adaptive and user-friendly explanations, and remain difficult to scale across diverse populations and contexts. In response, we propose an explainable AI (XAI) framework that integrates symbolic reasoning into data-driven models. By overlaying lightweight, interpretable logic atop the Jansen–Bennin engine [2], and drawing from techniques in rule-based justification [9], interactive guidance [11], and compliance-aware suggestions [10], our approach enables transparent, personalized, and scalable recommendations—bridging core gaps in trust, effectiveness, and accessibility.

III Research Design

This study adopts a deductive, hypothesis-driven approach to evaluate how explainable AI (XAI) improves the usability and health alignment of food recommender systems. We extend the Jansen–Bennin grocery engine [2], which combines gradient boosting and recurrent neural networks to rank grocery items based on behavioral and contextual data. While accurate, the original system lacks transparency and fails to reflect explicit dietary constraints.

To address this, we implement a symbolic post-filter that applies domain-specific nutritional rules (e.g., fibre-rich, low-sodium) to generate concise explanations for each suggested item. The rules are derived using the symbolic extraction method of Magnini et al. [9] and refined through participatory co-design, following the approach of Kansaksiri et al. [11]. Each recommendation is annotated with a traceable one-line rationale, such as "high fibre → supports digestion."

Evaluation involves 200 synthetic user profiles created from USDA dietary data to simulate diverse nutritional goals. Each profile is processed in two conditions: the unmodified base system (no explanations) and the XAI-enhanced version with rule-based filtering and justifications. Sixty participants are asked to rate the two outputs for trust, usability (SUS), and perceived health relevance. Additionally, we compute nutrient-density scores for each recommendation list. Paired t-tests ($p<0.05$) assess statistical significance between conditions.

Several limitations are acknowledged. Simulated user behavior may not capture real-world variability, and manually curated rule sets may become outdated. These issues are mitigated through modular rule design, logging of unmatched cases, and future integration of adaptive rule updates. Live trials with real users are planned as follow-up work.

Timeline: The study will proceed in six phases: (1) Literature review and research question formulation; (2) Rule base construction and integration with the recommender; (3) Synthetic profile generation and system setup; (4) Internal pilot testing and refinement of explanations; (5) User study and data collection; (6) Statistical analysis and final reporting.

IV Anticipated Results

The XAI-enhanced recommender is expected to show measurable improvements over the baseline across three key dimensions:

Trust and Interpretability: Users are projected to report higher trust ratings when shown concise, rule-based explanations. Mean Likert trust scores are expected to increase from 3.1 (baseline) to 4.2 (XAI), representing a 30% improvement ($p<0.01$). Faster decision times are also anticipated due to improved clarity [1], [11].

Nutritional Quality: The XAI condition is expected to yield grocery baskets with higher nutrient-density scores (mean 78 vs. 68, $p<0.05$) and lower added sugar (12g per basket), in line with prior results from health-aware recommenders [5], [10].

Usability and Engagement: System Usability Scale (SUS) scores are expected to increase from 70 to 80. Reuse intention is projected at 85% under XAI, compared to 60% for the baseline. Engagement metrics such as click depth and dwell time are also expected to improve [12].

These results would support the use of symbolic XAI to enhance trust, usability, and health relevance in food recommendation systems.

V Discussion

The anticipated improvements in trust (+30%), nutritional relevance (+15%), and usability (+10 SUS points) suggest that integrating symbolic explanations into food recommenders can significantly enhance user engagement and decision quality. These gains align with prior findings on explainable recipe models [1], symbolic pipelines [9], and health-aware food recommenders [5], [10].

Rule-based rationales such as "high fibre → supports digestion" provide low-friction interpretability while aligning with public nutrition goals [14]. This makes the approach attractive not only for end-users but also for stakeholders such as digital retailers (seeking AI transparency) and health authorities (promoting dietary compliance). The modular XAI layer offers a scalable enhancement compatible with ensemble innovation frameworks now gaining traction in food tech [12].

However, three limitations should be noted. First, the evaluation is based on synthetic profiles and short-term interaction. Real-world factors like promotions, social habits, and seasonal variability are not captured, which may affect generalizability [6]. Second, the nutritional rule base requires ongoing expert maintenance. While modularized, this upkeep remains a practical challenge observed in prior rule-driven systems [4]. Third, the system is validated only within the grocery domain. Transferability to restaurant menus or meal-planning apps will require separate evaluation.

Future work will focus on three extensions: (1) longitudinal trials with real user baskets and behavioral logging; (2) semi-automated rule refinement using many-objective optimisation [13]; and (3) incorporation of multimodal XAI, including image-based and conversational feedback [8], [11].

Overall, these findings support the role of symbolic XAI as a practical bridge between algorithmic performance and human-centered dietary guidance.

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