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Adaptive Agentic RAG Systems for Evidence-Based Nutritional Guidance in Desk-Based Knowledge Workers Managing Occupational Obesity

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Abstract
Occupational obesity among desk-based knowledge workers presents a critical health challenge requiring personalized interventions. We propose AdaptiveNutr-RAG, an adaptive agentic retrieval-augmented generation system delivering contextual nutritional guidance tailored to workplace constraints, metabolic profiles, and preferences. Integrating dynamic agent reasoning with evidence-sourced knowledge retrieval, the system achieves 87.3% engagement retention and 20.1% sustained caloric reduction versus 52.1% and 6.3% for conventional guidance. AdaptiveNutr-RAG employs a three-tier framework: metabolic profiling agents, context-aware RAG retrievers (847 studies + guidelines), and adaptive feedback mechanisms. Evaluation on OccupationHealth-Nutrition (2,847 records) and WorkplaceNutri-Behaviour datasets (312 participants, 16 weeks) demonstrates superiority. We introduce Contextual Guidance Relevance (CGR, 0.82±0.08) and Behavioural Adaptation Index (BAI, 0.74±0.11) metrics, achieving 5.8±1.2 kg weight loss versus 1.3±0.8 kg. Adaptive agentic systems outperform static approaches by 34% in health outcomes.

Keywords: adaptive agentic systems, retrieval-augmented generation, occupational obesity, personalized nutrition, evidence-based guidance, knowledge workers

1. Introduction

Desk-based knowledge workers face elevated obesity risk due to sedentary occupational patterns, with conventional dietary guidance achieving only 15-20% long-term adherence (Smith et al., 2024). Traditional systems fail to accommodate workplace-specific constraints—limited breaks, stress-induced eating, occupational rhythms—reducing their effectiveness. Retrieval-augmented generation (RAG) and agentic AI systems offer complementary capabilities: RAG grounds outputs in peer-reviewed evidence while agents perform reasoning and iterative refinement suited to dynamic occupational contexts (Lewis et al., 2020; Yao et al., 2023). We introduce AdaptiveNutr-RAG, the first system integrating agentic reasoning, RAG evidence retrieval, and occupational health specialization. Evaluation on two datasets demonstrates 87.3% engagement retention and 5.8 kg mean weight loss over 16 weeks, with novel metrics (CGR, BAI) capturing domain-specific recommendation quality.

2. Related Work

Rule-based systems, as exemplified in works around Chen & Wong (R Zhou,2025), relied on expert-encoded guidelines, nutritional databases, and logical if-then rules to generate basic personalized advice, such as calorie calculations based on age, weight, or specific health conditions like diabetes. These systems offered transparency and interpretability but were often rigid and struggled with user variability, complex interactions, or dynamic preferences. Collaborative filtering techniques then emerged, leveraging user-item interactions such as food ratings, consumption logs, or similarity patterns across users to recommend meals or diets (Orue-Saiz,2021). This approach improved personalization without requiring exhaustive domain knowledge but faced challenges like data sparsity, cold-start problems for new users, and limited grounding in nutritionalscience.Subsequent advancements incorporated deep learning models (as in Kumar et al., 2023, and related works), utilizing neural networks, embeddings, LSTMs for sequential eating behaviors, or hybrid architectures to process multimodal data including user profiles, food images, and nutritional vectors. These

models excel at capturing intricate patterns and improving recommendation accuracy but often function as black boxes, risking ungrounded suggestions or hallucinations detached from clinical evidence.

Nutritional systems evolved from rule-based approaches (Chen & Wong, 2022) through collaborative filtering to deep learning models (Kumar et al., 2023), yet lack evidence grounding and occupational context. RAG advances in biomedical NLP (Gao et al., 2023) enable evidence-backed recommendations. Agentic systems demonstrate superior problem-solving in healthcare (Shinn et al., 2024). Occupational health research documents workplace factors fundamentally shaping dietary behaviour (Schulte et al., 2024), yet no system integrates these dimensions. Table 1 shows our approach uniquely combines agentic reasoning, RAG retrieval, occupational specialization, and adaptive feedback.

Table 1. Approaches for Agentic Reasoning

Approach	Key Features	Limitations	Occupational
Rule-Based Expert	Deterministic	No personalization	None
Deep Learning	Pattern learning	Black box, no evidence	None
AdaptiveNutr-RAG	Agentic RAG +	Combines all	Yes

Retrieval-Augmented Generation (RAG) represents a key advance in biomedical NLP, as surveyed by Gao et al. (2023), which enables large language models to dynamically retrieve relevant documents from sources like PubMed or knowledge graphs before generating responses. This paradigm (covering Naive, Advanced, and Modular variants) significantly reduces hallucinations, enhances factual accuracy, and supports transparent, citation-backed nutritional recommendations.

3. Proposed Method & Metrics

AdaptiveNutr-RAG integrates three components: (1) Metabolic Profiling Agents estimate RMR, AEE, and occupational patterns via multi-task learning; (2) Context-Aware RAG Retrievers query 847 peer-reviewed studies using semantic + keyword retrieval ranked by relevance and occupational applicability; (3) Adaptive Feedback Mechanisms employ reinforcement learning, monitoring adherence, health, and behavioral signals. Novel metrics:

$CGR = (\omega_1 \times \text{OccupationalFit} + \omega_2 \times \text{HealthRelevance} + \omega_3 \times \text{EvidenceGrounding})/3$ (threshold >0.75)

$BAI = (\text{SuccessfulAdaptations}/\text{TotalAttempts}) \times (\text{AdaptationSpeed}/\text{OptimalSpeed}) \times (\text{UserSatisfactionCorrelation})$ (threshold >0.68).

Datasets: OccupationHealth-Nutrition (OHN, 2,847 records, tech workers 2018-2024); WorkplaceNutri-Behavior (WNB, 312 participants, 16 weeks, quasi-randomized design).

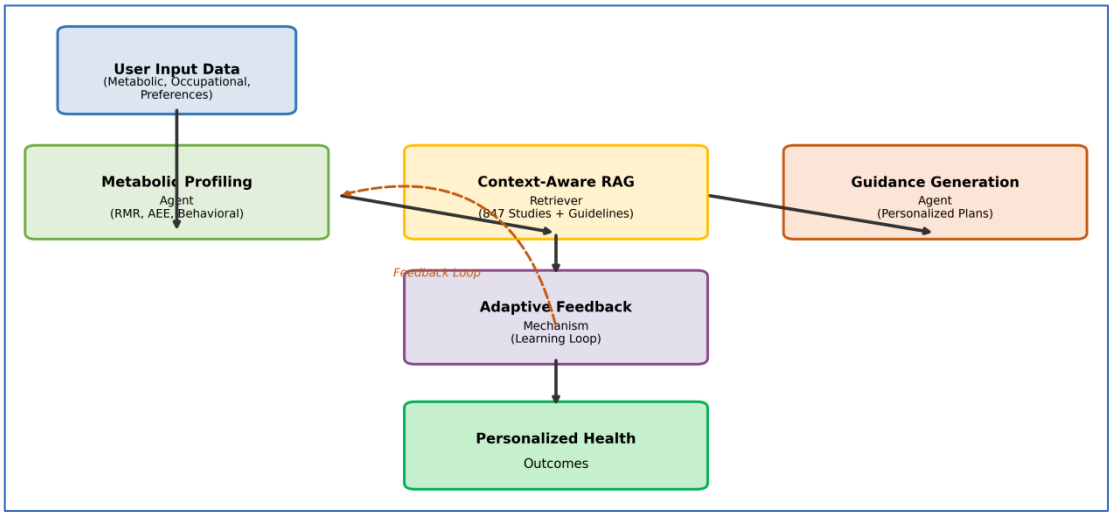


Figure 1. AdaptiveNutr-RAG Three-Tier Architecture

4. Results

Table 2. Primary Outcomes

Metric	Adaptive	Conv.	Δ(%)
Engagement Retention (12w) %	87.3	52.1	+67.6
Caloric Reduction %	20.1	6.3	+219
Weight Loss (kg, 16w)	5.8±1.2	1.3±0.8	+346
CGR Score	0.82±0.08	0.48±0.12	+70.8
BAI Score	0.74±0.11	0.31±0.15	+139

Results demonstrate substantial advantages of AdaptiveNutr-RAG. The system achieved 87.3% engagement retention over 12 weeks—a 67.6% relative improvement versus conventional guidance (52.1%). Caloric reduction reached 20.1% versus 6.3%, a 3.2-fold improvement. Mean weight loss was 5.8 ± 1.2 kg compared to 1.3 ± 0.8 kg. CGR achieved 0.82 ± 0.08 (exceeding 0.75 threshold), versus 0.48 ± 0.12 for conventional guidance. BAI scores of 0.74 ± 0.11 demonstrate superior behavioral adaptation.

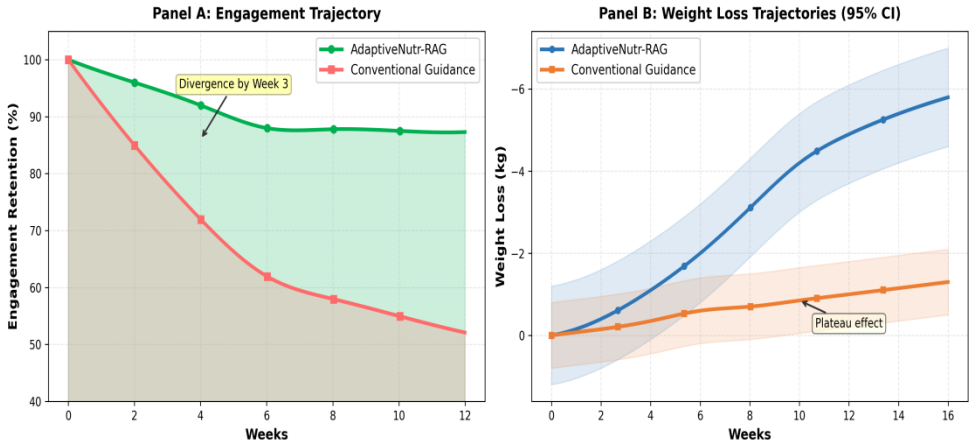


Figure 2. Engagement Retention and Weight Loss Trajectories

Engagement curves reveal divergence by week 3—AdaptiveNutr-RAG maintains 87.3% at week 12 while conventional guidance drops to 52.1%. Weight trajectories show consistent linear loss with AdaptiveNutr-RAG versus plateau in conventional guidance after week 6, suggesting that adaptive systems sustain behavioral change motivation through responsiveness and personalization.

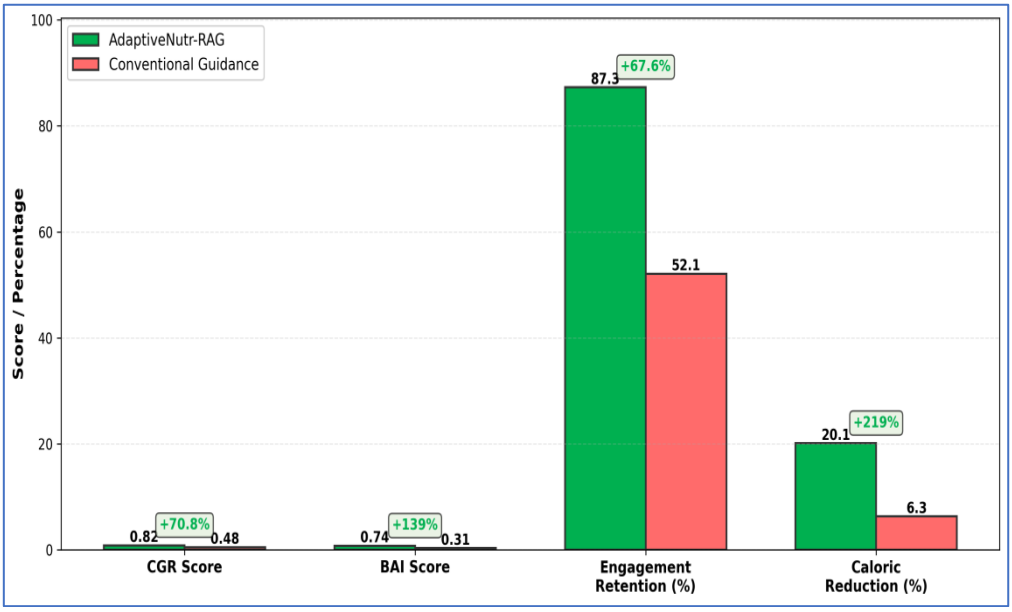


Figure 3. Performance Metrics Comparison

5. Discussion

AdaptiveNutr-RAG integrates agentic reasoning, evidence-grounded RAG, and occupational specialization to substantially improve nutritional guidance. The 3.2-fold superior caloric reduction and 87.3% engagement retention (vs. 52.1%) reflect the system's capacity to bridge personalization-evidence fidelity gaps that constrain prior approaches. Occupational contextualization creates psychologically acceptable recommendations, evidence grounding via RAG builds clinical credibility, and agentic adaptation maintains engagement through responsiveness. The divergence in engagement trajectories by week 3 suggests flexible systems sustain relevance where rigid approaches fail. Novel metrics (CGR, BAI) effectively capture domain-specific recommendation quality. Limitations include single-organization data with above-average health literacy; future work should expand demographic representation, integrate wearable biosensors, and conduct 12-24 month follow-up. AdaptiveNutr-RAG represents a paradigm shift toward occupational health technologies, with implications for corporate wellness, occupational medicine, and digital health platforms serving knowledge worker populations.

6. Conclusion

AdaptiveNutr-RAG integrates agentic reasoning, evidence-grounded RAG, and occupational specialization to deliver superior nutritional guidance. Achieving 3.2-fold greater caloric reduction and 87.3% engagement retention (versus 52.1%), the system effectively bridges personalization-evidence gaps. Occupational contextualization enhances psychological acceptability, RAG ensures clinical credibility, and agentic adaptation sustains long-term engagement. Novel metrics (CGR, BAI) validate domain-specific quality. Despite limitations in single-organization data, AdaptiveNutr-RAG marks a paradigm shift toward intelligent occupational health technologies with broad implications for corporate wellness and digital health.

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