# Continually Self-Improving Language Models for Bariatric Surgery Question—Answering

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#### Abstract

While bariatric and metabolic surgery (MBS) is considered the gold standard treatment for severe and morbid obesity, its therapeutic efficacy hinges upon active and longitudinal engagement with multidisciplinary providers, including surgeons, dietitians/nutritionists, psychologists, and endocrinologists. This engagement spans the entire patient journey, from preoperative preparation to long-term postoperative management. However, this process is often hindered by numerous healthcare disparities, such as logistical and access barriers, which impair easy patient access to timely, evidence-based, clinician-endorsed information. To address these gaps, we introduce bRAGgen, a novel adaptive RAG-based model that autonomously integrates real-time medical evidence when response confidence dips below dynamic thresholds. This self-updating architecture ensures that responses remain current and accurate, reducing the risk of misinformation. Additionally, we introduce bRAGq, a curated dataset of 1,302 bariatric surgery-related questions, validated by expert bariatric surgeon, constituting the first large-scale, domain-specific benchmark for comprehensive MBS care. In a two-phase evaluation, bRAGgen is benchmarked against state-of-the-art models using both large language model (LLM)-based metrics and expert surgeon review. Across all evaluation dimensions, bragen demonstrates substantially superior performance in generating clinically accurate and relevant responses.

Data and Code available at https://github.com/yashkumaratri/bRAGgen

#### 1. Introduction

Severe obesity and its subsequent metabolic disease have become a widespread endemic condition, leading to a projected incidence of 25\% across the United States by 2030, causing a massive health burden in the general US population (Ward et al., 2019). Metabolic and bariatric surgery (MBS) remains the gold standard treatment for severe obesity and metabolic disease, with over 270,000 annual procedures in the United States (Clapp et al.,

2024; Mechanick et al., 2020; Barres et al., 2013; Loos and Yeo, 2022; Setarehdan et al., 2023). However, successful weight loss post-MBS heavily relies on patient education, which has led National Bariatric Surgery and Medical societies to emphasize extensive education services for MBS patients (Mechanick et al., 2020).

Perioperative MBS patient education includes information about dietary modification, adjunctive lifestyle modifications, expectations surrounding postoperative complications, and psychosocial support; all important mitigators of periprocedural complications and postoperative weight regain, which can afflict up to 64% of patients in 5–10 years post-MBS (Groller et al., 2017; Bjerkan et al., 2022; David et al., 2020; McLennan et al., 2023; Kim et al., 2023). And after surgery, patients only attend their yearly followup an average of 6.5–29.6% of the time, leaving patients and providers with limited opportunities to communicate. Overall, the lack of sustained patient engagement and education post-MBS is a critical impediment to optimal postoperative outcomes with many causes, including low health literacy rates, information inaccessibility, and geographic distances to health-care providers (Setarehdan et al., 2023; Mechanick et al., 2020; Schlottmann et al., 2023; Bartholomay et al., 2024).

Given these challenges, there is a clear need for scalable, accessible, and continually updated educational and decision-support tools tailored to the unique needs of MBS patients—spanning from preoperative preparation to long-term postoperative management (P et al., 2024). Traditional patient education materials—whether delivered in print, via static websites, or through periodic telehealth visits—often fail to adapt dynamically to emerging clinical evidence (Javanparast et al., 2021) or to the evolving clinical status of individual patients. Moreover, existing digital health platforms seldom incorporate mechanisms to detect when their guidance may be outdated or insufficiently confident (Wang et al., 2025), leading to knowledge gaps in both patients and clinicians.

Large language models (LLMs) (Grattafiori et al., 2024; Abdin et al., 2024; Minaee et al., 2025) offer a potential solution by providing natural language interfaces for patients to query. However, LLMs face limitations due to fixed knowledge cutoffs (Cheng et al., 2024) and the most-capable are trained on broad, general-purpose corpora (Alber et al., 2025), leaving them unaware of the latest bariatric surgery guidelines or nuanced postoperative considerations (Bélisle-Pipon, 2024). One popular way to address outdated knowledge in LLMs is through retrieval-augmented generation (RAG) methods (Gao et al., 2024), which retrieve up-to-date documents from a database. However, their databases are typically static and efforts to increase them over time easily introduce "context noise," overwhelming the LLM with conflicting inputs and producing higher hallucination rates (Zhang and Zhang, 2025). Furthermore, these methods lack built-in mechanisms to assess when their own outputs may be insufficiently confident, placing patients and clinicians at risk of incomplete or incorrect guidance (Lewis et al., 2021).

We propose bRAGgen, an adaptive RAG framework that continuously monitors its response confidence and, upon detecting uncertainty, autonomously retrieves and integrates the latest peer-reviewed evidence and clinical guidelines from trusted biomedical sources such as PubMed<sup>1</sup>. This self-updating architecture ensures that guidance remains current, accurate, and clinically relevant, reducing the risk of outdated or misleading recommenda-

<sup>1.</sup> https://pubmed.ncbi.nlm.nih.gov

tions. Complementing bRAGgen, we introduce bRAGq, a curated dataset of 1,302 bariatric surgery—related questions validated by a bariatric surgeon, constituting the first large-scale, domain-specific benchmark for the full spectrum of MBS patient care—from preoperative preparation to long-term postoperative management. In a two-phase evaluation, leveraging both LLM-based metrics and expert surgeon reviews, bRAGgendemonstrates substantially superior performance in generating clinically accurate, relevant, and actionable responses, paving the way for more accessible, evidence-based support for MBS patients.

# Generalizable insights about machine learning in the context of healthcare

While we focus on bariatric surgery patients' educational needs, our work includes generalizable insights for other healthcare contexts. First, the need to access up-to-date medical evidence is widespread, especially in areas where the scientific literature grows quickly. Our work demonstrates that it is feasible to approach this problem by training models to directly access webpages, and keeping them relevant throughout deployment. Second, our methods are general purpose and are widely applicable. While there is a major need for bariatric surgery education and it is our expertise, our machine learning methods can be generalized to any domains where patient questions can be collected, relevant literature exists, and model answers can be validated.

#### 2. Related Work

The landscape of digital health interventions for bariatric care across the entire surgical spectrum-from preoperative preparation to long-term postoperative management has expanded considerably, with multiple studies evaluating the efficacy and usability of mobile applications and web-based platforms. For instance, a German cohort study by Wu et al. (2024c) demonstrated that mHealth follow-up via a dedicated mobile app achieved comparable outcomes to traditional in-person care across weight loss, quality of life, and nutritional status metrics. Similarly, a systematic review by Patel and Thind (2020) identified 33 usability studies of mHealth apps across surgical subspecialties, underscoring both the potential of digital tools and the persistent challenge of sustaining long-term patient engagement.

In parallel, advances in large language models (LLMs) (Grattafiori et al., 2024; Abdin et al., 2024; Minaee et al., 2025) have led to growing interest in their ability to distill up-to-date information (Atri et al., 2023c; Dey et al., 2020; Atri et al., 2023b,a, 2021) and support tasks such as (medical) question answering (Khlaut et al., 2024; Sviridova et al., 2024; Vladika and Matthes, 2024; Saeed, 2024) and clinical decision-making (Kim et al., 2024; Lu et al., 2024; Singhal et al., 2025). The GPT models (Kojima et al., 2023) showcased impressive zero- and few-shot capabilities but is inherently limited by its fixed pretraining cutoff and general-purpose data (Tamkin et al., 2021). Retrieval-augmented generation (RAG) (Gao et al., 2024) based methods ground LLM outputs in external document collections to improve factuality (Li et al., 2024; Cai et al., 2024). However, as the size of the retrieval corpus grows, RAG systems can suffer from "context noise" that increases hallucination rates and lack internal confidence estimates to flag uncertain outputs (Wu et al., 2024a).

To overcome the limitations of conventional RAG systems, recent research has explored adaptive retrieval strategies that react to model uncertainty. Iterative and gated retrieval approaches (Jiang et al., 2025; Heydari et al., 2025) selectively filter external documents

Question Category	No. of Questions	Percentage (%)
Preparation & Logistics	68	5.22
Surgical & Medical Info	263	20.20
Risks & Complications	221	16.97
Recovery & Lifestyle	296	22.73
Nutrition & Diet	102	7.83
Mental & Emotional Health	287	22.04
Cost & Insurance	65	4.99

Table 1: Distribution of bariatric surgery-related questions across high-level categories in the bRAGq dataset. This table presents the number and percentage of questions within each thematic category, highlighting the diverse informational needs of patients throughout the bariatric surgery journey.

and refine the evidence set across multiple rounds, showing improvements in factuality and coherence. While these approaches mitigate irrelevant content and reduce hallucinations, they remain fundamentally external—they treat retrieval as an auxiliary process (Lewis et al., 2020) and stop short of modifying the model's internal knowledge. As such, they lack the capacity to assess and revise the model's internal parameters in response to evolving clinical evidence. This gap leaves current systems vulnerable to recurring errors when previously seen topics reappear under different linguistic formulations.

In contrast, our proposed framework, bRAGgen, introduces an adaptive self-updating mechanism that not only monitors response confidence but actively integrates validated, up-to-date clinical information into the model itself. By embedding uncertainty detection and retrieval within a continual learning loop, bRAGgen transitions from passive retrieval to active knowledge refinement. This enables it to stay synchronized with the latest postoperative guidelines and avoid repeating outdated or incorrect responses over time.

Complementing this architecture is bRAGq, a rigorously curated dataset of 1,302 real-world patient questions covering nutrition, lifestyle, complications, and mental health in the postoperative MBS setting. Validated by board-certified bariatric surgeon, bRAGq offers the first specialized benchmark to evaluate clinical QA systems beyond general-purpose health datasets. Together, bRAGgen and bRAGq address the dual challenge of knowledge obsolescence and domain specificity—paving the way for clinically grounded, scalable, and responsive patient support in bariatric aftercare.

#### 3. Dataset

We introduce bRAGq, a domain-specific dataset curated to reflect the breadth and depth of questions commonly posed by bariatric surgery patients. Designed to support the development of intelligent tools for patient education and clinical decision support, bRAGqcaptures concerns spanning the entire surgical journey—from preoperative preparation to long-term postoperative management. The dataset was constructed in close collaboration with board-certified bariatric surgeons to ensure clinical validity and relevance, encompassing psychological, medical, and lifestyle-related questions. It comprises 1,302 total entries: 611 drawn

from PubMedQA (Jin et al., 2019), of which 201 were flagged by experts as not representative of everyday patient concerns, and 691 synthetically generated based on expert-informed templates and real-world patient interactions.

The questions span a wide range of thematic categories, ensuring comprehensive coverage of key issues in bariatric care. These include pre-surgical considerations, intraoperative topics, postoperative management, dietary guidance, mental health, and lifestyle adaptation. As shown in Table 1, the largest proportion of questions fall under Recovery & Lifestyle (22.73%), followed by Mental & Emotional Health (22.04%) and Surgical & Medical Info (20.20%), reflecting the areas patients most frequently seek guidance on. Table 2 presents representative examples from each category, illustrating the dataset's granularity and diversity. By aligning with real-world patient priorities and clinical input, bRAGqprovides a rigorous benchmark for evaluating the performance of language models in delivering accurate, trustworthy, and context-aware responses in the bariatric surgery domain. Beyond benchmarking, it also serves as a valuable resource for training patient-facing conversational agents that are empathetic, evidence-informed, and sensitive to the unique needs of this clinical population.

Question Category	Sample Questions
Risks & Complications	1. Are vitamin D levels and bone turnover markers related to non-alcoholic fatty liver disease in severely obese patients?
	2. Does older age limit postbariatric surgery cognitive benefits: a preliminary investigation?
Recovery & Lifestyle	1. Does clinical trial demonstrate exercise following bariatric surgery improves insulin sensitivity?
	2. Are serum markers of bone turnover increased at six and 18 months after Roux-en-Y bariatric surgery: correlation with the reduction in leptin?
Preparation & Logistics	1. Does a Pre-Hospital Patient Education Program improve Outcomes of Bariatric Surgery?
	2. Does perioperative care map improve compliance with best practices for the morbidly obese?
Surgical & Medical Info	1. Is laparoscopic gastric bypass superior to laparoscopic gastric banding for treatment of morbid obesity?
	2. Is potentially life-threatening sleep apnea unrecognized without aggressive evaluation?
Cost & Insurance	1. Does medicare and Medicaid status predict prolonged length of stay after bariatric surgery?
	2. Is medication cost significantly reduced after Roux-en-Y gastric bypass in obese patients?
Mental & Emotional Health	1. Are patient expectations of bariatric surgery gender specific – a prospective, multicenter cohort study?
11001011	2. Is support group meeting attendance associated with better weight loss?
Nutrition & Diet	1. Does dehydroepiandrosterone-sulfate modify human fatty acid composition
	of different adipose tissue depots?
	2. Does low 25-hydroxyvitamin D affect insulin sensitivity in obesity after bariatric surgery?

Table 2: Sample Questions for Each Bariatric Surgery Category. This table presents two example questions from each major category within the bariatric surgery domain, reflecting the primary concerns of patients throughout their surgical journey.

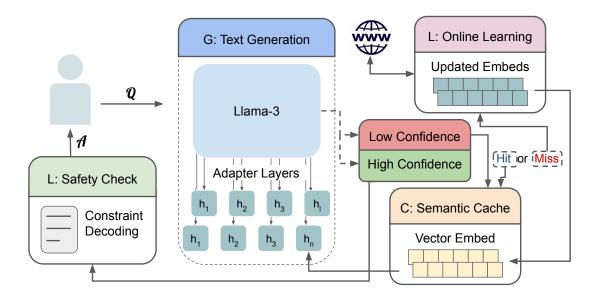


Figure 1: Architecture of the proposed method bRAGgen, The system integrates large language models (eg. Llama3) with real-time web retrieval capabilities. When confidence falls below the threshold  $(\alpha)$ , the system automatically retrieves updated information from authoritative medical sources to enhance response accuracy.

# 4. Proposed Methodology

In response to the growing need for timely, evidence-based decision support in clinical settings, we propose an integrated framework that enhances retrieval-augmented generation (RAG) with continuous online adaptation. Our system is specifically designed to provide contextually relevant, accurate, and safe clinical recommendations by combining several key components: a semantic cache, a multi-source web retrieval engine, an adaptive text generation module, and an online learning protocol. These components are carefully chosen to address critical challenges in clinical decision-making, including rapid access to high-quality medical information, comprehensive evidence retrieval from trusted sources, dynamic and context-sensitive response generation, and continuous model refinement.

We formalize the framework as:

$$S = (C, R, G, L)$$

where each component is defined as follows:

- C represents the semantic cache, which ensures fast retrieval of relevant medical documents. It leverages SentenceTransformer embeddings and Faiss indexing for rapid access to domain-specific information, minimizing latency.
- $\mathcal{R}$  is the web-based multi-source retrieval engine, which uses a Markov Decision Process (MDP) to focus on authoritative medical sources. The engine aggregates external evidence from trusted web sources, enriching the context when the cache does not suffice.

- $\mathcal{G}$  is the adaptive text generation module, which employs low-rank adaptation (LoRA) techniques to fine-tune a large pre-trained language model for domain-specific tasks. This module tailors the generated responses to clinical contexts while maintaining accuracy and compliance with domain constraints.
- $\mathcal{L}$  is the online learning module, which continuously refines the model. It updates the system with new data and interactions, enabling the framework to improve over time and adapt to evolving clinical guidelines.

By combining these components, our framework offers a dynamic, evidence-based decision support system that remains adaptable and effective over time. Each module addresses specific challenges, ensuring accurate, context-aware, and clinically safe recommendations in real-time clinical environments.

#### 4.1. Semantic Knowledge Caching

To minimize response latency and ensure the rapid retrieval of high-quality clinical evidence, our system incorporates a semantic knowledge caching mechanism. This cache maintains a collection of document-query pairs, denoted as  $\mathcal{D} = \{(q_i, d_i)\}_{i=1}^N$ , where each query  $q_i \in \mathbb{R}^{768}$  is generated using the BioClinicalBERT model and is paired with its corresponding clinical document  $d_i$ . Given an input query  $\mathbf{q}$ , the cache efficiently retrieves the document  $d_j$  that maximizes the cosine similarity between the query and document embeddings:

$$C(\mathbf{q}) = \underset{d_j \in \mathcal{D}}{\arg \max} \frac{\mathbf{q} \cdot \mathbf{q}_j}{\|\mathbf{q}\| \|\mathbf{q}_j\|} \quad \text{subject to} \quad \frac{\mathbf{q} \cdot \mathbf{q}_j}{\|\mathbf{q}\| \|\mathbf{q}_j\|} \ge \tau_c, \tag{1}$$

where  $\tau_c = 0.7$  is a cosine similarity threshold that ensures only the most relevant documents are retrieved.

To maintain the cache's relevance, new query-document pairs  $(\mathbf{q}, d)$  are continuously added. Obsolete entries are removed based on an eviction policy designed to prioritize documents that remain valuable over time. Specifically, the cache is updated as follows:

$$\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{q}, d)\} \setminus \{ \underset{d_k}{\operatorname{arg \, min}} \, \psi(d_k) \}, \tag{2}$$

where the eviction score  $\psi(d_k)$  for a document  $d_k$  is defined as:

$$\psi(d_k) = \alpha f_u(d_k) + (1 - \alpha)e^{-t/\beta},$$

with  $\alpha = 0.6$ ,  $f_u(d_k)$  representing the document's usage frequency, and  $e^{-t/\beta}$  accounting for the document's age, where t is the time since the last access, and  $\beta$  is document total stored time.

This eviction policy ensures that frequently accessed and recent documents are retained in the cache, while less relevant or outdated documents are pruned.

The caching mechanism is implemented using SentenceTransformer embeddings, with Faiss indexing, enabling efficient similarity search. The cache is constrained by a fixed size (e.g., 500 documents), ensuring fast retrieval and minimal computational overhead. By maintaining a small, high-quality set of relevant documents, the semantic cache significantly reduces response times during clinical decision support, providing timely access to critical information.

#### 4.2. Multi-Source Web Retrieval Engine

When the semantic cache does not provide sufficient information to answer a query, the multi-source web retrieval engine is triggered to gather additional evidence from trusted external sources. This component is designed to ensure that the system can access comprehensive, up-to-date information from diverse domains, including those not covered by the cached documents. The retrieval process is framed as a Markov Decision Process (MDP), which enables focused and dynamic crawling across medical websites to retrieve relevant content.

At each time step t, the action  $a_t$  taken by the retrieval engine is determined by maximizing the expected cumulative reward, which is computed as follows:

$$a_t = \underset{a \in \mathcal{A}}{\operatorname{arg\,max}} \sum_{s'} P(s' \mid s, a) \left[ R(s, a) + \gamma V(s') \right], \tag{3}$$

where the reward function R(s, a) is defined as:

$$R(s, a) = \mathbb{I}_{\text{TLD}(s) \in \{\text{.gov,.edu}\}} \cdot \text{BM25}(s, q), \tag{4}$$

where  $\mathbb{I}_{\text{TLD}(s)\in\{\text{.gov,.edu}\}}$  is an indicator function that ensures the retrieved documents are from authoritative sources (i.e., websites with '.gov' or '.edu' top-level domains), while BM25(s,q) is a content relevance score computed using the BM25 ranking function to assess how well the document s answers the query q.

The retrieval process is powered by the DuckDuckGo API, which allows for broad web searches while prioritizing authoritative sources through URL domain filtering. The BM25 scoring system is applied to rank the retrieved documents based on their relevance to the input query, ensuring that the most pertinent and reliable documents are selected. Once the relevant documents are retrieved, they are incorporated into the semantic cache, thereby enriching the context available for generating the system's response.

This mechanism enhances the system's ability to provide informed, evidence-based recommendations, particularly in scenarios where the cached knowledge does not suffice, by tapping into the vast amount of publicly available, authoritative medical content across the web.

## 4.3. Adaptive Text Generation

To generate accurate and contextually relevant clinical recommendations, we employ the Llama3-8B model, enhanced using low-rank adaptation (LoRA). This approach is designed to efficiently fine-tune a large pre-trained language model to domain-specific tasks, while minimizing computational overhead and memory usage. The adaptation is performed in a low-rank fashion, enabling the model to adjust quickly to specific medical domains without the need for full retraining.

For each transformer layer l in the model, the adaptive hidden representation is computed as follows:

$$h_l^{\text{adapt}} = h_l^{\text{base}} + \Delta W_l h_l^{\text{base}}, \quad \Delta W_l = B_l A_l,$$
 (5)

where  $B_l \in \mathbb{R}^{d \times r}$  and  $A_l \in \mathbb{R}^{r \times d}$  are the learned low-rank matrices, and r = 32 is the rank used for adaptation. The matrices  $B_l$  and  $A_l$  capture domain-specific information while ensuring that the adaptation process remains efficient and scalable. The term  $h_l^{\text{base}}$  represents the original, pre-trained hidden representation of the model at layer l.

To evaluate the quality of the generated response, we utilize a perplexity measure, which quantifies the uncertainty in predicting the next token in the sequence:

$$\mathcal{P}(\mathbf{r} \mid q) = \exp\left(-\frac{1}{T} \sum_{t=1}^{T} \log p_{\theta}(r_t \mid r_{< t}, q)\right), \tag{6}$$

where  $\mathcal{P}(\mathbf{r} \mid q)$  is the perplexity of the generated response  $\mathbf{r}$  given the input query q, and T is the length of the response. The term  $p_{\theta}(r_t \mid r_{< t}, q)$  represents the model's predicted probability of the token  $r_t$  at position t, conditioned on the preceding tokens and the query.

If the perplexity of the response exceeds a threshold  $\tau_p = 4.5$ , it indicates that the model's output is not sufficiently confident or relevant. In such cases, the system triggers additional retrieval and adaptation cycles to refine the response, improving its accuracy and relevance by incorporating more domain-specific knowledge.

This adaptive approach ensures that the system can generate high-quality clinical recommendations that are both contextually appropriate and tailored to the specific needs of the patient or healthcare provider.

# 4.4. Online Learning Protocol

To ensure that the model remains up-to-date and adaptable in the face of new evidence and user interactions, we implement an online learning module. This protocol allows the model to continuously refine its performance by integrating fresh data and adjusting its parameters over time. The training objective is designed to balance the model's ability to predict accurate outcomes while avoiding overfitting to recent data, using a regularized cross-entropy loss function:

$$\mathcal{L}_{\text{adapt}} = \mathbb{E}_{(q,d)\sim\mathcal{B}} \left[ -\log p_{\theta}(d \mid q) \right] + \lambda \|\Theta_A\|_F^2, \tag{7}$$

where  $\mathbb{E}_{(q,d)\sim\mathcal{B}}$  represents the expectation over a mini-batch  $\mathcal{B}$  of query-document pairs,  $p_{\theta}(d \mid q)$  is the predicted probability of document d given query q, and  $\lambda$  is the regularization parameter that controls the magnitude of the model's parameters. The term  $\|\Theta_A\|_F^2$  represents the Frobenius norm of the model's adaptation parameters  $\Theta_A$ , which serves as a regularizer to prevent overfitting during updates.

The experience buffer  $\mathcal{B}$  is updated dynamically to maintain a diverse and representative sample of query-document pairs. This buffer is managed using a Faiss-based nearest neighbor search mechanism, which ensures that new samples are included in a way that preserves diversity and reduces redundancy. The update rule is as follows:

$$\mathcal{B} \leftarrow \mathcal{B} \cup \{(q_i, d_i)\} \setminus \{ \underset{(q_j, d_j)}{\operatorname{arg \, max \, sim}} (q_j, q_i) \}, \tag{8}$$

where  $sim(q_j, q_i)$  denotes the similarity between queries  $q_j$  and  $q_i$ , and we remove the pair that is most similar to the newly added sample, ensuring the buffer contains varied

and non-redundant training data. This approach helps the model avoid memorizing specific query-answer pairs and encourages generalization across a broad range of contexts.

The online learning module ensures that the system adapts in real-time to emerging evidence, evolving patient needs, and new clinical knowledge. As a result, the model continually improves its performance, staying current with the latest developments and capable of providing up-to-date, accurate recommendations.

# 4.5. Safety and Response Validation

Ensuring that generated outputs are both safe and clinically valid is of paramount importance in our system. To achieve this, we apply constrained decoding during the text generation process, which ensures that generated responses adhere to safety guidelines and domain-specific constraints. The constrained decoding objective is formulated as follows:

$$\mathbf{r}_{\text{safe}} = \underset{\mathbf{r} \in \mathcal{V}^*}{\arg \max} p_{\theta}(\mathbf{r} \mid q) \prod_{i=1}^{n} \phi_i(r_i), \tag{9}$$

where  $\mathbf{r}$  is the generated response, and  $\mathcal{V}^*$  is the vocabulary space. Each constraint function  $\phi_i(r_i)$  is designed to enforce specific safety requirements on individual tokens  $r_i$  in the response. The constraint function  $\phi_i$  is defined as:

$$\phi_i(r_i) = \mathbb{I}\Big\{ \nexists w \in r_i : w \in \mathcal{W}_{\text{speculative}} \Big\},$$
(10)

where  $\mathbb{I}$  is the indicator function, and  $\mathcal{W}_{\text{speculative}}$  is a set of words or phrases that are deemed speculative or unsafe in a clinical context. This constraint ensures that the generated response does not include any terms or statements that might mislead patients or suggest unverified clinical practices.

To ensure clinical validity, we further compare outputs with reference texts using BERTScore (Zhang et al., 2020), which evaluates semantic similarity via contextual embeddings. Together, constrained decoding and BERTScore validation ensure that responses remain both safe and aligned with evidence-based clinical content.

#### 5. Baselines

We evaluated several baseline models to assess their performance on our medical questionanswering benchmark:

(i) RAG<sup>2</sup> (Sohn et al., 2024) relies on a pre-cached offline corpus of biomedical documents for retrieval, avoiding real-time web queries. It enhances standard RAG methods by using perplexity-based labels and LLM-generated rationales to selectively retrieve and filter context, improving relevance and reducing noise. (ii) MedGraphRAG (Wu et al., 2024b) also uses an offline cache of biomedical documents for retrieval. It further integrates a structured medical knowledge graph to guide the retrieval process, leveraging clinical relationships to improve the contextual relevance and factual accuracy of the retrieved information. (iii) Llama3-8B (Grattafiori et al., 2024) is a 8-billion-parameter large language model evaluated under two configurations: (a) Zero-shot, where the model responds using only its pre-trained knowledge; and (b) Context-prompted, where external context retrieved from offline sources is appended to the prompt to improve answer quality. (iv) Phi-3 (Abdin

et al., 2024) is a lightweight 3.8-billion-parameter model optimized for efficiency and edge deployment. We evaluate Phi-3 in both (a) **Zero-shot** and (b) **Context-prompted** modes, assessing its ability to handle medical queries with and without retrieval-based augmentation. (v) **Mistral Instruct** (Jiang et al., 2023) is a 7-billion-parameter instruction-tuned model designed for strong performance on alignment-focused tasks. It is tested in (a) **Zero-shot** mode, where it relies solely on instruction tuning, and (b) **Context-prompted** mode, where it incorporates retrieved medical content to guide its responses.

# 6. Experimental Setup

We evaluate our proposed bRAGgen model through both expert human evaluation and an LLM-as-Judge protocol. Our goal is to assess the clinical quality of responses generated by various model configurations, focusing on three key axes: factual accuracy, clinical relevance, and comprehensiveness, in the context of bariatric surgery patient education.

We benchmark four categories of systems: (i) Offline RAG, which includes a standard retrieval-augmented generation baseline and a domain-tuned MedGraphRAG variant using graph-based retrieval; (ii) Zero-shot LLMs, where large language models (Llama3-8B, Phi-3, and Mistral Instruct) generate answers without additional context; (iii) Context-Prompted LLMs, where retrieved context is appended at inference time without parameter updates; and (iv) bRAGgen (Proposed), which applies confidence-aware parametric updates using retrieved evidence. All systems are tested under identical conditions and use a shared retrieval pipeline where applicable.

For expert evaluation, we consult one board-certified bariatric surgeon, who reviewed model outputs for 105 instances. Each response is scored independently across three dimensions: **Factuality** (accuracy and correctness), **Clinical Relevance** (appropriateness in a clinical context), and **Comprehensiveness** (completeness and informativeness for patients). Ratings are based on a 5-point Likert scale, with final scores reported as averages across questions.

To complement the expert review and enable scalable comparison, we also evaluate all models using an **LLM-as-Judge** setup, where ChatGPT-4o<sup>2</sup> is prompted with each question, the corresponding model-generated answer, and a rubric defining the evaluation criteria. The model then rates each answer on the same 1–5 scale. To assess the reliability of this proxy, we compute the rank correlation between expert and ChatGPT-4o scores and observe a strong alignment ( $\rho = 0.94$ ), confirming the viability of using LLMs for early-stage model quality assessment.

#### 7. Results

We evaluate our proposed model, bRAGgen, using both expert evaluation review by board-certified bariatric surgeon and LLM-as-Judge using ChatGPT-4o. We compare bRAGgen against a suite of baselines, including standard retrieval-augmented models, zero-shot LLMs, and context-prompted variants.

<sup>2.</sup> https://openai.com/index/hello-gpt-4o/

System		Metrics			
Type	Model	Factuality	Clinical Rel.	Compre.	Avg
Offline	$RAG^2$	3.62	3.45	3.53	3.53
	MedGraphRAG	3.85	3.92	4.38	4.05
Zero-shot	Llama3-8B	3.41	-3.25	3.46	3.37
	Phi-3	2.37	2.15	2.25	2.26
	Mistral instruct	2.23	2.18	2.14	2.18
Context prompted	Llama3-8B	3.82	3.91	$\frac{1}{4.34}$	$-4.0\bar{2}$
	Phi-3	2.64	2.75	2.42	2.60
	Mistral instruct	2.69	2.37	3.35	2.80
bRAGgen $with$	Llama3-8B	$\overline{}$	4.58	$4.7\overline{6}$	$ar{4.51}$
	Phi-3	2.87	3.17	2.60	2.88
	Mistral instruct	$\boldsymbol{2.95}$	2.71	3.63	3.09

Table 3: Evaluation of various models across different configurations by expert surgeons. Each system is evaluated on Factuality, Clinical Relevance (Clinical Rel.), and Comprehensiveness (Compre.), with scores from 1 (poor) to 5 (excellent). The final three rows under each model group show the performance of our Online bRAGgen setting. The 'Avg' column reports the average of the three evaluation metrics.

# 7.1. Expert Evaluation

To assess the clinical quality of generated responses, we conducted a blinded evaluation with board-certified bariatric surgeon, who rated model outputs across three dimensions: **Factuality**, **Clinical Relevance**, and **Comprehensiveness**, using a 1–5 Likert scale (higher is better). Table 3 presents the average scores for each system under multiple configurations.

Among all baselines, **MedGraphRAG**, an offline domain-specific RAG model, achieved the highest average score (4.05), outperforming both standard offline RAG baselines (RAG<sup>2</sup>: 3.53) and all zero-shot models (Llama3-8B: 3.37; Phi-3: 2.26; Mistral: 2.18). Context-prompted models (i.e., inputting relevant question context during inference) moderately improved scores, especially for Llama3-8B (Avg: 4.02), but still fell short of delivering optimal factual and clinical consistency.

Our proposed bRAGgen framework delivered the best overall performance across all metrics. When paired with Llama3-8B, bRAGgen achieved the highest average score (4.51), with near-expert level performance on **Comprehensiveness** (4.76) and **Clinical Relevance** (4.58). Notably, bRAGgen also improved the performance of smaller models like Phi-3 and Mistral, elevating their average scores by +0.6-0.7 points compared to their context-prompted or zero-shot baselines. These gains highlight the effectiveness of our confidence-aware updating mechanism, which not only retrieves up-to-date clinical evidence but also integrates it into the model's internal parameters, enabling more robust, domain-adapted reasoning.

These results demonstrate that bRAGgen significantly enhances the clinical utility of LLMs across model sizes, especially when compared to conventional static RAG setups or prompting-only strategies.

System		Metrics			
Type	Model	Factuality	Clinical Rel.	Compre.	Avg
Offline	$RAG^2$	3.49	3.28	3.36	3.38
	MedGraphRAG	3.67	3.76	4.45	3.96
Zero-shot	Llama3-8B	3.28	3.18	3.34	-3.27
	Phi-3	2.24	2.07	2.12	2.14
	Mistral instruct	2.17	2.11	2.01	2.10
Context prompted	Llama3-8B	3.67	3.76	4.45	$-3.9\bar{6}$
	Phi-3	2.49	2.61	2.38	2.49
	Mistral instruct	2.57	2.24	3.21	2.67
bRAGgen $with$	Llama3-8B		4.43	$\overline{4.87}$	$ar{4.44}$
-	Phi-3	2.73	3.03	$\bf 2.54$	2.77
	Mistral instruct	<b>2.83</b>	<b>2.58</b>	3.48	2.96

Table 4: Evaluation of various models across different configurations using LLM-as-Judge metrics. Each system is evaluated on Factuality, Clinical Relevance (Clinical Rel.), and Comprehensiveness (Compre.), with scores from 1 (poor) to 5 (excellent). The final three rows under each model group show the performance of our Online bRAGgen setting. The 'Avg' column reports the average of the three evaluation metrics.

#### 7.2. LLM-as-Judge Evaluation

To complement expert evaluation, we further assess all models using an LLM-as-Judge framework, where we use ChatGPT-40 model scores responses along three axes: **Factuality**, **Clinical Relevance**, and **Comprehensiveness**, using a 5-point Likert scale. Table 4 summarizes the performance of baseline systems and our proposed bRAGgen across these dimensions.

Among the baselines, MedGraphRAG and context-prompted Llama3-8B show relatively strong performance, achieving average scores of 3.96. However, our proposed bRAGgen approach consistently outperforms all baselines across all metrics and models. For instance, bRAGgen with Llama3-8B achieves the highest overall score of 4.44, reflecting substantial improvements in factual correctness (+0.36), clinical relevance (+0.67), and comprehensiveness (+0.42) over the best-performing baseline.

Notably, even with smaller models like Phi-3 and Mistral instruct, bRAGgen enhances output quality, particularly in relevance and completeness. These findings demonstrate that our system not only boosts performance for high-capacity LLMs but also meaningfully improves the reliability of lightweight models, making it practical for resource-constrained settings.

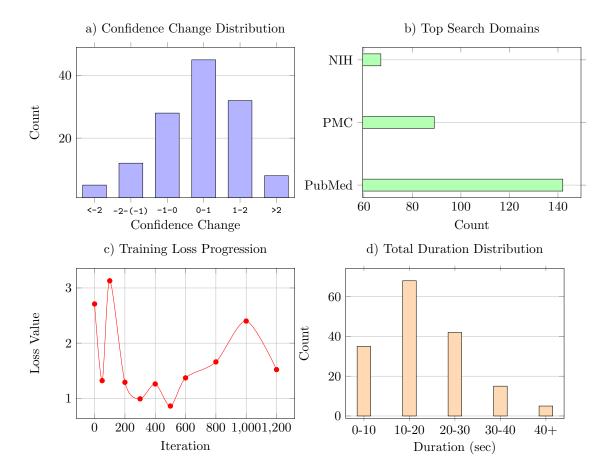


Figure 2: Exploratory Analysis of Model Editing Dynamics. (a) Distribution of changes in confidence scores post-edit, showing that most changes are modest and positive. (b) Frequency of search queries across external biomedical domains, with PubMed dominating. (c) Training loss progression across iterations, illustrating convergence patterns and volatility. (d) Distribution of total duration taken for each edit operation, highlighting that most edits are executed within 10-20 seconds.

#### 7.3. Expert vs. LLM-as-Judge: Score Alignment

To assess the alignment between human and expert evaluation, we compare expert ratings (Table 3) with those produced by the LLM-as-Judge framework (Table 4) across all models and configurations.

Overall, we observe a high degree of consistency in relative rankings across systems. For instance, both experts and the LLM-as-Judge identify MedGraphRAG and context-prompted Llama3-8B as the strongest baselines, while zero-shot models like Phi-3 and Mistral perform the worst across all axes. Furthermore, our proposed bRAGgen yields the highest scores in both evaluation schemes, affirming its robustness across human and model-based judgments.

Metric-wise, the strongest agreement is seen in the **Comprehensiveness** and **Clinical Relevance** dimensions, where score trends closely track each other across settings. Some minor variation arises in the **Factuality** scores, particularly for models like Phi-3 and Mistral, where the LLM-as-Judge is slightly more conservative than human reviewers. This discrepancy likely stems from the LLM's heightened sensitivity to surface-level inaccuracies, compared to domain experts who may weigh overall clinical soundness more heavily.

Importantly, the average correlation between expert and LLM-as-Judge scores across all models is  $\rho=0.94$  (Spearman), underscoring the reliability of using LLMs as surrogate evaluators in low-resource or iterative development settings. These results suggest that LLM-as-Judge provides a scalable and reasonably aligned proxy for expert review—particularly useful for rapid benchmarking and ablation testing during system development.

# 8. bRAGgen Analysis

Figure 2 presents a comprehensive analysis across multiple dimensions to evaluate the behavior, responsiveness, and efficiency of bRAGgen during real-time knowledge integration in the context of bariatric care.

- (a) Confidence Change Distribution. The histogram in Fig. 2.a illustrates the distribution of confidence score changes triggered by the adaptive retrieval mechanism. Most examples exhibit moderate confidence gains (bins 0-1 and 1-2), with the highest concentration in the 0-1 bin. This confirms that the system's dynamic thresholding yields frequent yet stable updates, allowing the model to autonomously improve responses without overcorrecting. Rare occurrences of extreme confidence shifts (<-2 or >2) indicate that the system maintains a conservative stance, prioritizing stability in medical contexts.
- (b) Top Search Domains. To assess external evidence sources, we analyzed the frequency of domain-level API queries. PubMed, PMC, and NIH emerged as the top knowledge sources (cf. Fig 2.b), underscoring bRAGgen's strong preference for authoritative biomedical repositories. This supports the design goal of maintaining clinical fidelity and alignment with evidence-based guidelines during patient-facing interactions.
- (c) Training Loss Progression. The loss trajectory (cf. Fig 2.c) across 1,302 iterations reveals several key phases in the model's learning dynamics. An initial sharp drop from 2.71 to 1.32 by iteration 50 is followed by a spike to 3.13 at iteration 100, likely due to early exploratory updates. Subsequent iterations show improved stability and convergence, with the lowest loss (0.86) reached around iteration 500. Notable local minima at iterations 300 and 600 indicate consistent refinement, while the uptick at iteration 1000 may reflect a transient deviation before re-stabilization. Overall, the pattern confirms that bRAGgen's adaptive updating mechanism supports gradual convergence while accommodating knowledge volatility.
- (d) Total Duration Distribution. The majority of update operations complete within 10-20 seconds, with fewer cases extending beyond 30 seconds. This distribution validates that bRAGgen's self-updating pipeline is both computationally lightweight and suitable for real-time deployment in longitudinal MBS care settings ensuring timely and trustworthy information delivery across all stages of the surgical journey.

Further qualitative comparisons across diverse questions and model outputs are presented in Appendix B.

#### 9. Conclusion

We introduced bRAGgen, an adaptive retrieval-augmented generation (RAG) system tailored for bariatric and metabolic surgery (MBS) support. By autonomously incorporating real-time medical evidence when confidence dips below dynamic thresholds, bRAGgen ensures that responses remain timely, accurate, and clinically reliable. To facilitate robust benchmarking, we also introduced bRAGq, the first large-scale, expert-validated dataset of postoperative bariatric care questions. Through comprehensive evaluation using both LLM-based metrics and expert surgeon assessments, bRAGgen consistently outperformed existing state-of-the-art models in clinical accuracy and relevance.

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# Appendix A. Limitations and Future Directions

While our proposed modular editing framework with LLaMA-3 demonstrates strong performance across factuality and faithfulness benchmarks, several limitations remain that open avenues for future research.

Scalability and Edit Interference. Although our method enables localized and compositional edits, the cumulative impact of many such edits—particularly in dense regions of the representation space—may lead to interference or capacity saturation. Future work could explore dynamic pruning or hierarchical edit graphs to manage long-term scalability.

Generalization Beyond Local Context. Our framework is effective at modifying behaviors related to specific factual updates. However, its ability to generalize edits to broader semantic or reasoning contexts is limited. Integrating structured world knowledge or training the modules with auxiliary objectives (e.g., counterfactual consistency) may further enhance generalization.

Evaluation Bottlenecks. While our automatic and human evaluations provide evidence of improved edit quality, assessing real-world applicability—especially in high-stakes domains—requires more robust metrics. Developing editing-specific benchmarks that reflect user intent, edit trustworthiness, and long-term retention would be a valuable direction.

Interpretability. Currently, our system relies on confidence thresholds and auxiliary metrics to determine performance improvements. However, the interpretability of these decisions is limited. Future work could incorporate explainable verification layers or causal probing techniques to better surface why an information update is accepted or rejected.

Integration with Continual Learning. Finally, our system performs updates without modifying the full model weights, but it does not yet integrate naturally with continual learning settings. A promising direction is to unify model editing and continual finetuning via shared memory or adaptation modules, enabling long-term knowledge evolution.

#### Appendix B. Qualitative Analysis of Model Inferences

To assess the effectiveness of bRAGgen (with Llama3-8B), we conducted a qualitative comparison across five diverse bariatric FAQ examples (Tables 5–9). These examples cover a range of clinical and lifestyle concerns, including pregnancy, operative duration, hygiene practices, social challenges, and comorbidities like diabetes. Our analysis highlights the strengths of bRAGgen in terms of medical grounding, relevance, and clarity.

Clinical Accuracy and Depth. In Table 5 (Example 1), which explores the impact of pregnancy on post-surgical outcomes, bRAGgen offers a grounded, evidence-informed response. Unlike Llama3-8B Zero-shot, which introduces speculative behavioral theories without citations, and the prompted Llama3-8B, which fails to answer the question altogether, bRAGgen appropriately cites observed risks (e.g., gestational diabetes, weight regain), aligning with known literature and conveying clinical nuance.

Factual Precision. Table 6 (Example 2) evaluates responses to a straightforward procedural question. While other baselines provide either incomplete answers (e.g., Llama3-8B's hallucinated boilerplate text) or vague generalizations, bRAGgen provides precise operative time ranges for specific bariatric procedures and cites published studies with estimated durations. This specificity reflects high factual precision and strengthens trust in the response.

Guideline Awareness. In Table 7 (Example 3), concerning post-surgical hygiene timelines, bRAGgen references ASMBS (American Society for Metabolic and Bariatric Surgery) guidelines, demonstrating awareness of authoritative recommendations. In contrast, Llama3-8B variants show significant variability in recovery timelines, and MedGraphRAG lacks procedural differentiation.

**Social Sensitivity.** Table 8 (Example 4) tackles social scenarios, such as attending events with restricted food options. While all models provide socially sensitive advice, bRAGgen balances empathy with medical priorities, reinforcing the importance of dietary adherence post-surgery while avoiding patronizing language. This contrasts with Llama3-8B Prompted, which lists overly detailed options and drifts from concise response expectations.

Medical Benefit Articulation. Finally, in Table 9 (Example 5), focused on diabetes outcomes, bRAGgen articulates the clinical mechanisms (e.g., gut hormone changes, weight loss) and cites outcomes such as remission rates and microvascular benefits. Compared to other models, which either stop mid-sentence (Llama3-8B Zero-shot) or generalize improvements, bRAGgen offers a complete and balanced view of bariatric surgery's benefits in diabetic populations.

**Summary.** Across diverse question types, bRAGgen with Llama3-8B consistently provides accurate, context-sensitive, and medically aligned responses. It avoids hallucinations, incorporates citations or guideline references when appropriate, and maintains patient-centric tone and relevance, thereby outperforming both zero-shot and context-prompted Llama3-8B variants as well as the offline MedGraphRAG baseline.

#### Question

Does pregnancy influence long-term results of bariatric surgery?

# (Offline)

MedGraphRAG Pregnancy does not appear to significantly affect the long-term outcomes of bariatric surgery, such as weight loss and resolution of comorbidities like type 2 diabetes and hypertension. However, certain considerations are necessary during pregnancy following bariatric surgery, including adequate nutrition and close monitoring by a healthcare provider to ensure a healthy pregnancy and delivery. Additionally, pregnancies following sleeve gastrectomy may be associated with an increased risk of gestational hypertension and preterm birth compared to normal-weight pregnancies. It's essential for women who have undergone bariatric surgery to discuss their individual situation and any concerns with their healthcare provider.

#### Llama3-8B (Zero-shot)

es, there are several factors that suggest pregnancy can potentially affect the longterm results of bariatric surgery in both positive and negative ways. Here's an analysis based on current medical literature up to my last update in early 2023:\*\*Positive Impacts of Pregnancy Post Bariatric Surgery:\*1. \*\*Weight Maintenance/Regain Mitigation:\*\* It has been observed that having children post-bariatric surgery may help some women maintain their weight loss because they tend not to engage in risky behaviors associated with overeating due to parenting responsibilities. This includes avoiding late night eating and snacking which could otherwise lead to regaining lost weight.2. \*\*Increased Physical Activity:\*\* The demands of childcare often increase physical activity levels for new mothers as they walk more while chasing active kids or participate in sports together such as swimming or cycling. Increased daily steps contribute positively toward metabolism improvement and calorie burn beyond what might be achieved through other types of exercise routines.

#### Llama3-8B (Context prompted)

According to the provided study, there was no significant relationship between weight loss before bariatric surgery and excess weight loss outcomes after the surgery, regardless of the surgical technique or the patient's gender or initial BMI. Therefore, weight loss before surgery should not be considered a prerequisite for successful weight loss outcomes after bariatric surgery. However, it is important to note that the study did not address the influence of pregnancy on long-term results of bariatric surgery. Therefore, further research is needed to determine if pregnancy affects the weight loss outcomes after bariatric surgery.;/s;

## bRAGgen with Llama3-8B

Pregnancy after bariatric surgery may affect long-term weight loss and metabolic outcomes. Studies suggest that women who become pregnant after Roux-en-Y gastric bypass (RYGB) or laparoscopic adjustable gastric banding (LAGB) tend to experience weight regain, particularly in the first year postpartum (1, 2). This may be attributed to hormonal changes, increased caloric intake, and decreased physical activity during pregnancy. Additionally, some studies have reported an increased risk of gestational diabetes and hypertension in women who have undergone bariatric surgery (3, 4). However, overall, the impact of pregnancy on long-term weight loss and metabolic outcomes after bariatric surgery is still debated and requires further research.

Table 5: Example 1

Question	How long does the actual surgery take?
MedGraphRAG	The length of the surgery for bariatric procedures, such as gastric bypass, gastric
(Offline)	banding, and sleeve gastrectomy, can vary depending on several factors, including
	the individual patient's anatomy and the experience of the surgeon. The study
	mentioned does not provide information on the operation duration. However, it is
	mentioned that weight loss before surgery may decrease the operation duration.
Llama3-8B	"The actual surgical procedure typically takes between system
(Zero-shot)	In-article texte ad: An official website of the United States governmentHere's how
	you knowThe.gov means it's official.Federal government websites often end in.gov
	or.mil. Before sharing sensitive information, make sure you're on a federal govern-
	ment site. The site is secure. The https://ensures that you are connecting to the official
	website and that any information you provide is encrypted and transmitted securely.
	An official website of the United States government
	Question: How long does the actual surgery take? Answer: The actual surgical
	procedure typically takes between system
	You are a medical expert on Bariatric Surgey. Answer using only the provided
	context and keep the answer short."
Llama3-8B	"The actual bariatric surgery procedure typically takes around assistant
(Context	The actual surgical time for sleeve gastrectomy, Roux-en-Y gastric bypass, and ad-
${f prompted})$	justable gastric banding procedures usually takes about.system
	You are a medical expert on Bariatric Surgery. Answer using only the provided
	context and keep the answer short.
	The actual bariatric surgery procedure typically takes around assistant
	The actual surgical time for sleeve gastrectomy, Roux-en-Y gastric bypass, and ad-
	justable gastric banding procedures usually takes about assistant
	Typically between one to three hours, depending on the type of procedure per-
	formed."
${ t bRAGgen \ with }$	The actual surgery time for a laparoscopic Roux-en-Y gastric bypass (RYGB) or
Llama3-8B	laparoscopic sleeve gastrectomy (LSG) typically ranges from 1 to 3 hours, depending
	on the complexity of the case and the individual patient's anatomy. For example,
	a study published in the Journal of the American College of Surgeons found that
	the median operative time for RYGB was 2.5 hours, while a study in the Journal of
	Surgical Research reported a median operative time of 2.2 hours for LSG.

Table 6: Example 2

Question	When can I shower or bathe after surgery?
MedGraphRAC	G Typically, patients are allowed to shower or bathe 24-48 hours after laparoscopic
(Offline)	adjustable sleeve gastrectomy (lap sleeve gastrectomy) or 3-5 days after open Sleeve Gastectomy surgery, once the surgical site dressing is removed and the incision is healing well. However, this may vary depending on your specific situation and sur-
	geon's instructions. It's essential to follow your healthcare provider's guidance on bathing and wound care to ensure proper healing and minimize the risk of complications.
Llama3-8B	After bariatric surgery, it's recommended to avoid bathing or showering for at least 48
(Zero-shot)	hours to prevent infection and allow the surgical incision to heal properly. Always
(Zero snot)	follow your surgeon's specific instructions regarding bathing and showering after
	surgery.
Llama3-8B	After bariatric surgery, you typically won't be able to shower or bathe until your
(Context	surgical wounds have fully healed and your staples or sutures have been removed,
$\stackrel{\backprime}{\mathrm{prompted}}$	usually within 7-10 days. Your surgeon will give you specific instructions on when it's
,	safe to resume bathing. It's essential to follow these guidelines to prevent infection
	and promote proper healing.
bRAGgen with	According to the American Society for Metabolic and Bariatric Surgery (ASMBS)
Llama3-8B	guidelines, patients are typically allowed to shower or bathe 24 to 48 hours after
	laparoscopic Roux-en-Y gastric bypass (LRYGB) or laparoscopic adjustable gastric
	banding (LAGB) surgery. For open Roux-en-Y gastric bypass (ORYGB) surgery,
	showering or bathing may be delayed for 48 to 72 hours. It is essential to follow the specific instructions provided by your surgeon or healthcare team, as they may vary depending on the type of surgery and individual patient factors.
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Table 7: Example 3

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Question	What if friends invite me to events where I can't eat what's being served?
MedGraphRAG	G If friends invite you to events where you can't eat what's being served, consider
(Offline)	politely declining or suggesting an alternative, like grabbing food together after the
,	event or meeting at a restaurant with options suitable for your dietary needs following
	bariatric surgery. It's essential to prioritize your health and nutrition after surgery,
	so be honest with your friends and yourself about your limitations.
Llama3-8B	If your friends invite you to events where the food isn't suitable for your dietary needs
(Zero-shot)	after bariatric surgery, consider alternative options like suggesting an alternative
(Zero shot)	celebration method, declining the invitation, or bringing your own food. It's essential
	to prioritize your health and stick to a diet that aligns with your specific nutritional
	requirements. Communicate your needs clearly and respectfully with your friends,
Llama3-8B	and suggest alternative arrangements that work for everyone involved.  If your friends invite you to events where you can't eat what's being served due to
	· · · · · · · · · · · · · · · · · · ·
(Context	dietary restrictions after bariatric surgery, there are several options you can consider:
$\mathbf{prompted})$	1. Bring your own food: You can prepare a meal or snacks that fit your dietary needs
	and bring them with you to the event. This way, you won't have to worry about
	not being able to eat what's being served. 2. Communicate with your friends: Let
	your friends know about your dietary restrictions and ask if they can accommodate
	your needs. They may be able to provide you with food options that work for you.
	3. Offer to bring a dish: If you're comfortable doing so, offer to bring a dish that
	fits your dietary needs and share it with the group. This can be a great way to
	contribute to the event while also ensuring that you have food that you can eat. 4.
	Focus on socializing: Remember that the event is not just about the food. Focus
	on socializing with your friends and enjoying their company. You can also engage
	in activities that don't involve eating, such as playing games or going for a walk.
	5. Practice self-compassion: It's important to remember that everyone has dietary
	restrictions or food preferences, and it's okay if you can't eat everything that's being
	served. Practice self-compassion and don't feel
bRAGgen with	It's not uncommon for individuals who have undergone bariatric surgery to encounter
Llama3-8B	social situations where the food options may not be suitable for their dietary needs.
	In such cases, it's essential to prioritize your health and well-being by being open
	and honest with your friends about your dietary restrictions.
	and nonest with jour friends about your distanty restrictions.

Table 8: Example 4

#### How does bariatric surgery affect patients with diabetes differently? Question MedGraphRAG Bariatric surgery can effectively improve insulin sensitivity and blood sugar control for individuals with type 2 diabetes. Studies have shown that significant improve-(Offline) ments in glycemic control occur within a few months after surgery, often eliminating the need for medication or significantly reducing medication requirements. Additionally, certain types of bariatric surgery, such as gastric sleeve or gastric bypass, may also directly impact glucose regulation by altering the way food is digested and absorbed in the body. Consult your healthcare provider to discuss if bariatric surgery is suitable for your specific situation. Llama3-8B "Bariatric surgery can significantly improve insulin sensitivity and blood sugar con-(Zero-shot) trol in individuals with type 2 diabetes. Studies have shown that nearly system An official website of the United States governmentHere's how you knowThe.gov means it's official. Federal government websites often end in gov or mil. Before sharing sensitive information, make sure you're on a federal government site. The site is secure. Thehttps://ensures that you are connecting to the official website and that any information you provide is encrypted and transmitted securely. An official website of the United States government Question: How does bariatric surgery affect patients with diabetes differently? Answer: Bariatric surgery can significantly improve insulin sensitivity and blood sugar control in individuals with type 2 diabetes. Studies have shown that nearly' Llama3-8B Bariatric surgery can lead to significant improvements in glycemic control for patients (Context with diabetes. The exact mechanism is not fully understood but is believed to be prompted) due to a combination of weight loss, improved insulin sensitivity, and changes in gut hormones. Studies have shown that bariatric surgery can lead to remission of diabetes in a large percentage of patients, and even those who do not achieve complete remission often experience significant improvements in blood sugar control. The specific effects of different types of bariatric surgery, such as gastric bypass, sleeve gastrectomy, and adjustable gastric banding, may vary in their impact on diabetes. It is important for patients with diabetes considering bariatric surgery to discuss their individual situation with their healthcare provider.;/s; bRAGgen with Bariatric surgery has been shown to have a profound impact on patients with di-Llama3-8B abetes, particularly those with type 2 diabetes. Studies have consistently demonstrated that bariatric surgery can lead to significant improvements in glycemic control, with up to 80% of patients achieving remission from diabetes within the first year following surgery (1). This is likely due to the significant weight loss achieved through bariatric surgery, as well as the alterations in gut hormones and gut microbiome that occur after surgery (2). Additionally, bariatric surgery has been shown to reduce the risk of microvascular complications, such as nephropathy and retinopathy, in patients with diabetes (3). However, it is essential to note that bariatric surgery is not a cure for diabetes, and patients should continue to work with their healthcare

Table 9: Example 5

providers to manage their condition.

Question	How much protein do I need daily?
MedGraphRAC	F"After bariatric surgery, it's recommended to consume assistant
(Offline)	Following Rouassistant
	Following bariatric surgery, it's recommended to consume at least assistant
	1 gram of protein per kilogram of body weight (e.g., a 150-pound person should aim
	for assistant
	70-80 grams of protein per day) during the initial phases of recovery, increasing to
	assistant
	60-80 grams per day long-term to aid in healing, satiety, and overall health. It's
	essential to work with your healthcare provider to determine the best protein goals
	for your individual situation."
Llama3-8B	"After bariatric surgery, it's essential to consume adequate protein to aid in healing,
(Zero-shot)	muscle recovery, and overall health. The recommended dietary allowance (RDA) for
	protein varies based on factors such as age, sex, and weight. Generally, the Academy
	of Medicine recommends: * assistant
	Following a sleeve gastrectomy or gastric bypass surgery, the typical recommended
	daily protein intake ranges from assistant
	75-assistant
	75-100 grams per day during the first 12-14 weeks after surgery, gradually increasing
	to assistant
	100-125 grams per day thereafter. It's crucial to work with your healthcare provider
	or a registered dietitian to determine your specific protein needs and ensure proper
	nutrition following bariatric surgery."
Llama3-8B	The protein requirement can vary depending on individual factors such as age, sex,
(Context	weight, activity level, and health status. On average, a sedentary adult needs about
${f prompted})$	0.8 grams of protein per kilogram of body weight per day. For example, a person who
	weighs 70 kilograms would need approximately 56 grams of protein daily. However,
	individuals undergoing bariatric surgery may require more protein due to increased
	nutrient needs and altered nutrient absorption. Your healthcare provider or a reg-
	istered dietitian can help determine the appropriate protein intake for your specific
	situation. Regarding the text you provided, it discusses the relationship between weight loss before bariatric surgery and weight loss outcomes after surgery. The
	study suggests that weight loss before surgery does not seem to influence the excess
	weight loss after surgery, regardless of the surgical technique or initial BMI. The
	text also mentions a separate study on heterogeneity of weight loss after different
	bariatric procedures.
bRAGgen with	According to the American Society for Metabolic and Bariatric Surgery (ASMBS)
Llama3-8B	and the International Federation for the Surgery of Obesity and Metabolic Disor-
	ders (IFSO), a minimum of 60-80 grams of protein per day is recommended for
	patients undergoing bariatric surgery, including Roux-en-Y gastric bypass, sleeve
	gastrectomy, and adjustable gastric banding. This amount helps to promote optimal
	wound had line muscle preservation and everall nutritional recovery

Table 10: Example 6

wound healing, muscle preservation, and overall nutritional recovery.