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Review

Machine Learning and Large Language Models in Preoperative Bariatric Surgery: From Risk Assessment to Shared Decision-Making

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Abstract: Recent increases in overweight and obesity have established Metabolic–Bariatric Surgery (MBS) as a principal intervention for durable weight reduction and metabolic improvement. Given the elevated perioperative complication risk among patients with obesity, there is a growing imperative to enhance the precision of preoperative management. This review synthesizes evidence from 2020–2025 on the application of artificial intelligence (AI) to bariatric surgery preoperative assessment, focusing on machine learning (ML), deep learning (DL), and large language models (LLMs). We summarize AI applications across three domains: preoperative risk prediction and individual assessment, patient stratification and procedure selection, and preoperative education and surgical training. The evidence suggests that integrating AI into routine preoperative workflows enables individualized, quantitative estimation of high-risk complications and weight-loss prognosis, thereby optimizing risk management; it can also support patient stratification and procedure matching to facilitate patient-centered shared decision-making; and NLP- and vision-based tools promote standardization and visualization of knowledge for patients and surgeons. Overall, AI is driving preoperative assessment toward greater individualization, interpretability, and multidisciplinary coordination, but its clinical generalizability requires validation in multicenter, prospective studies.

Keywords: Bariatric Surgery; Obesity; Artificial Intelligence; Preoperative Period

1. Introduction

Overweight and obesity have become a global public health challenge. Epidemiological forecasts indicate a gradual shift worldwide from overweight predominance to obesity predominance. Without effective interventions, by 2050 more than half of adults and roughly one third of children and adolescents will be living with overweight or obesity [1]. Beyond lifestyle modification and comprehensive medical management, bariatric surgery has been demonstrated to be the most effective and most durable strategy for reducing excess weight and ameliorating associated metabolic derangements in individuals with severe obesity [2,3]. Multiple studies further show that, following surgery, the risks of type 2 diabetes, malignant neoplasms, major adverse cardiovascular events, and mental health disorders decline significantly, indicating that bariatric surgery confers broad and sustained clinical benefits that extend beyond weight control [4–6].

Patients with obesity bear greater perioperative risk than the general population, with typical concerns including obstructive sleep apnea (OSA), difficult airway and ventilation management [7,8]. Accordingly, perioperative management in MBS remains an area of ongoing refinement, within which standardized and comprehensive preoperative assessment is pivotal [9]. In addition to routine anesthetic evaluation (e.g.

ASA Physical Status), dedicated respiratory screening is important: the STOP-Bang questionnaire is widely used for rapid OSA triage because of its high sensitivity and utility in selecting patients for polysomnography [10]. For overall mortality risk, the Obesity Surgery Mortality Risk Score (OS-MRS)—based on BMI, sex, hypertension, prior venous thromboembolism, and age—was developed in RYGB-dominant cohorts to predict short-term mortality [11]. However, recent validation studies highlight key limitations: STOP-Bang has low specificity in bariatric candidates, producing many false positives, while OS-MRS shows limited transportability and poorer discrimination for contemporary procedure mixes (notably sleeve gastrectomy) and for non-mortality endpoints [12,13]. Together, these tools are useful for population-level screening but lack the granularity and adaptability required for individualized preoperative prediction, underscoring the need for AI-driven, patient-specific models with robust external validation.

Given these limitations, there is an urgent need for more accurate and individualized preoperative assessment. Accumulating evidence indicates that artificial intelligence (AI) shows substantial promise in surgical preoperative evaluation [14,15]. As an overarching concept, AI aims to endow machines with capabilities for perception, reasoning, and decision-making. Within AI, machine learning (ML) learns mappings from data to enable prediction and decision support and has become a core technological pillar of modern AI [16]. Deep learning (DL), a subset of ML, employs multilayer neural networks to perform more complex representation learning. In bariatric surgery, ML is the most commonly applied branch of AI, providing reliable modeling techniques for preoperative risk assessment and procedure selection. Natural language processing (NLP) is an AI discipline concerned with enabling computers to handle human language, including its comprehension and generation in spoken or written form. Large language models (LLMs) are NLP-driven architectures that acquire linguistic structure and meaning through training on extensive textual datasets. Meanwhile, NLP and LLMs undertake evidence synthesis and interactive reasoning, and used in concert, these approaches enhance prediction and decision-making in the preoperative setting for patients undergoing bariatric surgery [17].

In summary, incorporating machine learning and large language models into preoperative management for bariatric candidates can generate synergistic benefits across multiple domains. For individual assessment, AI generates patient-specific risk estimates for high-risk outcomes based on standard history, physical examination, and nutritional and anesthetic evaluations. These estimates enable more precise preoperative stratification and prediction. For procedure selection, trained LLMs can perform evidence synthesis to support patient-center shared decision-making. For patient education, LLMs serve as knowledge carriers for counseling and informed consent, and on the surgeon-facing facilitate protocol comparison and automated annotation, as well as simulation-based training and step recognition for surgical procedures.

2. Artificial Intelligence in Preoperative Individual Assessment for bariatric surgery

Before entering the operative pathway, a systematic and standardized preoperative assessment is essential to ensure patient safety and improve surgical success. Routine evaluations typically include medical history taking, physical examination, basic laboratory testing, nutritional screening, and anesthetic assessment [18]. These procedures help identify potential high-risk factors and provide an evidence-based foundation for perioperative management. However, given the considerable heterogeneity among individuals with obesity, reliance solely on routine assessments may fail to capture all clinically relevant risks. Therefore, in clinical practice, additional individualized or selective evaluations should be incorporated for specific patient populations or those presenting with particular comorbidities and symptoms.

2.1. Routine Risk Assessment

Routine preoperative risk assessment constitutes a fundamental prerequisite for the safe implementation of bariatric surgery. Patients with obesity frequently present with multisystem comorbidities, such as respiratory, cardiovascular, and metabolic disorders; therefore, careful preoperative evaluation is essential. This process involves comprehensive assessment through medical history taking, physical examination, laboratory testing, and multidisciplinary consultation. Such an integrated approach allows clinicians to obtain a thorough understanding of the patient's overall condition and to ensure that surgery is performed under safe and well-controlled circumstances.

2.1.1. Airway Assessment

Airway assessment plays a pivotal role in the routine preoperative evaluation of bariatric surgery. In patients with obesity, accumulation of adipose tissue in the neck, tongue, and pharyngeal structures often results in upper airway narrowing and reduced ventilation, leading to an increased risk of difficult mask ventilation and tracheal intubation [19,20]. Predictors of difficult intubation include age, Mallampati airway classification, thyromental distance, and male sex. Studies have shown that severely obese male patients, especially those with a body mass index (BMI) > 50 kg/m², are more likely to experience difficult intubation [21,22]. Although these traditional indicators are commonly used clinically to predict difficult intubation, their sensitivity and specificity remain limited.

Recently, AI has shown promising applications in this field. Zhou et al. developed multiple machine-learning models based on multidimensional features including BMI, neck circumference, Mallampati grade, and neck mobility, and compared six commonly used algorithms. The XGBoost model achieved the highest predictive accuracy (>80%), outperforming any single clinical variable [23]. In addition, machine-learning and deep-learning techniques have been applied to broader aspects of airway management [24,25]. Sezari et al. compared several algorithms such as decision tree, gradient boosting machine (GBM), XGBoost, and support vector machine (SVM), and demonstrated that the K-nearest neighbor (KNN) model significantly improved prediction accuracy and clinical airway control [26]. These AI-based approaches enhance the objectivity of preoperative risk assessment and provide anesthesiologists with quantitative decision support, allowing preparation of alternative airway management strategies and reducing the likelihood of failed intubation or severe hypoxemia.

2.1.2. Obstructive Sleep Apnea (OSA)

Obstructive sleep apnea (OSA) is highly prevalent among individuals with obesity, and previous studies have reported that the incidence among bariatric surgery candidates may exceed 60% [27]. OSA is strongly associated with nocturnal hypoxemia, cardiovascular events, and metabolic dysfunction, and it significantly increases the risk of difficult mask ventilation, tracheal intubation, perioperative hypoxia, and respiratory complications. Therefore, international guidelines emphasize that OSA should be a key component of the preoperative evaluation in bariatric patients [28,29]. Common screening tools include the STOP-Bang questionnaire, which provides high sensitivity for identifying high-risk individuals, whereas polysomnography (PSG) remains the diagnostic gold standard. Recently, AI has introduced novel approaches to OSA screening and diagnosis. For example, integrating traditional screening questionnaires such as STOP-Bang with machine-learning algorithms has been shown to improve sensitivity and specificity, thereby reducing false-negative and false-positive results and enhancing efficiency in preoperative triage and risk stratification [30]. In addition, deep-learning models trained on large-scale PSG datasets can accurately estimate the apnea–hypopnea index (AHI) using only single-channel pulse oximetry, achieving diagnostic performance comparable to full PSG studies. This low-cost and scalable approach enables rapid deployment in outpatient or home settings, offering a practical alternative for preoperative evaluation when PSG resources are limited [31].

2.1.3. Upper Gastrointestinal Endoscopy

Whether esophagogastroduodenoscopy (EGD) ought to be used as a routine component of preoperative assessment in bariatric surgery candidates remains debated, especially for individuals who are asymptomatic and lack GERD, dyspepsia, or other gastrointestinal symptoms [32,33]. Despite divergent guideline recommendations, multiple studies indicate that preoperative endoscopy has substantial value in detecting occult lesions [34,35]. Even among obese patients without overt gastrointestinal symptoms, EGD frequently identifies chronic gastritis, reflux esophagitis, and hiatal hernia, findings that may directly influence procedure selection or necessitate preoperative intervention. Recent reviews have also summarized advances in AI for endoscopy. As highlighted by Chadebecq et al., major application domains include: endoscopic mapping and navigation, which reconstructs three-dimensional anatomy from video to enable intraoperative localization; anatomical structure recognition, providing real-time labeling of key regions and pathology; and surgical instrument detection and tracking, which automatically identifies, localizes, and follows instruments in endoscopic video to support workflow, reduce misuse, and enhance procedural safety [36].

2.2. Personalized Evaluations

Beyond routine assessment, a subset of patients should undergo individualized, conditionally indicated testing based on symptoms or risk factors—such as abdominal ultrasonography, deep-vein thrombosis (DVT) risk assessment, or hiatal hernia screening. In recent years, AI has been incorporated into this process to help identify patients who truly require additional testing, thereby avoiding over-screening and enabling precise risk stratification. Hany et al. analyzed preoperative records from 4,418 bariatric surgery candidates to assess the clinical utility of abdominal ultrasonography and to develop a machine-learning model to identify patients most likely to benefit. They reported that 1.5% of patients required postponement or cancellation based on sonographic findings, while 15.9% had gallbladder disease requiring treatment. The model achieved an AUC of 0.976, indicating excellent discriminative performance for selecting high-risk candidates for ultrasonography [37]. Assaf et al. reported that the conventional barium swallow has a sensitivity of approximately 38% for detecting hiatal hernia before bariatric surgery, implying a substantial risk of missed diagnoses. After incorporating machine-learning models, sensitivity increased to 60%, outperforming a single imaging modality. By integrating clinical and test features, the model more accurately identifies occult hiatal hernia, thereby informing procedure selection and perioperative risk management [38]. Regarding postoperative complications, investigators analyzing the bariatric surgery AQIP database developed models for gastrointestinal leak and venous thromboembolism, with AUC > 0.80 on external validation, surpassing traditional risk scores and supporting targeted perioperative interventions [39]. Using the bariatric surgery AQIP database, investigators developed models to predict major adverse cardiac events (MACE) after bariatric surgery. Although the incidence of MACE was only about 0.1%, logistic regression, neural networks, and XGBoost all demonstrated good discrimination (AUC ≈ 0.79–0.80), with neural networks providing superior risk stratification. These findings indicate that machine-learning approaches can leverage preoperative clinical and comorbidity data to more precisely identify cardiovascular high-risk patients and thereby enhance overall procedural safety [40].

3. AI for Preoperative Patient Stratification and Procedure Selection

In the preoperative phase of bariatric surgery, accurately identifying candidates and matching them to the most appropriate procedure is critical for perioperative safety and long-term outcomes. Traditionally, this process has relied on clinicians' synthesis of history, comorbidities, and imaging, yet variability in clinical judgment and limitations of the evidence base leave substantial uncertainty in individualized decision-making. The recent rise of machine learning and large language models offers new technical pathways for preoperative patient stratification and procedure selection.

3.1. Patient stratification

In terms of patient stratification, several studies have attempted to use machine learning for early identification of postoperative weight-loss response. In sleeve gastrectomy (SG) cohorts, investigators developed a multimodal, explainable Wide-and-Deep learning (WAD) model that integrates preoperative CT imaging with electronic medical record (EMR) variables to predict 1-year weight-loss level (%TWL, the percentage of initial body weight lost after surgery) and classify patients into different strata. Trained on a single-center, small sample, the model achieved good classification accuracy and, via saliency visualization and feature-importance analysis, highlighted key imaging regions and variable contributions, providing important reference for preoperative stratification and expectation management. However, its limited sample size and lack of external validation warrant multicenter confirmation before broader adoption [41]. In a single-procedure RYGB cohort (n=118), a machine-learning model built on preoperative clinical and metabolic variables predicted 1-year weight-loss outcomes. In the validation set, the model showed moderate discriminative ability (AUC 0.68); it identified insufficient weight loss (%TWL < 30%) with 71.4% accuracy, but misclassified a higher proportion of favorable responders (%TWL ≥ 30%). The sample size was limited and no external validation was performed [42]. SOPHIA, using interpretable machine learning with seven preoperative variables (height, weight, age, diabetes status and duration, smoking status, and the intended procedure), was trained and externally validated on multicenter adult cohorts (covering SG/RYGB/gastric band) to predict 5-year postoperative weight trajectories, and is available as an online calculator. In clinic, it enables comparative visualization of expected weight-loss curves across procedures to support candidate stratification and expectation management, thereby facilitating shared decision-making; it does not perform causal procedure prioritization or prescriptive recommendations [43]. Overall, these studies indicate that machine learning can help identify potential low responders preoperatively, thereby assisting screening and stratification of bariatric surgery candidates.

3.2. Selection of Surgical Technique

After preoperative patient stratification, the clinical focus shifts to matching each subgroup to the most appropriate procedure in bariatric surgery. Procedure choice directly affects the magnitude of weight loss, metabolic improvement, and long-term complications [44,45]. At present, procedure selection in bariatric surgery remains notably subjective, with patient and institutional preferences shaping final decisions [46,47]. Consequently, there is an urgent need for shared decision-making and quantitative predictive tools. Large language models, by integrating guidelines and evidence with explainable outputs, are emerging as a means to reduce subjectivity and improve procedure–patient matching.

Converging evidence shows that LLMs exhibit only modest agreement with expert decision-making and, at present, do not meet the threshold for replacing clinician judgment. It directly compared ChatGPT-4 with international, multicenter experts on both operability and procedure selection. Concordance was limited and within-model stability was poor, with disagreements particularly pronounced in complex scenarios such as gastric intestinal metaplasia and gastric cancer [48]. These findings raise additional challenges for using LLMs in procedure choice. To address these concerns, Lopez-Gonzalez and colleagues conducted a single-center, retrospective real-world cohort study. ChatGPT-4 was supplied with preoperative demographic and comorbidity data to generate a procedure recommendation for each case. Recommendations were compared case-by-case with the institution's standardized selection pathway and the operation actually performed. Although the model tended to recommend RYGB, overall concordance with the final procedure was 34.16%, and correlation with the institutional algorithm was not significant. Divergence was greater in cases with complex upper gastrointestinal disease (e.g., gastric intestinal metaplasia or gastric cancer) [49]. Building on this, the Moisès Broggi University Hospital team implemented a within-case pre–post evaluation: the model first generated procedure recommendations for real cases before exposure to evidence, then was primed with the institutional algorithm and guideline-based literature and retested; outputs from both phases were compared case by case with the actual clinical decisions. After training, the recommendation profile shifted (e.g., RYGB increased from 26.8% to 30.3%; SG decreased from 56.8% to 35.7%). However, agreement with the final clinical procedure rose only from 20.0% to 25.8%, remaining low and well below any threshold for substituting expert- and pathway-based decision-making [50].

In aggregate, these three studies indicate that ChatGPT-4 is not a substitute for expert decision-making and should be used only as an adjunct. Its appropriate role is patient education and shared decision support within expert-led, guideline-based frameworks rather than independent decision-making. Future work should focus on richer MBS-specific data and prospective evaluations to validate and optimize its use.

4. Applications of AI in Preoperative Education and Knowledge Support

With the rapid diffusion of generative artificial intelligence, clinical workflows increasingly incorporate tools that can produce new content such as text, images, and audio. Large language models (LLMs) are a prominent class of generative AI that are trained on massive text corpora to generate and interpret natural language. LLMs therefore often serve as the engine for patient-facing chatbots, automated summaries, and clinician decision aids. Consequently, preoperative education is shifting from experience-based counseling to an intelligent paradigm that links outputs to evidence with explicit source attribution and provenance. Figure 1 organizes key application scenarios of AI along two axes—patient-facing and surgeons-facing—and maps where they act across the preoperative pathway.

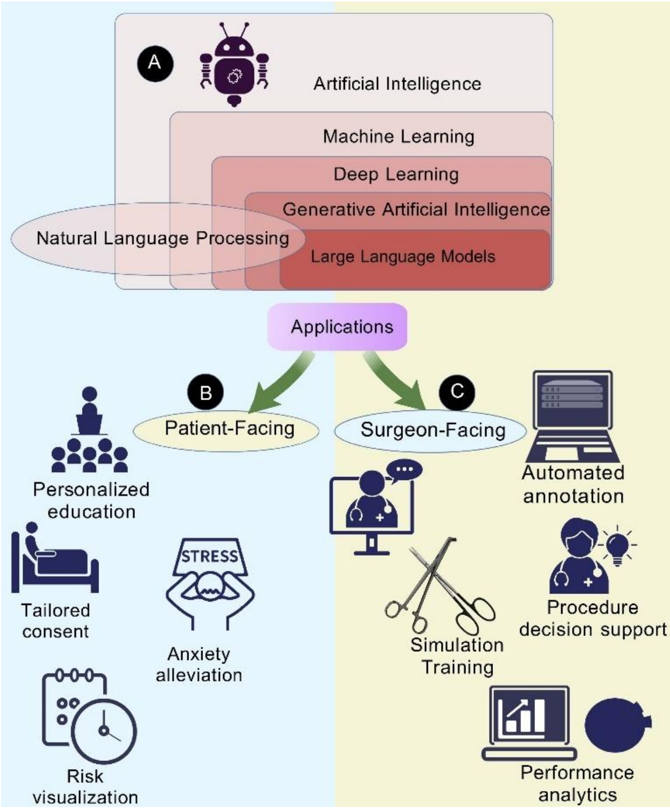

Figure 1. Key Patient-Facing and Surgeon-Facing applications of artificial intelligence in the preoperative pathway for metabolic–bariatric surgery. A: Relationship between artificial intelligence, machine learning, deep learning, natural language processing, generative AI, and large language models; B: Patient-Facing tools emphasize personalized education, tailored consent, anxiety alleviation, and risk visualization; C: Surgeon-Facing tools focus on automated annotation, simulation training, procedure decision support, and performance analytics.

4.1. Value of Patient-Facing Preoperative Education

With the rapid spread of generative AI, an increasing number of patients consult intelligent tools before clinic visits and form preliminary judgments. This trend further underscores the need for standardized and verifiable preoperative education. As a pivotal link between risk assessment and shared decision-making, structured preoperative education has been shown to reduce anxiety, improve adherence, facilitate fully informed consent, and enhance perioperative outcomes [51,52]. Accordingly, embedding clinically validated AI into preoperative education workflows can translate guideline-based evidence and individual patient data into readable, patient-facing information, thereby lowering health-literacy barriers and calibrating expectations.

Using a blinded dual-review, researchers compared ChatGPT-4's responses to a high-frequency bariatric Q&A against authoritative guidelines, finding overall concordance on indications, complications, and perioperative pathways but noting delayed updates and imprecise wording in complex areas such as regional eligibility thresholds and management of concurrent upper-GI pathology (e.g., intestinal metaplasia, gastric neoplasia) [53]. A separate comparative study employed standardized case vignettes and scoring rubrics to assess three LLMs (ChatGPT-4, Bing, Bard) against major guidelines, covering accuracy, completeness, internal consistency, and potentially harmful recommendations. ChatGPT-4 demonstrated superior overall accuracy and consistency and more comprehensively covered indications, procedure selection, and perioperative management [54].

Overall, LLMs can serve as a powerful adjunct to patient-facing preoperative education by improving information accessibility and comprehensibility, but their factual accuracy and timeliness should be verified by clinical professionals to ensure safe and reliable guidance.

4.2. Surgeon-Facing Skills Training

In surgical skills training, the core value of AI lies in converting clinical experience into quantifiable, reproducible training workflows. Models built on operative video and kinematic data enable objective scoring and deliver real-time or delayed individualized feedback, thereby shortening learning curves and reducing dependence on instructor time [55,56]. Leveraging simulation and remote platforms, AI can also standardize curricula and improve training accessibility [57]. Substantive advances have been reported in bariatric surgery. One study enrolled trainees who had completed at least 50 hours of basic and advanced laparoscopic simulation and practiced key tasks such as hand-sewn gastrojejunostomy (GJ) and stapled jejunojejunostomy (JJO), with pre- to post-training performance evaluated using the Global Rating Scale (GRS), the Specific Rating Scale (SRS), and operative time. Technical scores improved significantly and procedure time decreased, indicating that the program effectively enhanced GJ and JJO skills in a simulated setting [58]. A single-center study further embedded AI computer vision into intraoperative sleeve gastrectomy videos, using standardized safety milestones (e.g., bougie insertion, distance from the pylorus, parallel to the lesser curvature, fundus mobilization) for step recognition and automatic annotation, which were compared against surgeon judgments. With the exception of "≥1 cm from the esophagus," most milestones showed high agreement with experts, enabling objective, quantifiable evidence for postoperative debriefing to locate deviations and reinforce critical views, thereby supporting education and quality improvement [59]. In addition, an AI model that automatically labels Roux-en-Y gastric bypass steps achieved accuracy comparable to trained surgeon annotators for most key steps. It even outperformed them on certain anatomic landmarks. These findings indicate that AI can scale and objectify surgical workflow quantification, enabling learning-curve assessment and training-effect monitoring, and providing a data foundation for education and quality improvement [60].

5. Future Perspective

The multifaceted value of AI in preoperative management for bariatric surgery is increasingly evident. First, in individualized risk stratification, machine learning can build multi-parameter models on top of routine assessments by incorporating personalized investigations such as abdominal ultrasound, cardiopulmonary function testing, and comorbidity profiling, thereby enabling proactive stratification of short-term complications and resource needs. Second, for procedure selection and shared decision-making, although large language models (LLMs) are not yet a substitute for expert judgment, they provide support for evidence synthesis and option comparison, improving the efficiency and transparency of clinician–patient communication. Third, in education and capacity building, computer vision can automatically annotate key surgical steps and generate objective metrics for training, assessment, and process improvement, while LLMs facilitate patient education and the preparation of individualized informed-consent materials. Overall, AI is steering preoperative management toward greater precision, standardization, and intelligence. The next phase should prioritize multi-center, real-world studies to verify clinical and economic benefits, and should refine integration with existing pathways alongside robust monitoring and governance mechanisms.

Despite progress in AI-assisted preoperative assessment and procedure selection for bariatric surgery, key gaps remain, notably a weak evidence chain and divergent guidelines. First, for OSA and preoperative mental-health screening, our current search and evidence synthesis found no prospective or purpose-designed AI/ML studies in which bariatric surgery candidates are the primary population; most existing models derive from general-surgery or sleep-clinic cohorts, with insufficient evidence on external transportability and workflow fit for bariatric patients. Second, positions differ on whether preoperative EGD should be routine: the EAES stance has shifted from "routine screening" to a "conditional recommendation." EAES initially (2005) incorporated UGI or EGD into the standard preoperative pathway—i.e., all patients undergo an upper-GI series or endoscopy [61]. By the 2020 update, considering additional observational studies and meta-analyses and their associated risks of bias and inconsistency, the panel issued a conditional recommendation favoring selective endoscopy for patients with upper-abdominal symptoms [33]. In North America, individualization has been the through-line: the AACE/TOS/ASMBS perioperative guideline (2019 update) treats endoscopy as context-dependent and does not endorse blanket routine use in asymptomatic patients [62]. ASMBS 2021 statement adds that preoperative EGD is justifiable (actionable findings may exist even without symptoms), but whether to perform it for all should depend on institutional resources and risk–benefit considerations [63]. By contrast, Chinese guidelines consistently recommend routine preoperative EGD [64]. In sum, the optimal strategy for preoperative EGD—and the effective AI pathways for OSA/psychological screening—require multicenter, prospective, high-quality studies to be clarified.

Looking ahead, AI for preoperative assessment in bariatric surgery can advance through a three-pronged approach. First, the application of AI to structured data. Structured data are information organized and encoded under a predefined schema. In EHRs these typically include demographics, vital signs, laboratory values, procedure and diagnosis codes, and medications [65,66]. In contrast, unstructured data include free text (e.g., discharge summaries and radiology reports), medical imaging or endoscopy videos, and audio or waveforms. These are not directly searchable or analyzable in their raw form and usually require NLP or computer-vision processing before analysis and decision support [67]. Research teams have used automated EHR data ingestion and machine-learning pipelines to process preoperative and perioperative structured variables in real time, fuse multiple predictors, estimate individualized risks for several postoperative complications and mortality, and push the results into clinical workflows. This demonstrates the value of converting structured EHR data into bedside decision support [68]. Second, the focus is multimodal fusion of unstructured data, including clinical text, medical imaging, and endoscopic video. The Iacucci group combined endoscopy video with whole-slide histopathology in a clinical trial dataset to automatically assess histologic remission and treatment response in ulcerative colitis. The results showed high concordance with central reading and support the feasibility of video plus pathology fusion for standardized and automated trial reads [69]. Finally, true cross-modal fusion between structured and unstructured data is the goal. Studies already show that combining structured variables with imaging or pathology yields consistent clinical gains [70]. As early as 2022, a journal in the Nature reported the HAIM (Holistic AI in Medicine) framework. It integrates multiple modalities within a single system, including EHR tabular data, time-series signals, clinical text, and medical imaging. The study systematically showed that multimodal models outperform single-modal models, with AUROC improvements of approximately 6–33% [71]. A unified multimodal model tailored to bariatric surgery is still lacking. Multicenter studies are urgently needed, and broader contributions in this area are encouraged in the future.

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