# Digital transformation of the postoperative follow-up after bariatric surgery: evaluation and proof-of-concept

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# List of Abbreviations

AI: Artificial intelligence

AUC: Area under the curve

BMI: Body mass index

GAD-7: Generalized anxiety disorder

GP: General practitioner

HADS: Hospital anxiety and depression scale

HCP: Healthcare professional

mHealth: Mobile health

ML: Machine learning

NLP: Natural language processing

PCA: Principal component analysis

RM: Remote monitoring

RYGB: Roux-en-y gastric bypass

SADI-S: Single anastomosis duodeno-ileal bypass with sleeve

# Déclaration de non-conflit d'intérêts

Je déclare qu'aucun conflit d'intérêts n'est associé à ce travail de recherche. L'application mobile Care4Today, utilisée dans le cadre de l'étude prospective interventionnelle, a été mise à disposition à titre compassionnel par la firme Ethicon (Johnson & Johnson) exclusivement pour des fins d'évaluation clinique. Aucune compensation financière ou matérielle n'a été reçue par l'équipe de recherche ou par l'institution pour l'utilisation de cette application. L'ensemble des analyses, interprétations et conclusions présentées dans cette thèse ont été réalisées en totale autonomie et indépendance scientifique, sans aucune influence d'Ethicon, de Johnson & Johnson, ni d'aucune autre entité externe.

# Chapter 1

# 1 General Introduction

## 1.1 Background and importance of bariatric surgery

### 1.1.1 Obesity: a global epidemic

Over the past five decades, the prevalence of obesity has risen dramatically across the globe, reaching pandemic proportions. The rapid rise in obesity has made it a serious public health issue that can no longer be ignored. Today, it's not just seen as a simple risk factor for other illnesses, but as a chronic and degenerative disease in its own right, one that requires long-term care, understanding, and a comprehensive approach to treatment. Obesity contributes significantly to the global burden of non-communicable diseases (NCDs), such as type 2 diabetes, cardiovascular disease, musculoskeletal disorders, and several forms of cancer, leading to reduced life expectancy and quality of life [4].

Morbidity and mortality associated with morbid obesity are alarmingly high. According to the World Health Organization, obesity is responsible for approximately 4 million deaths per year globally, primarily due to its role in exacerbating non-communicable diseases such as cardiovascular conditions, type 2 diabetes, and certain cancers [5]. Individuals with a body mass index (BMI) over 40 kg/m$^2$ have a significantly increased risk of premature death—up to 2 to 10 times higher than individuals with a normal BMI, depending on age and comorbidities [6]. Beyond mortality, morbid obesity is also associated with considerable morbidity, including reduced mobility, obstructive sleep apnea, fatty liver disease, and psychological distress, all of which severely impair quality of life and increase the burden on healthcare systems [7]. These alarming statistics highlight the need for early intervention and multidisciplinary management strategies for those living with severe obesity. Eating well and being active are essential, but they're not always enough to achieve lasting weight loss.

### 1.1.2 Medical treatments

Recently, new anti-obesity medications (AOMs) have arrived to help overweight people lose weight more effectively [8]. The AOM treatments mimic natural hormones that regulate hunger and metabolism. For example: Liraglutide [9,10], one injection a day, helps a patient lose around 5% of their body weight; Semaglutide [9], one injection a week, can lead to weight loss of up to 11%; Tirzepatide [11], the most powerful, helps to lose up to 20% of body weight.

The AOMs represent a major advance in the treatment of obesity. Their efficacy offers new hope for sustainable weight loss and a reduction in the complications associated with morbid obesity. The AOMs are associated with cardiometabolic improvements, such as lower blood pressure, blood glucose (HbA1c), cholesterol and cardiovascular risk. They are well tolerated, although they may initially cause side effects such as nausea or constipation. With their high efficacy, new anti-obesity medications such as semaglutide and tirzepatide have rapidly become the talk of the town in several European countries, including Belgium. These treatments, initially developed for people with type 2 diabetes, have also shown impressive results in weight loss, leading to a sharp increase in [9,11].

The role of these new drugs in the years to come remains uncertain. Given the failure of long-term diets, bariatric surgery appears today the most effective and long-lasting solution for the treatment of morbid obesity, both medically and economically [12].

### 1.1.3 Overview of bariatric surgery

Bariatric surgery induces weight loss primarily through two physiological mechanisms: restriction, by reducing the stomach's capacity, and/or malabsorption, by rerouting the digestive tract to limit calorie and nutrient absorption. In addition to these mechanical effects, these procedures also provoke hormonal changes, such as increased GLP-1 secretion, that reduce appetite and enhance glucose metabolism, especially in patients with type 2 diabetes [13]. Clinical evidence shows that bariatric surgery can lead to an average excess weight loss of 50% to 75%, depending on the procedure, with type 2 diabetes remission rates reaching up to 80% in certain populations [14]. Additionally, significant improvements are observed in hypertension, dyslipidemia, and sleep apnea, contributing to reduced cardiovascular risk and improved quality of life.

However, despite its benefits, bariatric surgery carries risks. Micronutrient deficiencies, including vitamins B12 and D, iron, and calcium, are common, particularly following malabsorptive procedures like Roux-en-Y gastric bypass or biliopancreatic diversion. Studies estimate that up to 50% of patients may develop at least one nutritional deficiency postoperatively if supplementation and monitoring are inadequate [15]. Consequently, lifelong medical and nutritional follow-up is essential to monitor deficiencies, support behavioral changes, and maintain long-term outcomes.

Several types of bariatric surgery exist, each offering specific benefits, limitations, and clinical indications, as shown in Table 1. Sleeve gastrectomy (SG) [16], currently the most commonly performed procedure, consists of removing about 70 to 80% of the stomach. This technique is relatively simple, leads to rapid and significant weight loss, and decreases levels of the hunger hormone ghrelin. Nonetheless, it can result in gastric reflux and long-term weight regain. Roux-en-Y gastric bypass (RYGB)[17,18], historically considered the "gold standard", combines a significant reduction in stomach size with a partial bypass of the small intestine. While it is highly effective, it can cause dumping syndrome—an intolerance to fast sugars—and leads to more pronounced nutritional deficiencies. More recent procedures, such as the Single Anastomosis Duodeno-Ileal Bypass with Sleeve Gastrectomy (SADI-S)[19] or the Single Anastomosis Sleeve Ileal Bypass (SASI-S) [20], aim to enhance outcomes by merging restrictive and metabolic mechanisms. The SADI-S and SASI-S, as more recent surgical approaches, aim to enhance the release of satiety hormones while maintaining partial normal digestion, thus minimizing the side effects associated with severe malabsorption [21,22].

**Table 1. Summary table of bariatric surgery types.**

| Type of Surgery | How it Works | Pros | Cons |
|---|---|---|---|
| **SG** | A large part of the stomach is removed, leaving a narrow tube. | - Easy to perform<br>- Very effective at first<br>- Fewer nutrient deficiencies | - Possible acid reflux<br>- Weight regain over time<br>- Risk of leaks or narrowing |
| **RYGB** | The stomach is reduced to a small pouch, and part of the intestine is bypassed. | - Very effective long-term<br>- Quickly improves type 2 diabetes | - Risk of vitamin/mineral deficiencies<br>- Digestive issues (ulcers, hernias)<br>- Possible weight regain |
| **SADI-S** | Sleeve + intestinal rerouting to better control hunger and blood sugar. | - Strong effect on fullness and sugar levels<br>- Fewer digestive complications | - Risk of deficiencies<br>- Not enough long-term studies yet |
| **SASI-S** | Sleeve + a lighter intestinal bypass for balance. | - Helps control hunger and sugar<br>- Safer than more aggressive options | - Possible deficiencies<br>- Still under evaluation |

Bariatric surgery must be accompanied by rigorous medical follow-up, patient commitment and lasting lifestyle changes. For all types of surgery, pre-operative preparation, regular medical and nutritional monitoring, and appropriate vitamin and mineral supplementation are essential as they can lead to significant deficiencies if the patient is not properly monitored [12,23,24]. Despite this, bariatric surgery is today considered the most effective treatment option for morbid obesity, with a constant increase in the total number of procedures performed worldwide [25].

### 1.1.4 Postoperative complications (early and late)

However, bariatric surgery, like any surgical procedure, carries the risk of postoperative complications, both early (in the days or weeks following surgery) and late (months or years later). Some complications may be minor, while others may be life-threatening if not promptly managed. Among early complications, anastomotic leakage (or "leak") is one of the most feared, as it can lead to severe infection and death (with a mortality rate of up to 15%), particularly in cases of late diagnosis or management. It is more frequent after SG than RYGB, observed in 1 to 7% of SG and 0.6 to 4.4% of RYGB [26]. Other early complications include postoperative bleeding, which can occur in up to 11% of cases, and anastomotic strictures, reported in up to 19% of patients after RYGB [27]. Thromboembolic events (TEV), although relatively rare, represent the main cause of postoperative mortality associated with bariatric surgery. Overall, these complications, despite their overall low frequency, can be responsible for significant mortality [26,28,29].

Late complications vary according to the type of surgery. Late complications include gastric band migration or erosion (0.3-8%), marginal ulcers (≈5%), internal herniation (≈2.5% after RYGB) and the development or worsening of gastroesophageal reflux disease (GERD), which is particularly common after SG.[30,31]

Table 2 below summarizes the main complications reported in the literature.

**Table 2. Main postoperative complications in bariatric surgery: frequency, severity, and timing.**

| **Main Complication** | **Type of Surgery Concerned** | **Estimated Frequency** | **Clinical Severity** | **Time of Onset** |
|---|---|---|---|---|
| Anastomotic leak | SG / RYGB | 1–7% (SG)<br>0.6–4.4% (RYGB) | High | Early (≈ Post-op Day 3) |
| Stenosis / torsion / kink | SG / RYGB | 0.7–2% (SG)<br>8–19% (RYGB) | Moderate to high | Early to intermediate |
| Postoperative hemorrhage | SG / RYGB | Up to 11% | Moderate | Early (first few days) |
| Pulmonary embolism (VTE / PE) | All types | Rare | High | Early (first 3 weeks) |
| Internal hernia | RYGB | ≈ 2.5% | High | Late (months to years) |
| Marginal ulcer / perforation | RYGB | ≈ 5% (ulcers)<br>1–2% (perforation) | Moderate to high | Late |

### 1.1.5 Literature review

In literature, complication, reoperation and mortality rates vary according to the technique used. For example, Chang et al. performed a meta-analysis of 164 studies, including 37 randomized clinical trials and 127 observational studies involving over 161,000 patients, to assess the benefits and risks of the main bariatric surgery techniques.[31] Although operative mortality remains low overall, the rate of postoperative complications can be as high as 17% in some studies, underlining the importance of a rigorous assessment of the benefit-risk ratio prior to any intervention. These data come from both randomized clinical trials and observational studies, providing a comprehensive overview of the safety of different techniques [31].

Table 3 below presents a comparative summary of mortality rates, postoperative complications and reinterventions, based on data from several major publications. The figures are taken in particular from the review by Arterburn et al., which assessed the benefits and risks of modern bariatric surgery in a large adult population, [26] as well as the meta-analysis by Osland et al. comparing early postoperative complications between SG and RYGB [28].

**Table 3. Incidence of complications and mortality after bariatric surgery.**

| Outcome | Reported Range |
|---|---|
| **Mortality ≤ 30 days** | 0.08% – 0.22% |
| **Mortality > 30 days** | 0.31% – 0.35% |
| **Postoperative complications** | 10% – 17% |
| **Reoperations** | 6% – 7% |

### 1.1.6 Postoperative adherence and recovery

In the immediate period following bariatric surgery, patients enter a delicate phase of both physiological and behavioral transition. During this time, strict adherence to medical and dietary instructions plays a central role. Following recommendations, such as gradually reintroducing food, maintaining proper nutritional supplementation, and attending regular medical check-ups, is essential to prevent early postoperative complications like vomiting, nutritional deficiencies, or anastomotic leaks [15,23]. Several studies have shown that patients who comply with these instructions from the early weeks after surgery not only experience fewer complications but also achieve better long-term outcomes in terms of weight loss and metabolic improvements [32,33].

However, this level of adherence is influenced by many factors. Preoperative education, social support, and the quality of postoperative follow-up have been shown to positively impact compliance [33]. On the other hand, lack of support, psychological difficulties, or poor understanding of medical instructions can hinder patient adherence.

## 1.2 Technological innovations in surgery: AI and mHealth

### 1.2.1 AI concepts and applications in surgery

AI and the rapid development of digital technology are drastically changing healthcare, with important implications for surgical procedures. Because of its rigorous adherence requirements and complicated postoperative care, bariatric surgery, which is acknowledged as the most effective treatment for extreme obesity, offers a special chance to take advantage of recent advances in digital technology among surgical specialties.

Despite existing efforts to optimize patient recovery, emergency department visits, hospital readmissions, and postoperative complications remain substantial challenges. Emerging solutions, such as mHealth applications and predictive AI algorithms, promise substantial improvements by enhancing patient education, compliance, and timely intervention. Algorithms used in AI allow machines to carry out cognitive tasks including recognition, problem-solving, and decision-making [32, 33]. To fully utilize AI in healthcare and reach its full potential, surgeons must be knowledgeable in its fundamental subfields, which include machine learning (ML), natural language processing (NLP), artificial neural networks (ANNs), and computer vision [34].

ML allows computers to recognize patterns in order to learn and make predictions. Unlike traditional programs that require explicit instructions, ML uses either labeled data (supervised learning) or data structure (unsupervised learning) to generate predictions. Supervised learning trains algorithms to predict known outcomes, while unsupervised learning looks for hidden patterns in the data [34]. Another area of ML is reinforcement learning, where programs learn from experience to perform tasks such as driving or making medical decisions. NLP allows computers to understand and interpret human language by analyzing electronic medical records (EMRs). In surgery, NLP has been used to identify signs of complications in operative reports and clinical notes. It is also applied in EMRs to automate medical coding and improve administrative workflows [35].

ANNs are computer systems inspired by the human brain. They are used in many areas of AI. ANNs are made of layers of "neurons" that process information. As the network trains, it adjusts the connections between these neurons to learn how to recognize patterns or classify data. Deep learning networks, which have many layers, can learn more complex patterns. In healthcare, ANNs have often performed better than traditional methods for predicting patient risk [36]. Computer vision allows machines to analyze images and videos to recognize objects and scenes with accuracy close to that of humans. In medicine, it is used in areas such as virtual colonoscopy, image-guided surgery, and computer-aided diagnosis [37]. Recent research focuses on real-time analysis of surgical videos, for example, to automatically identify steps of a procedure or detect anomalies. Although this technology is still in its early stages, it has the potential to improve decision-making during surgery. The promise of AI lies in combining its subfields with other computing elements like database management and signal processing [36].

The success of AI depends on asking the right questions and using high-quality data [38]. ML can detect complex patterns, but its reliability depends on data quality. Biases or poor labeling can distort results, especially for underrepresented groups [39]. This lack of transparency can limit their use in sensitive areas such as medicine [40]. Finally, AI cannot yet interpret clinical data on its own or establish causal relationships. Medical professionals are still essential to evaluate and validate AI predictions.

AI is increasingly used to support and enhance human performance in healthcare. In the field of surgery, AI has already shown promising results—helping pathologists reduce diagnostic errors in cancer detection and identifying high-risk patients to avoid unnecessary procedures [34]. To fully benefit from these tools, surgeons must actively participate in their development, particularly by contributing to clinical data registries that ensure prediction models are based on high-quality, representative datasets. Collaboration between clinicians and data scientists is essential to design ethical, effective, and transparent AI systems. This includes ensuring data protection, clarifying responsibility in case of AI-driven errors, and informing patients about how their data are used.

### 1.2.2 Definition

Digital surgery also encompasses technologies such as surgical robotics, virtual reality, and augmented reality. These innovations are reshaping modern surgical practice by improving precision, intraoperative performance, and risk evaluation. However, the definition of "digital surgery" remains vague, which complicates the standardization of procedures, the assurance of patient safety, and the design of robust clinical trials. A Delphi consensus study [41] defined digital surgery as *"the use of technology to enhance preoperative planning, surgical performance, therapeutic support, or training, with the goal of improving patient outcomes and minimizing harm."*

AI is a core component of digital surgery due to its ability to improve decision-making, reduce errors, and increase efficiency [42,43]. Ethical integration into healthcare systems requires clear guidelines, especially concerning private partnerships and commercial data use [44,45].

AI-powered tools, particularly deep learning models using medical imaging, have transformed diagnostics but are still underused for predicting surgical outcomes. AI explored also the use of deep learning models to forecast surgical complexity and complications [46] and developed a ML model using data from over one million patients' electronic health records to predict 30-day risks of death or serious cardiovascular events [47]. This model showed higher accuracy than traditional tools such as the NSQIP risk calculator, thanks to the integration of variables like patient age, medical history, lab results, and planned procedure type.

### 1.2.3 mHealth and telemedicine in surgical care

Despite existing efforts to optimize patient recovery, emergency department visits, hospital readmissions, and postoperative complications remain substantial challenges. Emerging solutions, such as mHealth applications and predictive AI algorithms, promise substantial improvements by enhancing patient education, compliance, and timely intervention. In parallel, telemedicine has emerged as a natural extension of digital surgery, allowing for real-time RM and follow-up. Telemedicine reinforces continuity of care, especially in the postoperative period. One of the most promising models is the Surgical Home Hospital (SHH), which delivers hospital-level care directly in patients' homes using digital tools. During the COVID-19 pandemic, SHH programs gained popularity as effective and safe alternatives to conventional hospitalization, although they remain underused in surgical care [48]. SHH programs rely heavily on wearable technology and RM tools to detect complications early. Predictive AI models help select suitable patients and monitor recovery, while virtual consultations ensure timely medical support. Despite their benefits, SHH programs face challenges such as data interoperability, signal accuracy, and integration with existing clinical workflows. Addressing these issues is crucial for its wider adoption and long-term success [49].

# 1.3 Digital and AI tools for bariatric surgery challenges

## 1.3.1 Role of mHealth

Improving compliance in the immediate postoperative phase is therefore a key lever for making the recovery process safer and maximizing the benefits of surgery. This highlights the need for well-coordinated, personalized, and multidisciplinary approaches. In particular, the rise of digital tools, such as mHealth applications and remote monitoring (RM) platforms, opens new opportunities to strengthen continuity of care, improve patient safety, and encourage active engagement throughout the recovery journey.

Given the importance of close monitoring in ensuring the short- and long-term success of surgery, the digitization of monitoring (applications, dashboards, automated alerts) could represent an effective solution for optimizing post-operative management, improving communication between patients and healthcare teams, and reinforcing patients' involvement in their own care. Mobile technology may improve surgical outcomes by promoting patient adherence to perioperative protocols and enabling early identification of postoperative complications. In fact, studies have shown that mobile technology can accurately evaluate postoperative symptoms, improve patient adherence to prescribed perioperative protocols, and improve clinical participation [50]. Mobile applications, in particular, are expanding more rapidly than traditional telemedicine approaches due to the extensive use of smartphones [50]. For patients undergoing bariatric surgery, who are required to follow strict perioperative protocols, mobile apps could play a key role in supporting and optimizing their perioperative care [51].

Patients undergoing bariatric surgery often have specific characteristics, including comorbidities related to severe obesity and a higher risk of postoperative complications. This vulnerability increases their chances of being readmitted to the hospital or making unplanned visits to the emergency department, even when standardized care pathways are in place.

At the same time, the postoperative recovery phase presents several challenges for patients, such as pain management, dietary adjustments, and early detection of complications.

In this context, personalized and enhanced follow-up is essential to prevent complications, detect problems early, and improve long-term outcomes. However, maintaining effective communication between patients and healthcare professionals (HCPs) after surgery is often difficult, which can lead to unnecessary visits to general practitioners (GPs) or emergency services.

Bariatric surgery, with its short hospital stay and well-structured follow-up protocol, provides an ideal setting for the implementation of digital health solutions [52]. mHealth applications (mHealth) represent a promising opportunity to enhance continuity of care and optimize clinical practice [53]. Thanks to the extensive use of smartphones, these tools allow for secure communication between patients and healthcare providers, while also reducing costs and improving resource management [54]. Recent advances in mobile technologies also enable the real-time delivery of personalized information, continuous monitoring of patient health data, increased patient engagement through automated reminders, and support for remote medical decision-making. In particular, home telemonitoring after surgery can help free up hospital beds and reduce the workload of medical teams, while ensuring continuous and structured patient support. For example, a study by Heuser et al. [55] showed that using a mobile app in bariatric surgery patients helped 48.5% of them avoid at least one phone call to the hospital, and 12.9%

avoid an in-person visit. These findings highlight the practical value of such tools in improving home follow-up and reducing unnecessary demands on the healthcare system.

Despite these benefits, most mHealth applications currently available on the market are not based on strong scientific evidence. This underscores the need for further research to validate their effectiveness, assess their real impact on patient care, and support their integration into routine clinical practice.

### 1.3.2 Solutions offered by AI and mobile technologies

Bariatric surgery presents a number of clinical and organizational challenges, including the need for patient education, adherence to postoperative care, and early [55] detection of complications.

The integration of digital tools and AI offers innovative solutions to support both patients and healthcare providers throughout the care pathway. Table 4 below summarizes key challenges and how digital and AI-driven approaches can effectively address them.

**Table 4. Challenges and digital/AI solutions for bariatric surgery**

| Clinical Challenge | Digital & AI Solution |
|---|---|
| Need for preoperative education and patient information | Digital app delivers structured pre-op education |
| Standardized surgery and shortens hospital stays | Digital follow-up supports enhanced recovery protocols (ERAS) |
| Adherence to postoperative guidelines (treatment, diet, etc.) | Home-based digital monitoring ensures better compliance |
| Postoperative anxiety | Mobile support helps reduce anxiety |
| Risk of early complications | AI-based risk stratification helps prioritize high-need patients |
| Risk of readmission | AI and digital tools reduce unnecessary ER visits and rehospitalization |

## 1.4 Research objectives

This research project aims to evaluate the role of a digital RM tool in improving postoperative management. It will assess the effectiveness, feasibility, and acceptability of this approach using a rigorous methodology that includes systematic reviews, prospective studies, and predictive modeling.

This study is built around three main objectives, each addressing a critical aspect of postoperative care in bariatric surgery:

1. To conduct a comprehensive review of the literature in order to identify and evaluate existing digital tools used for postoperative monitoring. This step will provide an overview of current practices, shedding light on their benefits, limitations, and areas in need of further development.
2. To evaluate the clinical impact of a dedicated mobile health application by comparing outcomes between patients receiving standard follow-up and those monitored through digital means. Key aspects will include the early detection of complications, reduction of unnecessary hospital visits, patient engagement, and overall satisfaction.
3. To develop a predictive model for postoperative complications, using real-world data collected via the mobile application. By applying machine learning techniques, the aim is to anticipate risks more effectively, tailor interventions to patient needs, and optimize the allocation of healthcare resources.

To achieve these goals, the project follows a structured and multidisciplinary approach that integrates exploratory, evaluative, and predictive methods. The systematic review lays the foundation by mapping existing digital solutions. The prospective clinical study brings real-world evidence of the mobile app's usefulness and feasibility. Lastly, the predictive model adds an innovative layer by transforming collected data into actionable insights for risk stratification and decision-making.

Together, these three steps combine exploratory, evaluative, and predictive methods to generate practical and meaningful insights that could improve how we support patients after bariatric surgery.

# Chapter 2

# 2 Patients and Method

## 2.1 Study design

### 2.1.1 Systematic review and meta-analysis

A systematic review and meta-analysis were conducted following the PRISMA guidelines [56]. The Medline, Scopus, CINAHL, and CENTRAL databases were searched from their inception up to November 23, 2023. Search terms included: *eHealth*, *digital health*, *mHealth*, *telemedicine*, *text message*, *digital application*, *smartphone application*, *bariatric surgery*, and *obesity surgery*, combined using Boolean operators AND/OR.

Eligible studies included randomized controlled trials (RCTs), quasi-RCTs, or controlled before-and-after studies with a comparison group. Selected studies had to involve adults (≥18 years) who had undergone or were awaiting bariatric surgery and were using an eHealth intervention in the postoperative phase. The main outcomes were weight loss at 12 months (%TWL and %EWL) and emergency room visits. Data were analyzed using a random-effects model [57], and the risk of bias was assessed using the ROBINS-I tool [57] and the Cochrane RoB2 tool [58] for RCTs.

### 2.1.2 Prospective interventional study

A prospective study was conducted at CHU Saint-Pierre between September 2022 and October 2023 to assess the feasibility of digital postoperative follow-up using the mobile application *Care4Today*. Adult patients with a BMI greater than 40, or over 35 with comorbidities, were included after giving informed consent.

The study was approved by the local ethics committee (protocol B0762022220903) and followed the STROBE guidelines [59]. Patients were monitored for 60 days after surgery using the app, which offered a daily questionnaire and a three-level alert system (orange, red, red+). Alerts were sent to the medical team through a secure dashboard.

Data were collected on postoperative complications, emergency visits, hospital readmissions, and weight loss.

### 2.1.3 Observational study with digital follow-up

An observational study was conducted to develop and test predictive models for postoperative risk using machine learning (ML). These models combined preoperative clinical data with digital follow-up data collected through the *Care4Today* mobile app. The data were analyzed using various ML techniques, including one-hot encoding, imputation of missing values, and dimensionality reduction with Principal Component Analysis (PCA) [59].

To take full advantage of the clinical and behavioral data collected through the mobile app, multiple machine learning methods were applied to build strong and reliable predictive models.

First, the data were preprocessed to ensure compatibility with supervised learning algorithms. Missing values were handled through imputation: missing numerical data were replaced with the mean, and missing categorical data were replaced with the most frequent category (mode). This helped stabilize the dataset without excluding important records.

Next, categorical variables, such as type of surgery or alerts from the app, were converted into numeric format using one-hot encoding. This method creates a separate binary column (0 or 1) for each category, preventing any artificial ranking among values. This step is crucial for allowing algorithms to process qualitative data without bias.

To avoid overrepresentation of some variables and to reduce data noise, dimensionality reduction was applied using PCA. This technique compresses information from many correlated variables into a smaller number of principal components, while preserving most of the data's variance. This also helps with result visualization and interpretation.

By combining these steps, imputation, one-hot encoding, and dimensionality reduction, the data were carefully prepared for use in machine learning models aiming to predict postoperative complications, patient responses to alerts, and adherence to digital follow-up.

Two predictive models were developed:

- A **preoperative model** based on demographic and clinical characteristics, and
- A **postoperative model** that included alerts and questionnaire responses from the app.

The models were validated using cross-validation and assessed using AUC F1 score and accuracy.

To test the reliability and generalizability of the models, a widely used method in ML, **cross-validation** [60], was applied to help prevent overfitting and ensure that the model's performance wasn't due to random chance or overfitting to a specific dataset.

More specifically, **5-fold cross-validation** [61] was used. The full dataset was randomly divided into five equal parts. For each round, four parts were used to train the model and the remaining one to validate it. This process was repeated five times, so that each part was used once as a test set. The final performance scores were averaged across the five runs to provide a more accurate estimate of the model's true performance.

The validated models were evaluated using several standard performance metrics:

- **AUC (Area Under the Curve)** [62]: measures the model's ability to distinguish between classes (e.g., presence or absence of complications). A score close to 1 indicates excellent classification performance.
- **F1-score** [63]: the harmonic mean of precision and recall. It's especially useful when dealing with imbalanced data, such as rare postoperative complications.
- **Accuracy** [64]: the overall proportion of correct predictions, calculated by dividing the number of correct predictions by the total number of cases.

Additionally, visual tools such as **confusion matrices** [64] and **ROC curves** [62] were generated to help interpret each model's ability to correctly classify observations. This rigorous validation process helped identify the most reliable models for potential use in clinical practice.

## 2.2 Design and Search Methods for Systematic Review and Meta-analysis

### 2.2.1 Databases used

The systematic review was based on four major medical databases: Medline (via PubMed), Scopus, CINAHL, and the Cochrane Library (CENTRAL). These databases were selected for their complementary coverage of topics related to surgery, digital health, and evidence-based medicine. They allowed for a comprehensive search of relevant publications, including all articles indexed from the databases' inception until the end of November 2023.

### 2.2.2 Keywords and Boolean operators

The search terms were chosen based on the study objectives and target population. They included: *eHealth*, *digital health*, *mHealth*, *telemedicine*, *text message*, *digital application*, *smartphone* *application*, *bariatric surgery*, and *obesity surgery*. These keywords were combined using Boolean operators AND and OR to improve both the sensitivity and specificity of the search. The search queries were adapted to match the syntax of each database.

### 2.2.3 Selection process and inclusion/exclusion criteria

After removing duplicates, the titles and abstracts of the identified publications were independently reviewed by two authors to assess their relevance. Studies that appeared eligible were then assessed in full text. In case of disagreement, a third reviewer made the final decision.

To be included, a study had to involve adults who had digital postoperative follow-up after bariatric surgery and include a comparison group. Excluded studies were those without a comparison group, single-time interventions, preoperative-only approaches, or those using outdated surgical procedures.

### 2.2.4 Time frame of the searches

The literature search was conducted up to and including November 23, 2023. No start date was imposed, allowing the inclusion of all relevant publications since the rise of digital health tools. However, only studies published in English or French were included. This strategy ensured an up-to-date and relevant collection of literature aligned with the latest advances in digital follow-up for bariatric surgery.

### 2.2.5 Eligibility criteria for studies and patients

Studies included in this research had to meet clear methodological standards. Eligible studies were randomized controlled trials (RCTs), quasi-RCTs, and controlled before-and-after studies.

Observational studies with a comparison group, such as cohort or case-control studies, were also included. Publications had to clearly describe a digital postoperative intervention (such as a mobile app, remote monitoring, or eHealth platform) and report measurable clinical outcomes, especially weight loss at 12 months, readmission rates, or emergency visits.

Patients included in the analyzed studies had to be adults aged 18 or older who had undergone or were waiting for bariatric surgery. Accepted types of surgery included SG, RYGB, and SASI-S.

In interventional studies, patients needed to have a compatible smartphone (Android or iOS), understand the study language, and agree to a minimum of 60 days of postoperative follow-up.

Excluded were minors, individuals without access to a mobile device, those with major language barriers, or anyone who dropped out before completing the required follow-up. All participants provided informed consent, and data were managed in compliance with GDPR regulations.

## 2.3 Study variables, digital tools, and statistical methods in a prospective interventional study

### 2.3.1 Definitions and Terminology

“Digital interventions” refers to technological tools used for remote patient monitoring after bariatric surgery. The term eHealth refers to the use of information and communication technologies (ICT) for healthcare purposes. This includes telemedicine, secure web platforms, video calls, text messaging, and medical emails.

The term “mHealth” specifically refers to using mobile devices such as smartphones and tablets to monitor patients. In this study, postoperative monitoring was done through a dedicated mobile application (*Care4Today*), which enabled real-time collection of clinical data, automatic alert generation based on a decision-making algorithm, and two-way communication between patients and healthcare providers. The main clinical outcomes assessed are described in table 5.

**Table 5. Main Clinical Outcomes Assessed**

| Outcome | Definition/Formula | Notes |
|---|---|---|
| Total Weight Loss (TWL) | (Preoperative weight - Current weight) / Preoperative weight × 100 | Used to assess general weight reduction |
| Excess Weight Loss (EWL) | (Preoperative weight - Current weight) / (Preoperative weight - Ideal weight) × 100 | Ideal weight is based on a target BMI of 25 $kg/m^2$ |
| Postoperative Complications | Classified using the Clavien-Dindo system | Grade III or higher = major complications |
| Mobile App Alerts | Categorized as Orange (mild), Red (moderate), Red+ (critical) | Indicates severity of symptoms and guides clinical response |

### 2.3.2 Digital monitoring via the "Care4Today" Mobile App

The *Care4Today* app, developed by Q1.6, was used as the main tool for postoperative remote monitoring. It allowed patients to answer a set of daily questions about their health, diet, pain, and wound healing, while also supporting communication between patients and healthcare professionals at a distance. The app uses a decision-tree algorithm with personalized questions depending on the stage of the postoperative follow-up. Patient responses generate color-coded alerts that trigger specific actions: medical consultation, emergency call, or monitoring. This algorithm manages all interactions between patients and the care team through a series of customized daily and weekly questionnaires. The algorithm is designed to follow the patient's surgical journey, from the preoperative period to several months after surgery. It includes modules on general condition, pain, wound healing, nutrition, physical activity, potential complications, mental health, and satisfaction with care. Based on the patient's answers, alerts are automatically generated using a three-level system (orange, red, red+), guiding the medical team's actions quickly and effectively. The decision tree explains how each response can trigger an automated action or notify the care team. For example, high pain levels, redness around the surgical site, or breathing issues may trigger immediate alerts that require fast medical response. On the other hand, reassuring responses are logged in the monitoring dashboard without triggering action.

The app's alert system is based on three levels, as described in table 6.

**Table 6. Mobile App Alert Levels**

| Alert Level | Description |
|---|---|
| **Orange** | Alert sent in the morning for review. |
| **Red** | Immediate alert requiring a quick medical response. |
| **Red+** | Clinical emergency requiring immediate contact or going to the emergency department. |

### 2.3.3 Role of the digital coordinator

As part of the digital postoperative follow-up, a digital coordinator[2] played a key role in supporting patients and acting as a bridge between them and the medical team. The main mission of the coordinator was to help each patient install, understand, and effectively use the Care4Today mobile application. This personalized support helped reduce digital inequalities, especially for patients who were less familiar with technology. The digital coordinator also ensured that patients stayed engaged with the follow-up process by checking their participation and making sure that alerts generated by the app were understood and properly communicated to the medical staff. In cases of technical issues or missed responses, the coordinator followed up to re-engage the patient[2]. Combining technical assistance, education, and emotional support, the digital coordinator proved essential in making the remote monitoring process safe, effective, and fully integrated into the patient care pathway.

## 2.4 Data Collection Tools for Prospective Interventional Study

### 2.4.1 Electronic database and data capture

Clinical data and patient responses were entered into a secure electronic database that met quality standards. Data collection and management were done using an Electronic Data Capture (EDC) system.

All clinical and digital data were gathered and centralized through this specialized EDC system, which allows for real-time collection, recording, organization, and secure storage of data from various sources. This includes patient questionnaires submitted through the mobile app, automatically generated alerts, and clinical variables recorded in medical records.

In this study, the EDC system helped ensure compliance with regulatory standards, especially regarding personal data protection. It included features such as pseudonymization, access control, and automatic backups. Each entry was linked to a pseudonymous patient ID, ensuring both confidentiality and data integrity throughout the monitoring period.

### 2.4.2 Data security and GDPR compliance

The storage and transfer of data collected in this study were carried out in strict compliance with the General Data Protection Regulation (GDPR)[65], the European legal framework governing the collection, use, and storage of personal data.

To meet these requirements, several security measures were implemented. First, data were encrypted both at rest (in databases) and in transit (between patients' devices and platform servers), preventing unauthorized access. Next, direct identifying information was replaced with anonymous IDs through a pseudonymization process. This ensures that personal data cannot be traced back to an individual without access to a separate, securely stored key. Additionally, access to data was controlled through a multi-level access system, limiting access only to authorized study or care team members based on their role. Every access required secure authentication, often with two-factor verification, and all logins were recorded in an audit log.

All these measures were designed to protect participants’ privacy during data collection, analysis, and storage, in full alignment with the strictest European standards for health data security and confidentiality.

### 2.4.3 Q1.6 platform and AWS infrastructure

The Q1.6 platform used a cloud infrastructure hosted by Amazon Web Services (AWS), certified under ISO 27001. It allowed for secure collection, processing, and storage of patient data, with automatic backups, strong authentication, and access monitoring through a professional dashboard.

The Q1.6 system chosen for this study is built on AWS, a cloud provider internationally recognized for its high levels of security and regulatory compliance. All services used by Q1.6 are certified under ISO/IEC 27001, a global standard for information security management systems (ISMS). This ensures that strict processes are in place to maintain data confidentiality, integrity, and availability.

Technically, Q1.6 applies several layers of security within the AWS environment, including:

- **Geographic redundancy** of servers, ensuring high availability and continuity in case of hardware failure
- **Daily automatic backups**, stored in separate environments (AWS S3) to avoid data loss
- **Multi-level encryption**, both at rest and during transmission, using encryption keys managed according to best practices (e.g., AWS Key Management Service)
- **Access logging and audit trails**, allowing every action on the data to be tracked
- **Role-Based Access Control (RBAC)**, limiting user access according to their function (e.g., clinician, administrator, coordinator)

Q1.6 also ensures that all hosted data remains within the European Union, in compliance with GDPR requirements. Thanks to this infrastructure, the data collected via the mobile app are not only centralized and structured for analysis, but also protected against unauthorized access, accidental loss, or tampering.

### 2.4.4 MAUQ questionnaire and patient satisfaction

Patient satisfaction with the app was measured using the **MAUQ** [53] (mHealth App Usability Questionnaire). This validated tool is specifically designed to assess the usability of mobile health apps in clinical settings.

For this study, the version for **stand-alone apps** (not connected to electronic health records) was used. The MAUQ contains 18 items, grouped into three key areas:

1. **Ease of Use and Learnability** (5 items)

   Assesses how easily patients can navigate the app, understand its features, and learn to use it without too much help.

2. **Interface and Satisfaction** (7 items)

   Focuses on user comfort, visual clarity, navigation flow, and the sense of trust and autonomy during app use.

3. **Usefulness** (6 items)

   Evaluates how the app impacts the patient's ability to manage their health, stay engaged in follow-up, and improve their overall postoperative care experience.

Each item is scored on a 7-point Likert scale, from 0 (*strongly disagree*) to 6 (*strongly agree*). The scores for each domain can be added together for a total score out of 108 points, which can also be converted to a 0–10 scale for easier interpretation and comparison. The MAUQ was completed by patients at the end of their 60-day digital follow-up. This provided valuable quantitative feedback on their experience and overall satisfaction with the *Care4Today* tool. This approach offered a standardized way to evaluate the app's usability and patient acceptance.

## 2.5 Variables of interest for prospective interventional study

### 2.5.1 Patient characteristics and clinical data

The collected variables included age, sex, preoperative BMI, medical history, type of surgery performed, and associated comorbidities. To describe the study population in detail and assess the impact of digital interventions on clinical outcomes, a range of sociodemographic, clinical, and surgical variables were collected prospectively. These data were extracted from medical records and enriched with information provided through the *Care4Today* mobile application.

The table below summarizes the main variables and how they were collected:

| Category | Variable | Data Type | Description / Coding |
|---|---|---|---|
| **Sociodemographic Data** | Age | Quantitative (years) | Age at the time of surgery |
| | Sex | Categorical | Male / Female |
| **Clinical History** | Preoperative BMI | Quantitative ($kg/m^2$) | Calculated from measured weight and height before surgery |
| | Associated comorbidities | Multiple categorical | Diabetes, hypertension, sleep apnea, dyslipidemia, etc. |
| | Surgical history | Free text / coded | History of abdominal or bariatric surgery |
| **Surgical Data** | Type of surgery | Categorical | SG / RYGB / SASI-S / Conversion |
| | Date of surgery | Date | Day of surgery |
| **Digital Follow-up** | Participation via the app | Binary | Yes / No |
| | Alerts generated | Quantitative | Total number and by level (orange, red, red+) |
| | Questionnaire response rate | Percentage | Completion rate over 60 days |
| **Postoperative Outcomes** | Emergency visits | Binary | Yes / No |
| | Hospital readmissions | Binary | Yes / No |
| | Postoperative complications | Categorical | Classified using Clavien-Dindo (grades I to V) |
| | %TWL at 1, 3, and 6 months | Quantitative (%) | Total weight loss as a percentage |
| | %EWL at 1, 3, and 6 months | Quantitative (%) | Excess weight loss based on ideal weight (BMI target = 25 $kg/m^2$) |
| | MAUQ satisfaction score | Quantitative (0–90) | Total and dimension-specific scores |

### 2.5.2 Primary and Secondary Outcome Measures

The *primary outcomes* included weight loss at 12 months (%TWL, %EWL) and emergency department visits.

The *secondary outcomes* included hospital readmissions, length of hospital stay, patient satisfaction, and adherence to digital follow-up.

### 2.5.3 Data from the mobile application

The data collected from the *Care4Today* app included:

- the number of alerts generated (by type)
- daily patient responses
- usage indicators (such as frequency of use and response time)

The alerts generated by the app were classified into three increasing levels of severity, each triggering a specific clinical response based on a built-in color-coded triage system:

- **Orange Alert**: Indicates minor issues or moderate symptoms (e.g., mild pain or digestive discomfort). These alerts generate a daily report for the care team the following morning. They do not require immediate action but may suggest the need to adjust care.
- **Red Alert**: Represents more concerning clinical signs (e.g., moderate to severe pain, fever, or mild bleeding) and requires quick attention. An email is instantly sent to the assigned healthcare professional, who must follow up with the patient promptly.
- **Red+ Alert**: Refers to potentially critical situations (e.g., difficulty breathing, chest pain, signs of severe infection, or acute complications). The algorithm instructs the patient to

immediately contact the medical team or go to the emergency department. These alerts are also highlighted in the dashboard for urgent review.

Each patient response is automatically analyzed by an intelligent decision tree, which considers the postoperative day, the type of symptom reported, and any previous patterns to determine whether an alert should be triggered.

Healthcare professionals access a secure dashboard where all alerts are listed by severity and by patient. In addition, usage indicators from the app were analyzed, including:

- the frequency of daily responses,
- average response time to questionnaires,
- and overall engagement rate over the 60-day follow-up period.

These data helped assess both the patients' adherence to the digital follow-up and the effectiveness of the alert system in detecting early complications.

# 2.6 Statistical analysis for prospective interventional study

## 2.6.1 Descriptive analysis and statistical tests

Descriptive statistics were performed for continuous variables (mean, standard deviation) and categorical variables (frequencies, percentages). Depending on the case, Fisher's exact test, ANOVA, Mann-Whitney, or Kruskal-Wallis tests were used.

All collected data underwent descriptive and inferential statistical analyses, adapted to the type and distribution of each variable. Continuous quantitative variables, such as age, BMI, or weight loss (%TWL, %EWL) and results were reported as means ± standard deviations when normally distributed, or as medians with interquartile ranges when the distribution was not normal.

Qualitative variables (e.g. sex, type of surgery, presence of complications) were reported as absolute numbers and percentages.

To compare patient subgroups, different statistical tests were applied based on data characteristics:

- **Fisher's exact test** [66] was used to compare proportions in small samples or when cell sizes were less than 5. It is especially suitable for assessing the relationship between two categorical variables (e.g. presence of complications by surgery type).
- **ANOVA (Analysis of Variance)** [67] was used to compare means across more than two groups, provided the data followed a normal distribution and had equal variances. For example, it was used to compare %EWL between surgical techniques.
- When normality was not confirmed, **non-parametric tests** were used: the **Mann-Whitney U test** [68] for comparing two independent groups, and the **Kruskal-Wallis test** [69] for more than two groups. These tests can detect distribution differences without assuming a specific data distribution.

All analyses were performed using a significance level of $p < 0.05$, and all tests were two-sided. These methods were chosen to ensure robust and reliable interpretation of clinical outcomes from the digital postoperative follow-up.

### 2.6.2 Regression models and intergroup comparisons

**Binary logistic regression models** [70] were used to evaluate the impact of digital interventions on primary outcomes, adjusting for confounding factors such as age, sex, and BMI.

This statistical method estimates the likelihood of an event occurring (e.g., a postoperative complication or emergency visit) based on one or more explanatory variables. It is especially suited for binary (yes/no) outcomes.

In this context, the dependent variables were clinical outcomes of interest (e.g. presence of major complication, insufficient weight loss, or non-adherence to digital follow-up), while the independent variables included use of the *Care4Today* app and several potential confounding factors such as age, sex, preoperative BMI, surgery type, and associated comorbidities.

The models produced **odds ratios (ORs)** [71] with 95% confidence intervals, estimating the strength of association between the digital intervention and the outcome while adjusting for other included variables.

Additionally, **intergroup comparisons** were conducted to explore differences between patients who used the app and those who received standard care. These comparisons looked at clinical outcomes (e.g. %TWL, readmissions) as well as indicators of engagement and satisfaction. Depending on the nature and distribution of the variables, statistical tests used included **ANOVA**[67], **Mann-Whitney** [68], and **Chi-squared** [72] **or Fisher's exact test** [66].

### 2.6.3 Heterogeneity analysis and publication bias

**Inter-study heterogeneity**—the variability in results between the included studies—was assessed using the **$I^2$ statistic** [73]. This measure expresses the percentage of total variation in estimated effects that is due to real differences between studies rather than random chance.

- An $I^2$ value below 30% is usually considered low heterogeneity,
- 30-60% as moderate,
- and over 60% as substantial heterogeneity.

When substantial heterogeneity was detected, **subgroup analyses** were carried out to explore possible sources of variability. These subgroup comparisons were based on predefined factors such as:

- the type of surgery (e.g., SG vs. RYGB),
- the length of follow-up,
- or the type of digital platform used (app alone vs. app with human support).

**Publication bias**—the tendency for studies with positive or statistically significant results to be more likely published—was assessed using a **funnel plot**. This graphical tool helps to visualize the symmetry of reported effects relative to statistical precision.

A clearly asymmetric funnel plot may suggest the presence of publication bias or size-related effects. Although interpretation of the funnel plot remains somewhat subjective, it serves as a helpful additional method for evaluating the overall reliability of the combined results.

## 2.7 Machine learning for predictive modeling

### 2.7.1 Data preprocessing and cleaning

Missing data were handled using either the **mean** (for numerical values) or the **mode** (for categorical values). Categorical variables were converted into numerical format using **one-hot encoding** [74].

Before training the machine learning models, a careful process of data cleaning and preparation was carried out to ensure quality, consistency, and interpretability of the variables.

First, missing values were handled through statistical imputation:

- For continuous numerical variables (e.g. BMI, %EWL), missing values were replaced with the average of the variable.
- For categorical variables (e.g. sex, type of surgery), the most frequent category (mode) was used.

This approach allowed the full dataset to be preserved without excluding participants and helped minimize bias.

Next, **categorical variables** were transformed into numeric format using **one-hot encoding**.

This technique converts each category into a separate binary column (0 or 1).

For example, a variable like "Type of Surgery" with three categories (SG, RYGB, SASI) would become three columns: "Surgery_SG", "Surgery_RYGB", and "Surgery_SASI".

This method avoids introducing artificial order among categories and allows machine learning algorithms to handle qualitative data correctly.

These preprocessing steps resulted in a clean, well-structured, and machine-readable dataset, ready for supervised learning and complex predictive analysis.

In addition to standard imputation and encoding techniques, the predictive modeling process incorporated advanced preprocessing strategies to enhance data quality and model accuracy. Data from the Care4Today application were carefully curated by excluding questions with a response rate below 20% and consolidating multi-response items into unified categories. Several new features were engineered, including the average number of daily alerts and the most frequently reported symptoms. These enriched variables provided deeper insights into patient behavior and clinical status, significantly boosting the overall predictive power of the models.

### 2.7.2 SMOTE methodology and One-Hot encoding

The **SMOTE algorithm** [75] was used to address **class imbalance**, particularly for rare outcomes like postoperative complications. This helped improve the model's ability to learn from underrepresented cases.

Instead of simply duplicating rare examples (which can cause overfitting), SMOTE creates new synthetic cases by interpolating between an existing minority data point and its nearest neighbors. This increases the number of minority cases while preserving the data structure.

In addition, to avoid the influence of different scales on model performance, all **numerical variables were standardized** before training. This means each variable was transformed to have a **mean of 0** and a **standard deviation of 1**, ensuring equal weight in algorithms that are sensitive to scale (e.g. logistic regression, SVM, KNN).

Combining **SMOTE** for balancing rare outcomes and **standardization** for numerical consistency helped optimize model conditions, especially for predicting rare but clinically important complications. To address the class imbalance in the dataset, where only 22% of patients experienced complications, the SMOTE algorithm (Synthetic Minority Oversampling Technique) was used in combination with feature standardization. SMOTE generated synthetic examples of the minority class, helping to balance the training data without duplicating existing cases. This approach enhanced the models' ability to detect rare but clinically important outcomes. In particular, it improved the sensitivity of classifiers such as **Naive Bayes** [76] and **LightGBM** [77] in identifying patients at higher risk of postoperative complications.

### 2.7.3 Feature selection (SelectKBest and PCA)

To improve the performance of predictive models, dimensionality reduction was applied using two complementary methods: **SelectKBest** and **Principal Component Analysis (PCA)**.

- **SelectKBest** [78] is a statistical feature selection method that assigns a score to each variable based on how well it predicts the target variable (e.g., presence or absence of complications). The top K variables with the highest scores are kept for model training. This helps reduce noise, remove irrelevant or redundant variables, and speed up modeling while maintaining good accuracy.
- **PCA (Principal Component Analysis)** [79] is a linear transformation method that condenses information from a large number of correlated variables into a smaller set of **principal components**. These new variables are weighted combinations of the original ones and capture the most significant variability in the data. Often, just 2 to 5 components can retain most of the useful predictive information.

By combining SelectKBest for targeted selection and PCA for synthetic transformation, the complexity of the models was reduced, overfitting was limited, and data visualization was improved, especially for 2D plots used in clinical interpretation.

To optimize model performance and reduce complexity, two complementary dimensionality reduction techniques were applied: SelectKBest for targeted feature selection and PCA for transforming correlated variables. After comparison, SelectKBest alone yielded the best results, identifying a subset of just eight highly predictive features, including 'Readmission', 'sympt_type_vomiting', 'pain when eating', 'Red_avg_day', and 'Orange alerts'. Using this refined feature set, the Naive Bayes classifier achieved outstanding performance, with an accuracy of 92.88% and an F1-score of 81.33%.

### 2.7.4 Models evaluated (logistic regression, random forest)

Around fifteen supervised machine learning models were tested, including logistic regression, random forest, XGBoost [80], Support Vector Machine (SVM) [81], k-Nearest Neighbors (KNN) [82], and Naive Bayes [76].

The goal was to identify the best-performing algorithm for predicting postoperative outcomes based on clinical and behavioral data collected. These models represented a wide range of algorithm families—from simple linear models to more complex ensemble techniques.

The models tested included:

- **Logistic Regression** [83] – Used as a baseline model for its simplicity and ease of interpretation.
- **Random Forest** [84] – An ensemble model based on multiple decision trees trained on random subsets of the data. Known for robustness and the ability to handle complex, mixed-type datasets.
- **XGBoost (Extreme Gradient Boosting)** [80] – A high-performance gradient boosting algorithm that is particularly effective for tabular data, offering both accuracy and speed.
- **SVM (Support Vector Machines)** [81] – Suitable for high-dimensional data, maximizing the separation margin between classes.
- **K-Nearest Neighbors (KNN)** [82] – Classifies a new observation based on the majority class among its K nearest neighbors.
- **Naïve Bayes** [76] – A simple probabilistic model that works well when variables are assumed to be conditionally independent.

All models were trained, validated, and compared using the same preprocessing pipeline [78] and **cross-validation procedure** [61], ensuring consistency and fair evaluation.

This comparative approach helped identify which algorithms were best suited for predicting **rare and complex clinical events** in the context of postoperative bariatric surgery follow-up.

### 2.7.5 Performance metrics (Accuracy, F1, AUC)

The predictive models were compared using standard performance metrics: **accuracy**, **F1-score**, and the **Area Under the ROC Curve (AUC)** These metrics provided a global evaluation of each model's classification quality and clinical relevance.

- **Accuracy** [64] measures the overall proportion of correct predictions out of all cases. While easy to interpret, this metric can be misleading in imbalanced datasets (e.g., when complications are rare), as it tends to favor the majority class.
- To correct for this bias, the **F1-score** [64] was also calculated. It is the harmonic mean of **precision** (positive predictive value) and **recall** (sensitivity). The F1-score is especially useful when false positives and false negatives both have clinical importance—as is often the case in postoperative care.
- The **AUC (Area Under the Curve)** [85] represents the model's ability to distinguish between classes, regardless of the decision threshold. An AUC close to **1.0** indicates excellent classification performance, while an AUC near **0.5** suggests the model performs no better than random guessing.

Using these three metrics together allowed for an objective comparison of models, helping to identify those with the best balance between sensitivity and specificity—and ultimately, the most clinically appropriate algorithms.

### 2.7.6 Cross-Validation

A **5-fold cross-validation** [61] was performed to assess the robustness and generalizability of the machine learning models.

This method involves dividing the entire dataset into five equally sized subsets. In each iteration, four subsets are used to train the model, and the fifth is used for validation.

The process is repeated five times so that each subset serves once as the validation set. The results from all five runs are then averaged to produce a reliable estimate of the model's predictive performance.

Cross-validation helps reduce the risk of **overfitting** [86],when a model performs well only on the training data but poorly on new data. It ensures the model works consistently across different subsets of the data.

This method is particularly useful in studies with **limited sample sizes** or **heterogeneous data**, as is common in bariatric surgery follow-up. Therefore, cross-validation was a key step in ensuring the scientific quality and reliability of the predictive models developed.

### 2.7.7 Ethical Considerations

The study was approved by the ethics committee of CHU Saint-Pierre (protocol number: B0762022220903). All participants gave their **informed consent** before being included in the study. They were free to withdraw at any time. All data were **pseudonymized** and securely stored in accordance with **GDPR** [65] standards. Access was limited to **authorized medical staff** only.

# Chapter 3

# 3 The Utilization of Digital Applications for Measuring Patient Outcomes Following Bariatric Surgery: A Systematic Review and Meta-analysis of Comparative Studies [1]

## 3.1 Abstract

In the context of escalating obesity rates, bariatric surgery holds a crucial role in managing severely obese patients. With demonstrated effectiveness for weight loss and with the advent of ambulatory surgery, bariatric surgery allows for a streamlined care pathway, ideally suited for postoperative surveillance using digital health applications. The aim of this systematic review and meta-analysis is to evaluate the effect of eHealth-delivered health services or support for adults undergoing bariatric surgery. Five studies, encompassing 2210 patients, were analyzed. The intervention group showed a 10% increase in total weight reduction and a 22% reduction in excess weight loss. ED visitation rates also trended towards reduction. Despite the absence of clear statistical superiority for DHA, the findings suggest potential benefits of DHA in postoperative monitoring.

## 3.2 Introduction

### 3.2.1 Obesity and bariatric surgery: a clinical context

Obesity is a commonly encountered modern condition, and constitutes a major cause of chronic disease and morbidity [87]. Harmful eating practices, decline of physical activity and genetic reprogramming in metabolism collectively contribute to this emerging global crisis [4]. Lifestyle interventions, incorporating behavioral therapies and increased physical activities form the cornerstone of obesity management [87]. Medication is recommended for overweight patients with body-mass index (BMI) exceeding 30, while bariatric operations are reserved for clinically severe obesity cases (those with BMI over or a BMI over 35 or higher and associated obesity-related comorbidities) [87].

### 3.2.2 Postoperative challenges and follow-up needs

The long-term efficiency of bariatric surgery in weight loss has already been conclusively demonstrated [88]. Following discharge, patients assume primary responsibility for monitoring their own recovery adhering to self-care recommendations. Discrepancies in following the suggested recommendations can produce variable outcomes. Patients commonly face significant challenges in post-operative rehabilitation, nutrition, pain management as well as surgical complications. More than 10% of patients aged 45 and above encounter major postoperative complications [89], often occurring after discharge, necessitating readmission and associated with increased postoperative mortality across a range of surgical populations [90]. Moreover, even minor events following surgery, such as nausea and pain, are recognized to substantially affect patient satisfaction and wellbeing [91,92], carrying significant implications for affected patients.

### 3.2.3 Emergence of Digital Health Applications (DHA)

Nonetheless, bariatric surgery offers a highly standardized care pathway, with short hospitalization and longer outpatient follow-up, making it well-suited for digital integration [89]. Patients and healthcare providers engaging through a Digital Health Application (DHA) facilitate a secure follow-up on early postoperative complications, weight loss and self-efficacy [93].

### 3.2.4 Objectives of the Review

The aim of this systematic review and meta-analysis is twofold: firstly, to investigate whether newly implemented DHA protocols are as effective as conventional practices in achieving and maintaining postoperative weight loss, and secondly, to assess any potential advantages in reducing the need for in-house medical counselling.

## 3.3 Materials and Methods

### 3.3.1 Review design and protocol

This systematic literature review was conducted in compliance with the methods elaborated in a protocol developed a priori. The results are reported according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement [56].

### 3.3.2 Search strategy and selection process

A comprehensive literature search of the Medline, Scopus, CINAHL and CENTRAL databases was undertaken, from their inception until 23 November 2023, using the search terms “ehealth”, “digital health”, “mhealth”, “telemedicine”, “text message”, “digital application”, “smartphone application”, “bariatric surgery”, “obesity surgery”, combined with the Boolean operators AND/OR as appropriate for each database.

After excluding duplicate studies. The generated abstract list was independently screened by two authors (NL, NB) for articles of potential relevance. Such articles were bookmarked for full-text review. Any ensuing disagreements were arbitrated by a senior author (EF). The reference lists of relevant studies were also further manually checked for additional studies that potentially met the inclusion criteria.

### 3.3.3 Definitions and terminology

Digital health or eHealth applications: interventions that provide remote healthcare monitoring and support using telephone, videoconferencing, mobile texting, smartphone applications, online learning platforms, internet applications, email, or web-based platforms. These healthcare support services pertain to those provided by a bariatric surgery healthcare provider, including a clinical nurse, dietitian, endocrinologist, exercise specialist, medical doctor, psychologist, or surgeon. While DHA may be utilized both pre and postoperatively, in the present study, only postoperative eHealth interventions were considered.

%TWL = % Total Weight Loss = (pre-op weight – follow up weight)/(pre-op weight) x 100.

%EWL = % Excess Weight Loss = (preoperative weight − current weight)/ (preoperative weight − ideal weight) × 100.

%EBL = % Excess BMI loss percentage = (preoperative BMI − current BMI)/ (preoperative BMI − 25) × 100.

### 3.3.4 Eligibility criteria

To be eligible for inclusion, each study had to satisfy the following criteria: 1) the study is by design a randomized control trial (RCT), Quasi-RCT, or a controlled before-and-after study with a comparator group receiving usual care or no intervention; 2) the study includes adult participants over 18 years old; 3) the study is conducted in a population that has undergone or has a scheduled bariatric procedure (waitlisted); 4) the study documents postoperative provision of healthcare support or services using eHealth techniques.

A set of predetermined exclusion criteria was also utilized to guide the study selection process: 1) studies reporting on single session interventions, 2) non-comparative studies, 3) studies on preoperative eHealth interventions, 4) studies including procedures that are no longer commonplace such as banded gastroplasty, biliopancreatic diversion without a duodenal switch, jejunoileal bypass, vertical banded gastroplasty, and vertical gastroplasty (unbanded), 5) studies with non-extractable data, 6) studies not reporting 12 month postoperative weight loss outcomes.

### 3.3.5 Outcomes of interest and data extraction

The primary endpoint of the present study was to evaluate the impact of the digital eHealth follow-up on weight loss and gauge for any noticeable reduction in postoperative Emergency Department (ED) visitation rates. In this context, the primary outcomes evaluated were the TWL, EWL, expressed as percentages after one year of follow-up, as well as the number of patients recording a postoperative visit to the ED. Secondary data of interest were the study and patient baseline characteristics, the type of surgery employed and the preoperative BMI and weight measurements.

All data pertaining to the primary and secondary outcomes of the study were extracted by two authors (EF, NK) and were subsequently entered into standardized excel spreadsheets (Microsoft, Redmond, Washington, USA) for further data tabulation.

### 3.3.6 Risk of bias assessment

The risk of bias assessment was performed independently by two authors (DP, GB) using the ROBINS-I tool developed by the Cochrane collaboration [57]. This risk of bias tool assesses retrospective studies across seven domains: bias due to confounding, bias due to selection of participants, bias in classification of interventions, bias due to deviations of intended interventions, bias due to missing data, bias in measurement of outcomes, bias in selection of the reported results. In cases of randomized controlled trials (RCT) a modification was utilized, incorporating five criteria instead of seven (bias arising from the randomization process, bias due to deviations from intended intervention, bias due to missing outcome data, bias in measurement of the outcome, bias in selection of reported result). For each domain, the risk of bias can be low, moderate or serious.

### 3.3.7 Statistical analysis

Statistical analyses were performed using Stata v. 17 (StataCorp. 2021. Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC). A random effects model (DerSimonian-Laird) was a priori selected due to expected high clinical heterogeneity in terms of patient baseline characteristics and body measurements. Weighted mean differences (WMD) and corresponding 95% Confidence Intervals (95% CI) were calculated for continuous outcomes, while Odds Ratios (OR) were utilized to synthesize categorical data. Interstudy statistical heterogeneity was quantified using the Higgin's $I^2$ statistic [94], with values below 30% represent low heterogeneity, values between 30 and 60% represent moderate heterogeneity, and values above 60% represent substantial heterogeneity. In all statistical analyses in the present study, a p-value below 0.05 was considered statistically significant. Testing for publication bias could not be performed due to the small number of included studies.

# 3.4 Results

## 3.4.1 Study selection and general characteristics

Through our systematic search, 252 unique articles were retrieved, of which ultimately five (four retrospective cohorts and one RCT) were included in the quantitative analysis (Figure 1) [55,95–98]. Three studies were excluded from the present review; the first one recorded outcomes of text-message surveillance on weight recurrence after the first 18-month postoperative period [99]. One more study displayed the role of a digital application in postoperative adherence to vitamin and mineral supplementation [100] while the third analyzed the self-care quality, body image, and QoL 3 months postoperatively [101].

In total, included studies reported on 2210 patients (1261 in the eHealth intervention group versus 949 in the control group) undergoing bariatric surgery for clinically severe obesity between 2009 and 2021. Two studies originated from North America and three studies from Europe. Regarding the type of eHealth application utilized, four studies reported use of mobile applications and one study made use of videoconference postoperative surveillance. Table 1 summarizes patient baseline demographic data.

## 3.4.2 Risk of bias summary

Risk of bias assessment indicated low risk in three studies, moderate risk in one and serious risk in another (Tables 3 and 4). The risk for confounding bias was found to be moderate in two studies which did not report on patient baseline characteristics and serious in one study which reported imbalances in the baseline characteristics of the compared groups. Three studies were judged to be of moderate risk for bias in classification of interventions, considering that they utilized combined pre- and postoperative eHealth interventions and that the present study primarily focuses on postoperative interventions. The RCT conducted by Wild et al. was found to be the study with the highest methodological quality [96].

### 3.4.3 Total Weight Loss Outcomes (%TWL)

Three studies incorporating 1333 patients (837 in the intervention group versus 496 in the control group) [95–97] reported postoperative total weight loss, 12 months after the index bariatric operation (Table 2). Meta-analysis of available data indicated that %TWL was on average 10% higher in the experimental group, albeit without any statistical significance (WMD 0.1, 95% CI -0.08 to 0.28, p=0.27, Figure 2). Interstudy statistical heterogeneity was low ($I^2$=27.7%).

### 3.4.4 Excess Weight Loss Outcomes (%EWL)

Another three studies totaling 258 patients (130 in the intervention group versus 128 in the control group) [95,96,98] provided data on excess weight loss 12 months postoperatively (Table 2). No statistically significant differences were detected between the compared groups, despite a trend towards increased excess weight loss in the experimental group (WMD 0.22, 95% CI -0.34 to 0.78, p=0.45, Figure 3). Interstudy statistical heterogeneity was considerable ($I^2$=79.9%).

### 3.4.5 Emergency Department Attendance

ED attendance rates during the postoperative period were reported in two studies which included 942 total patients (440 in the intervention group versus 502 in the control group) [55,95]. No statistically significant results were demonstrated, with ED visitation rates being comparable between the two groups, with a trend towards ED visit reduction in the eHealth intervention group

(OR 0.8, 95% CI 0.49 to 1.32, p=0.38, Figure 4). No interstudy statistical heterogeneity was detected between the two evaluated studies ($I^2$=0%).

# 3.5 Discussion

## 3.5.1 Summary of key findings

The worldwide prevalence of obesity has exceeded 10%, necessitating higher awareness [4]. Surgical interventions for obesity have plateaued during the last decade [102], representing 70 per 100,000 people undergoing surgical procedures annually, as reported by the US national database [103]. Among the various surgical procedures, sleeve gastrectomy is the most frequent, followed by LGBP, adjustable gastric banding and biliopancreatic diversion with duodenal switch [103]. Bariatric surgery demonstrates the potential for achieving at least 20% long-term weight loss, surpassing the efficacy of non-operative methods, all while maintaining a favorable safety profile [104].

## 3.5.2 Comparison with previous research

Previous systematic reviews have examined the impact of eHealth applications on preoperative and postoperative outcomes, including weight loss, quality of life, depression and self-efficacy [105–107]. However, their findings predominantly rely on preoperative behavioral interventions, non-comparative studies and pilot randomized trials. From 2013 to 2015, the total number of smartphone applications related to obesity surgery available to patients and health professionals has increased from 28 to 39 [108,109]. Regrettably, there is a scarcity of published evidence regarding the distinctive features of e-health applications in use by patients, staff and health-care facilities [107]. Consequently, a substantial gap exists in our understanding of how socio-economic factors impact the preoperative and postoperative courses of bariatric patients.

### 3.5.3 Impact of digital health tools beyond weight loss

Most of the published comparative studies on postoperative digital follow-up focus on investigating the role of digital health interventions (DHI) in postoperative weight loss. Specifically, during the early postoperative period, Doğan and Arslan reported a statistically significant difference regarding the 1st, 2nd, and 3rd month BMI averages ($p < 0.05$) using a mobile application-based follow-up. However, they did not find any differences in self-care quality, body image, and quality of life scale mean scores [101]. In contrast, two other authors observed that this effect does not extend beyond the first 6 months postoperatively [110]. The limited effectiveness of eHealth interventions in providing better outcomes may be attributed to the flattening of the weight-loss curve during the first 3 to 6 months following a bariatric procedure [110].

The primary objective of this meta-analysis was to assess the impact of digital transformation on postoperative total and excess weight loss, 12 months after the index bariatric operation. Despite an observed trend towards increased weight loss in the experimental group, no statistical significance was demonstrated. Among the included studies, two demonstrated a clear advantage of digital follow-up in enhancing long-term patient outcomes. These studies suggested that the utilization of mobile applications significantly improved the effectiveness of LSV and LGBP on weight loss 24 months postoperatively [97,98]. The impact of eHealth interventions was less pronounced in other studies, particularly in the RCT conducted by Wild et al. who observed equivalent long-term weight loss outcomes irrespective of postoperative eHealth monitoring [111].

Weight recurrence after bariatric surgery is currently a significant concern, often attributed to exaggerated intake of calorie-dense liquids, underlying hormonal disorders and psychiatric conditions and inadequate physical activity [112]. Regular postoperative follow-up meetings provide bariatric patients with opportunities to discuss concerns related to surgical issues, nutritional habits, behaviors and psychological conditions with healthcare professionals [113]. Kim et al., have indicated that long-term postoperative follow-up correlates with increased weight loss and a simultaneous reduction in the risk for weight recurrence [114]. The efficacy of digital health technology in reducing weight recurrence following sleeve gastrectomy was evaluated in a single study, focusing on the role of text message surveillance after the first 18-month postoperative period. While the results did show a tendency, no significant difference in weight recurrence among compared groups was noted. Lauti et al. suggested further investigation, proposing combined eHealth approaches such as personalized messages paired with a mobile health application [99].

### 3.5.4 Limitations of the Current Meta-analysis

Only a small subset of studies, encompassing 942 total patients, investigated the effectiveness of follow-up digitalization in addressing patients' postoperative concerns, which could potentially lead to emergency department visits [55,95]. Despite an overall reduction in emergency department visits in the intervention group, the results did not reach statistical significance, leaving the evidence on this topic inconclusive. Conversely, Hlavin et al. recently reported that exclusively preoperative care based on telemedicine may be sufficient to significantly decrease postoperative ER visits and hospital readmissions [115]. Despite conflicting results, it is crucial to note that the implementation of technological innovations in the field of bariatric surgery has given rise to modern-day ambulatory surgery, which provides vastly superior outcomes when compared to conventional surgical practices. Similarly, the digital transformation of the postoperative care of bariatric patients may yet prove valuable as a complementary tool facilitating social and physical rehabilitation. A notable example of this is the promotion of self-efficacy through a video-conference based follow-up platform, as a necessary first step in the actualization of weight reduction [96,111]. Moreover, in the same study dataset, patients with preoperative depression-related symptoms were effectively managed postoperatively through an online remote communication process, indicating another potential use for eHealth applications [96,111].

### 3.5.5 Implications for clinical practice and future research

Although the present systematic review and meta-analysis was conducted in an exhaustive manner from a methodological standpoint, the limited availability and non-homogeneity of literature data, coupled with the heterogeneity between the different means of digital follow-up and the dissimilar primary and secondary research objectives, resulted in a small number of studies being included and by extension a low overall impact of the meta-analysis. This is further compounded by the fact that statistical significance was not achieved during the analyses, plausibly due to the presence of a type II statistical error stemming from the small number of included studies. Furthermore, inherent limitations such as the potential for selection bias, selective reporting, and attrition bias stemming from the retrospective nature of the evaluated studies and the encountered interstudy statistical heterogeneity, need to be acknowledged. Taking these constraints into account, further investigation by means of cohort studies should be pursued and standardized patient outcome reporting needs to be strongly encouraged.

### 3.5.6 Conclusion

The digitalization of the postoperative care pathway following bariatric surgery seems a safe and feasible option with potential benefits. While evidence is as yet inconclusive, isolated studies indicate multiple roles for eHealth monitoring of bariatric patients, spanning from the preoperative to the postoperative period, until social and physical rehabilitation has been achieved and healthy eating practices restored. Current literature is limited and observed results remain, in many cases, controversial largely due to differences in evaluated patient populations and methods for digital follow-up. In the current analysis, a trend towards increased overall and excess weight loss, as well as a reduction in emergency department visitation rates was noticeable in the eHealth intervention group, albeit without statistical significance. Despite literature constraints, evidence indicates that the digitalization of patient follow-up after bariatric procedures is comparable to conventional practices, offering additional potential merits in terms of patient support and remote counselling.

### 3.5.7 Figures and tables

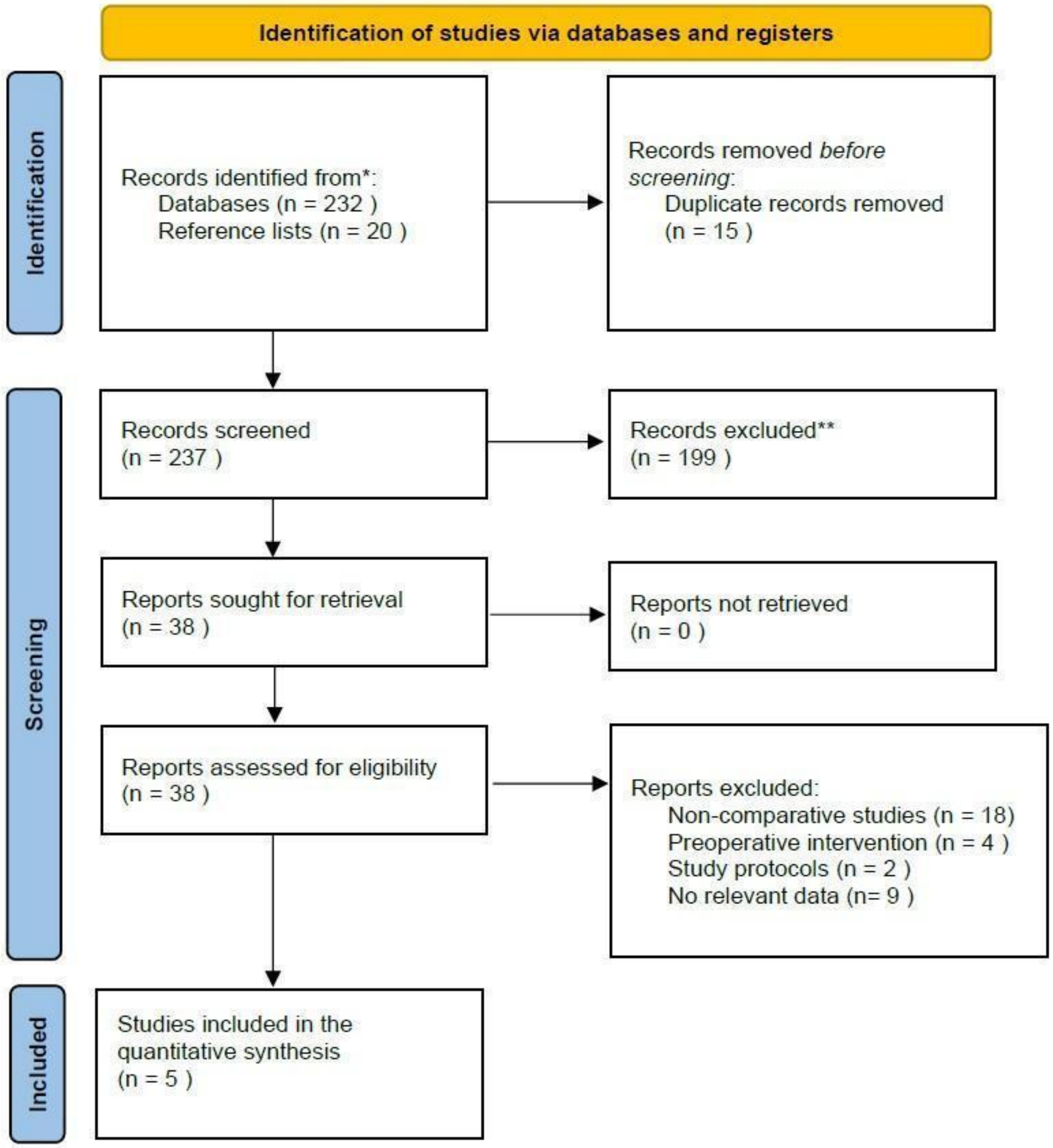


**Figure 1.** Prisma flowchart of the study selection process.

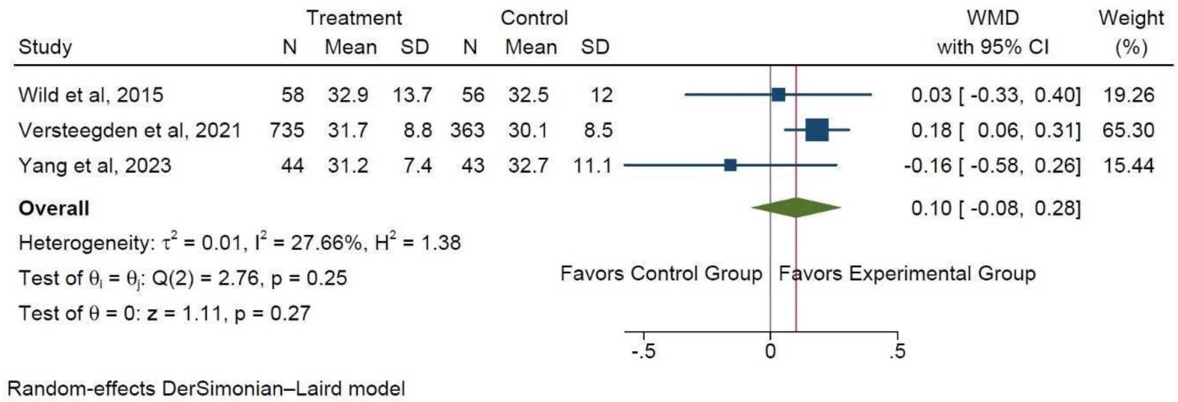


**Figure 2.** Forest plot of the weighted mean difference in % total weight loss at one year postoperatively between the eHealth intervention and control groups.

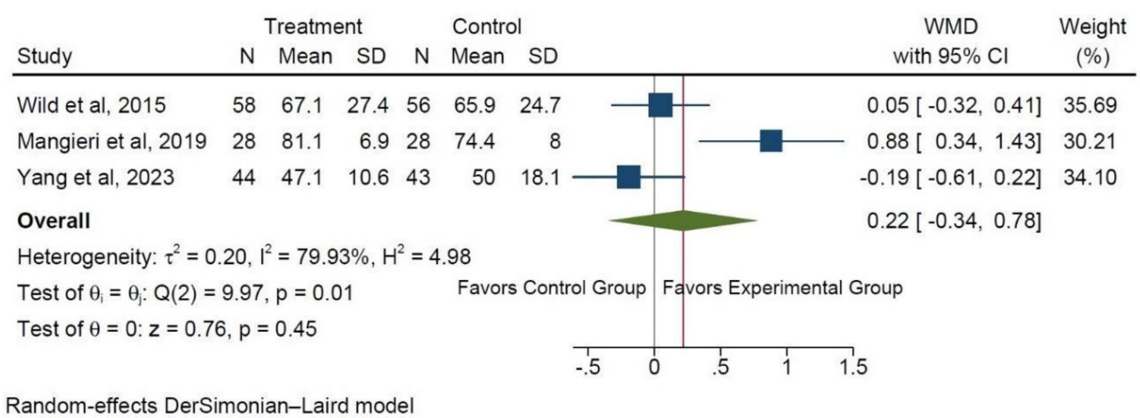


**Figure 3.** Forest plot of the weighted mean difference in % excess weight loss at one year postoperatively between the eHealth intervention and control groups.

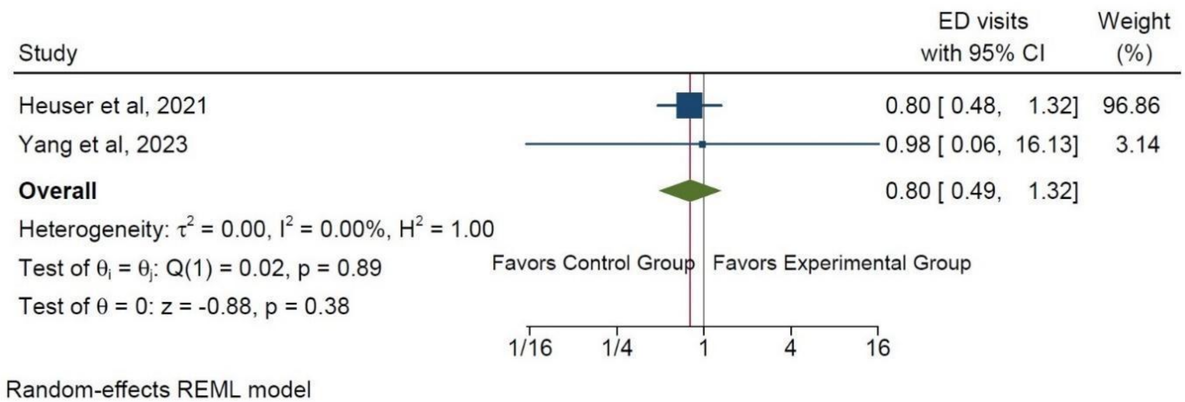


**Figure 4.** Forest plot regarding emergency department visitation rates between the eHealth intervention and control groups.

**Table 1.** Included studies and patient characteristics. IG= intervention group, CG= control group.

| Author | Year | Type of intervention | | Number of patients, n (%) | Age | Sex (Female) | BMI | Weight |
|---|---|---|---|---|---|---|---|---|
| Yang et al. | 2023 | Mobile application | IG | 44 (50) | 42.5±10.8 | 31 (70.5) | 47.0±7.1 | 133.8±23.8 |
| | | | CG | 44 (50) | 43.8±12.4 | 35 (79.5) | 48.4±7.8 | 136.9±29.2 |
| Versteegden et al. | 2021 | Mobile application | IG | 735 (66.9) | N/a | N/a | N/a | N/a |
| | | | CG | 363 (33.1) | N/a | N/a | N/a | N/a |
| Heuser et al. | 2021 | Mobile application | IG | 396 (46.4) | 44.8±9.9 | 308 (77.8) | 47.6±8.2 | N/a |
| | | | CG | 458 (53.6) | 47.6±10.7 | 376 (82) | 48.2±8.7 | N/a |
| Mangieri et al. | 2019 | Mobile application | IG | 28 (50) | 52.5±9 | 24 (85.7) | 35.3±8.2 | N/a |
| | | | CG | 28 (50) | 53±10.6 | 26 (92.9) | 36.9±6.9 | N/a |
| Wild et al. | 2015 | Videoconferencing | IG | 58 (50.8) | 41.2±9 | 35 (60.3) | 50.1±6.6 | 150.7±24.2 |
| | | | CG | 56 (49.2) | 41.9±9.6 | 45 (80.4) | 49.4±6.2 | 144.2±22.7 |

**Table 2.** Reported weighted loss and emergency department visitation rates. ED= Emergency Department, IG = intervention group, CG= control group, TWL= total weight loss, EWL= excess weight loss.

| Author | | Preoperative weight | Postoperative weight at 1 year | %TWL | %EWL | ED visits, n (%) |
|---|---|---|---|---|---|---|
| Yang et al. | IG | 133.8±23.8 | N/a | 31.2±7.4 | 47.1±10.6 | 14 (31.8) |
| | CG | 136.9±29.2 | N/a | 32.7±11.1 | 50±18.1 | 8 (18.6) |
| Versteegden et al. | IG | N/a | N/a | 31.7±8.8 | N/a | N/a |
| | CG | N/a | N/a | 30.1±8.5 | N/a | N/a |
| Heuser et al. | IG | N/a | N/a | N/a | N/a | 33 |
| | CG | N/a | N/a | N/a | N/a | 32 |
| Mangieri et al. | IG | N/a | N/a | N/a | 81.4±6.9 | N/a |
| | CG | N/a | N/a | N/a | 74.4±8 | N/a |
| Wild et al. | IG | 150.7±24.2 | 99.1±2.8 | 32.9±1.8 | 67.1±3.6 | N/a |
| | CG | 144.2±22.7 | 99.8±2.5 | 32.5±1.6 | 65.9±3.3 | N/a |

**Table 3**. Risk of bias summary for non-randomized studies using the ROBINS-I tool. R1= Bias due to confounding, R2= Bias due to selection of participants, R3= Bias in classification of interventions, R4= Bias due to deviations of intended interventions, R5= Bias due to missing data, R6= Bias in measurement of outcomes, R7= Bias in selection of the reported results.

| Study | R1 | R2 | R3 | R4 | R5 | R6 | R7 | Overall |
|---|---|---|---|---|---|---|---|---|
| Yang et al. | Moderate | Low | Low | Low | Low | Low | Low | Low |
| Versteegden et al. | Moderate | Low | Moderate | Low | Low | Low | Low | Moderate |
| Heuser et al. | Serious | Low | Moderate | Low | Low | Low | Low | Serious |
| Mangieri et al. | Low | Low | Moderate | Low | Low | Low | Low | Low |

**Table 4**. Risk of bias summary for randomized controlled trials using the RoB 2 tool. R1= Bias arising from the randomization process, R2= Bias due to deviations from intended intervention, R3= Bias due to missing outcome data, R4= Bias in measurement of the outcome, R5= Bias in selection of reported results.

| Study | R1 | R2 | R3 | R4 | R5 | Overall |
|---|---|---|---|---|---|---|
| Wild et al. | Low | Low | Low | Low | Low | Low |

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# Chapter 4

# 4 Feasibility and Satisfaction with Remote Digital Postoperative Follow-up Using a Three-Tiered Alert System after Bariatric Surgery [2]

## 4.1 Abstract

**Introduction.** With the global prevalence of obesity steadily increasing, bariatric surgery has gained significance in managing this health challenge. Fast-track healthcare pathways have shown promise in improving outcomes and patient satisfaction for bariatric surgery. In this study, we aimed to evaluate the safety and feasibility of responsive remote digital postoperative follow-up using a smartphone application.

**Materials and methods.** Consecutive patients undergoing bariatric surgery at CHU Saint-Pierre university hospital between September 2022 and October 2023 were prospectively enrolled. Patients were instructed to download and install the application on their smartphones, which prompted them with predetermined daily questions. Depending on their responses, alerts could be generated for review by medical staff. A three-tiered alert system (orange, red, red+) was implemented to signify increasing significance. Comparisons between categorical variables were conducted using Fisher's exact test, while comparisons between continuous variables were assessed using the one-way Analysis of Variance (ANOVA) test for normally distributed data and the Mann-Whitney U test for non-normally distributed data.

**Results.** During the study period, a total of 1119 alerts were recorded from 104 patients, with 39.3% occurring within the first seven postoperative days. Patient alert profiles were significantly associated with postoperative outcomes, with worsening outcomes observed from basic orange alerts to red+ alerts. Patients with red+ alerts had nearly a threefold increase in postoperative morbidity rates, emergency department visits, and readmissions. No significant differences in weight loss outcomes were observed. Patient response adherence was 67.5%, while overall satisfaction with the use of the application was 94%.

**Conclusion.** Remote follow-up via a mobile application holds promise for enhancing the management of bariatric surgery patients, complementing traditional practices. The implementation of a three-tiered alert system may help identify patients at risk of serious complications, potentially reducing unnecessary emergency department and hospital resource utilization.

# 4.2 Introduction

## 4.2.1 Context and rationale for digital postoperative follow-up

Obesity has become a significant global health concern, affecting approximately 18.5% of women and 14% of men worldwide, according to recent estimates [116]. Over the past four decades, there has been a steady rise in the prevalence of obesity, surpassing the prevalence of underweight individuals. This trend can be attributed largely to technological and economic advancements, which have led to a convergence in malnutrition rates across different countries. Consequently, obesity has emerged as a pressing health issue, overshadowing malnutrition in many regions. Against this backdrop, obesity surgery has gained increasing relevance in addressing associated morbidity, with sleeve gastrectomy and Roux-en-Y gastric bypass (RYGB) emerging as primary interventions [103]. This trend can be attributed in part to the standardization and improved safety of such procedures in recent years. The adoption of minimally invasive surgery techniques and enhanced recovery (ERAS) protocols has played a pivotal role in this regard, facilitating faster patient recovery and shorter hospital stays without compromising outcomes [117].

Consequently, this shift not only underscores the growing favorability of bariatric surgery but also highlights its potential cost-effectiveness, particularly considering the substantial socio-economic impact of obesity-related morbidity on affected populations.

### 4.2.2 Role of bariatric surgery and early discharge challenges

With the role of obesity surgery firmly established, ongoing efforts are directed toward optimizing patient outcomes. Despite the already short postoperative hospitalization period, typically averaging one to two days, in most cases attention must now shift to the immediate post-discharge phase for two primary reasons: firstly, to ensure successful and sustained weight loss within an acceptable timeframe, and secondly, to facilitate smooth patient recovery [118]. It is noteworthy that a significant proportion of complications arise in the days following hospital discharge, underscoring the imperative need for postoperative patient surveillance [118].

In this regard, the widespread adoption of modern technologies, particularly mobile smartphones, holds promise for substantial benefits by facilitating remote patient follow-up without the need for cumbersome office or hospital visits. This approach not only minimizes the time spent in healthcare facilities but also ensures timely and accurate addressing of patient concerns, thereby potentially enhancing the appeal of such interventions to the general public. While evidence on this topic remains limited, a previous meta-analysis comparing remote digital surveillance with conventional follow-up has shown equivalence in terms of safety and weight loss outcomes, suggesting the feasibility of such a strategy [1].

### 4.2.3 Aim of the study

The aim of the present study is to assess the effectiveness of remote patient follow-up utilizing a mobile phone application and to examine its safety, patient satisfaction, and overall influence on the utilization and accessibility of healthcare services for individuals undergoing bariatric surgery who opt for remote monitoring during the postoperative phase.

## 4.3 Materials and Methods

### 4.3.1 Study design and setting

Consecutive patients undergoing bariatric surgery at the CHU Saint-Pierre university hospital between September 2022 and October 2023 were prospectively enrolled in this study, which involved remote perioperative follow-up via a mobile application. Ethical approval was obtained from the medical ethics committee of CHU Saint-Pierre (Protocol number: B0762022220903). The study was conducted in accordance with the STROBE guidelines [59].

### 4.3.2 Description of the mobile application and alert system

The "Care4Today monitoring" mobile application, developed by Q1.6, was selected in the current study for the digital follow-up of patients. This application engages patients in active monitoring during the crucial 60-day period following their discharge, addressing various aspects such as nutrition, wound care, pain management, and patient well-being. The objective of this mobile application is to serve as a communication tool between Health Care Professionals (HCPs) and patients, facilitating post-discharge patient surveillance. The software comprises a patient interface and an HCP portal. The patient interface is a smartphone application available for Android and iOS devices, which prompts patients with a set of daily predefined questions. Based on the patients' responses, alerts are generated and transmitted via daily emails, direct email, or directly to the healthcare provider dashboard. This system enables informed decision-making and proactive intervention as necessary. All data stored within the Q1.6 application adhere to GDPR compliance standards, employing multi-layered encryption and anonymized formats wherever feasible.

### 4.3.3 Questionnaire structure and alert classification

The questionnaire framework is structured in a smart decisional algorithmic tree format, with questions tailored to various aspects of postoperative care based on their timing (Figure 1). Depending on the patients' responses, a color-coded alert (orange, red, or red+) may be generated, reflecting the severity and projected clinical impact of the response. Orange alerts prompt an automatic email sent to the medical staff in the morning for review. Red alerts trigger an immediate email to be sent and reviewed by the medical staff, while red+ alerts prompt the patient to immediately contact the medical staff or present to the Emergency Department for further evaluation (Table 1). The questionnaire framework and notification decision tree were meticulously crafted by a team of experienced surgeons specializing in obesity surgery, in collaboration with Ethicon (Johnson & Johnson Medical Technologies). This collaborative effort ensures that the application addresses pertinent concerns and provides tailored support to patients.

### 4.3.4 Role of the digital coordinator

All patients were encouraged to download and install the application on their devices with the support of a digital coordinator who served as a liaison between patients and medical staff. This initiative aimed to reduce the digital divide and enhance access to postoperative remote follow-up. The digital coordinator's role included ensuring that each patient understood and effectively utilized the application, as well as promptly communicating any alerts to the medical staff.

### 4.3.5 Eligibility criteria and patient recruitment

All adult patients scheduled for primary obesity surgical intervention or conversion surgery from one type of intervention to another were considered potentially eligible for the study. Informed consent was obtained through the application, and patients were explicitly given the opportunity to opt out of the study at any time. Given the observational nature of the study, no prospective sample size calculation was applicable. Patients were excluded from the study if they were underage (<18 years old), unwilling to participate, lacked a mobile phone capable of installing the application, were unable to use it due to language constraints, or initially agreed to participate but failed to provide any answers via the application.

### 4.3.6 Surgical procedures and patient management

All bariatric interventions were performed by the same team of five surgeons specializing in obesity surgery. Bariatric surgery options included sleeve gastrectomy, Roux-en-Y gastric bypass (RYGB), single anastomosis stomach-ileal bypass with sleeve gastrectomy (SASI-S), or conversion to a RYGB following a previous bariatric intervention. Patients were considered for bariatric surgery if their BMI was greater than 40 or greater than 35 with associated obesity-related comorbidities, following established conventions. A multidisciplinary committee comprising members of the surgical team, a psychologist, and a nutritionist engaged with patients to determine the most appropriate surgical approach. In cases of revisionary bariatric surgery, the decision for conversion was based on patients' symptoms, complaints and overall weight loss status. The study did not alter the standard of practice or routine patient follow-up. Discharge criteria remained unchanged, and no additional drugs, placebos, or non-food substances were administered as part of the study. Staff members were trained to verbally inform patients about the study's purpose, and data generated by the application were managed in a time sensitive manner.

### 4.3.7 Data collection and outcome measures

Study site personnel utilized an electronic database capture system to transfer data from source records (including medical records and source document worksheets). Q1.6 managed the data according to the data processing agreement. The primary data of interest included the number and type of alerts registered, as well as the timing of alerts during the 60-day postoperative follow-up period. Early alerts occurred within 7 days from the surgery, while late alerts were those communicated thereafter. Additionally, patient baseline demographics and procedure-related outcomes, such as complication rates and severity classified by the Clavien-Dindo scale, were collected. Data on postoperative visits to the emergency department (ED), hospital readmissions, and reinterventions within the 60-day postoperative timeframe were also gathered. These data were supplemented with information on postoperative weight loss at 1-month, 3-month, and 6-month milestones. A longer follow-up period for weight loss outcomes was considered more appropriate to provide a comprehensive assessment. Secondary data of interest encompassed patient compliance and mobile application utilization rates, as well as satisfaction with the application's usability. To ensure uniformity in data presentation, the following definitions regarding postoperative weight loss were applied:

% Total weight loss (%TWL): (preoperative weight - current weight) / preoperative weight * 100

% Excess weight loss (%EWL): (preoperative weight - current weight) / (preoperative weight - ideal weight) × 100

The ideal BMI was estimated at 25 $kg/m^2$, with the ideal body weight calculated directly from it, factoring in patients' heights.

### 4.3.8 Compliance and satisfaction evaluation

Patient compliance with the use of the mobile application was assessed at the 60-day postoperative milestone. The number of responses for each previous day was calculated during this period, resulting in an overall response rate.

Patient satisfaction was evaluated using the mHealth App Usability Questionnaire (MAUQ), specifically designed for stand-alone applications [61]. This tool comprises 18 items categorized into three main components: ease of use (5 items), interface and satisfaction (7 items), and overall usefulness (6 items). Each item was scored from 0 to 5, with 0 indicating complete disagreement with the statement and 5 indicating complete agreement. An overall satisfaction score between 0 and 90 was generated for each patient who responded to the questionnaire. These scores were then converted to a scale from 0 to 10 to facilitate data presentation.

### 4.3.9 Statistical analysis

Descriptive statistics were employed to present the collected data. Categorical variables were expressed as absolute numbers with corresponding percentages, while continuous variables were represented as means with standard deviations for those exhibiting a normal distribution and as medians with ranges for those displaying non-normal distributions. The normality of the data was assessed using the Kolmogorov-Smirnov test. Comparisons between categorical variables were conducted using Fisher's exact test, while comparisons between two groups of continuous variables were assessed using the one-way Analysis of Variance (ANOVA) test for normally distributed data and the Mann-Whitney U test for non-normally distributed data. Additionally, the Kruskal-Wallis non-parametric test was employed for comparing multiple groups of non-normally distributed variables. A significance level of $p < 0.05$ was applied to determine statistical significance and two-tailed tests were used where applicable.

## 4.4 Results

### 4.4.1 Patient characteristics and surgery types

A total of 136 patients undergoing bariatric surgery from September 2022 to October 2023 were initially considered for inclusion in the study. After the exclusion of 32 patients (Figure 1), 104 patients who utilized the "Care4Today monitoring" application were ultimately included. No patients were lost during the follow-up period. Among these participants, 85 (81.7%) were female and 19 (18.3%) were male, with an average age of 35.6 ± 12 years (range: 18 – 66 years). The median patient BMI at the time of operation was 41.5 (range: 21.4 – 64.8), with patients at the lower end of the spectrum receiving secondary conversion bariatric surgery. Specifically, 10 patients (9.6% of the sample) underwent revisionary surgery with conversion to RYGB, while the majority underwent primary obesity procedures, primarily RYGB (n = 67, 64.4%), sleeve gastrectomy (n = 20, 19.2%), or single anastomosis stomach-ileal bypass with sleeve gastrectomy (SASI-S) (n = 7, 7.6%). Overall, 101 patients (97.1%) exhibited at least one obesity-related comorbidity, with sleep apnea and arterial hypertension being the most predominant (n = 41, 39.4% and n = 24, 23.1%, respectively).

### 4.4.2 Alert distribution and postoperative complications

A total of 1119 alerts from 101 patients were registered during the 61-day period, starting from the day before surgery (postoperative day -1) up to the 60th day postoperative milestone. Among these alerts, orange alerts were the most frequent (n = 1027, 91.8%), followed by red alerts (n = 74, 6.6%) and red+ alerts (n = 18, 1.6%). The median number of orange alerts per patient was 10, while three patients did not register any alerts despite using the application.

Postoperative complications were observed in 24 patients (23%), with only 4 (16.7%) classified as potentially serious (Clavien-Dindo grade > II). No patient deaths occurred during the study period. In total, there were 17 visits to the emergency department by 12 patients (11.5%), resulting in 10 readmissions for 8 patients (7.7%), of which three underwent a reintervention in the form of exploratory laparoscopy. Table 2 provides a high-level overview of patient baseline data.

### 4.4.3 Postoperative weight loss outcomes

Most patients experienced steady weight loss from baseline during the 6-month postoperative follow-up period (refer to Table 3). The median weight loss at the 6-month milestone was 27 kg (range: 7.2–58.9 kg), corresponding to a reduction in median BMI from 41.5 at baseline to 31.2 (range: 22.5-46.1). At the end of the follow-up, the median %TWL was 22.8% (range: 7.5%-

39.8%), with an associated median %EWL of 57.9% (range: 26.8%-124.5%), indicating effective weight control through the interventions employed. Notably, there was a single patient who initially experienced a 1.4 kg weight gain one month following sleeve gastrectomy, which subsequently reverted to a 14.5 kg weight loss by the end of follow-up.

### 4.4.4 Impact of alert type on patient outcomes

Nausea/vomiting and abdominal pain were identified as the primary triggers for both orange and red alerts. Orange alerts, by definition, were associated with symptoms of lower severity compared to red alerts, while red+ alerts always indicated symptoms suggestive of a potentially significant postoperative complication requiring immediate medical attention. Consequently, patients were categorized into four subgroups based on their alert profiles to facilitate comparisons of postoperative outcomes. The first subgroup comprised patients with fewer than 10 orange alerts and no red or red+ alerts, while the second subgroup consisted of patients with more than 10 orange alerts but no red or red+ alerts. The third subgroup included patients with a red alert (irrespective of whether they also had orange alerts), and the fourth subgroup encompassed patients with red+ alerts (Table 4).

While the mean age did not exhibit significant differences between the compared subgroups, a trend toward higher mean age was noticeable in the subgroups with orange-only alerts. Emergency department (ED) visits and hospital readmissions were significantly higher in the red and red+ subgroups ($p=0.002$ and $p=0.008$, respectively) compared to the other subgroups. Interestingly, among the 8 patients with red+ alerts, only four ED visits were recorded that led to three rehospitalizations. %TWL and %EWL at 30 days postoperatively were comparable across the subgroups. However, morbidity rates were significantly elevated in the red and red+ subgroups (45.5% and 75%, respectively) compared to the orange alert subgroups ($p<0.001$).

### 4.4.5 Alert timing: early vs late postoperative phase

Of the total number of alerts, 439 (39.2% of the entire pool) were recorded within the first postoperative week (early postoperative alerts), while the remaining 680 (60.8%) were registered in the 53-day period that followed (late postoperative alerts). Although orange alerts were predominant in both time periods, the early postoperative period saw an almost double prevalence of red alerts. Table 5 provides a detailed breakdown of alert types based on their timing of presentation. Notably, only two patients (1.9%) visited the Emergency Department during the early postoperative period, with one patient (0.9%) being readmitted during the early postoperative period. Most ED visits occurred during the late postoperative period, involving 10 patients (9.6% of the entire cohort), of whom 7 (6.9%) were rehospitalized.

### 4.4.6 Patient compliance with application usage

Out of a total of 19,325 questions sent out during the 60-day postoperative period, 13,049 responses were received, resulting in an overall response rate of 67.5%. The highest adherence rates were observed during the first postoperative week, ranging from 75% to 92%, and gradually declining thereafter.

### 4.4.7 Patient satisfaction with the mobile application

In total, 75 patients responded to the satisfaction questionnaires. All these patients successfully adhered to the 60-day postoperative monitoring period using the application. The overall median satisfaction score was 9.3 out of 10 (ranging from 7.8 to 10). Concerning the subcomponents of the MAUQ questionnaire, the median patient satisfaction with the ease of use was 10 out of 10 (range: 6 to 10). Satisfaction rates were also comparable regarding the interface usability (median score of 9.8, range: 8.2 to 10), while patient perception of the overall usefulness of the application was slightly lower (median score of 8, range: 5.7 to 8.6).

# 4.5 Discussion

## 4.5.1 Feasibility and predictive value of the alert system

In the present study, we aimed to outline our experience with digital follow-up for patients undergoing bariatric surgery and assess its integration within a streamlined postoperative healthcare pathway designed to minimize healthcare resource utilization while maintaining patient safety and satisfaction. To achieve this goal, we propose a mobile application solution featuring a three-tiered alert system. This system serves a dual purpose: firstly, to provide patients with guidance on addressing any healthcare concerns that may arise during the postoperative period, and secondly, to provide healthcare personnel involved in their management with real-time updates on the patient's status. The rationale behind this approach is clear: remote follow-up via a digital mobile application aims to shorten hospitalization duration, reduce unnecessary utilization of emergency services, thereby lowering the rate of hospital readmissions, and enhance satisfaction among all stakeholders by offering an easy-to-use platform that complements existing standards of care. Bariatric surgery is well-suited for remote follow-up, given its short hospitalization period and prolonged postoperative monitoring phase. Mangieri et al. [98] conducted the first assessment of a commercially available mobile application as a postoperative adjunct in a randomized controlled trial (RCT) with 56 patients. They found that application users experienced significant weight reduction over a 24-month follow-up period compared to non-users, suggesting potential postoperative outcome enhancement. However, the selected mobile application lacked specific adjustments for bariatric surgery and thus did not include postoperative patient surveillance. In a subsequent study, Heuser et al. [55] observed comparable length of hospital stay, ED visitation rates, and readmission rates between patients using a mobile application for follow-up and those who did not. Similarly, Yang et al. [95] investigated replacing standard office-based follow-up with digital application follow-up, concluding that remote follow-up is as effective as traditional practice. While these studies demonstrate the feasibility of remote follow-up via mobile applications, none of them effectively enabled real-time patient status monitoring.

One of the key findings of our study was the association between patients' alert profiles and not only emergency department presentations and rehospitalizations but also the presence of postoperative complications. Patients with red and red + alerts exhibited a two to three times higher incidence of postoperative complications compared to those with orange or no alerts ($p < 0.001$).

### 4.5.2 Implications for healthcare resource optimization

This strong association underscores the mobile application's ability to predict postoperative complications and promptly notify medical staff, facilitating timely intervention to minimize patient risk. This feature has the potential to be pivotal in shifting the current practice paradigm from a reactive stance to a more proactive one. Furthermore, despite nausea, vomiting, and abdominal pain being the predominant triggers for alerts in the majority of patients, the application's scope was expanded to encompass a broader range of topics that may affect patient well-being during the postoperative period, thus allowing for a more accurate portrayal of current patient status.

### 4.5.3 Comparison with previous studies

It's worth noting that more than a third of the total number of alerts occurred during the first 7 postoperative days, coinciding with the period when bariatric patients typically experience transitory symptoms and are most susceptible to postoperative leaks [119]. During this early phase, patients exhibited nearly double the rates of red and red+ alerts compared to the later postoperative period, although most emergency department visits and rehospitalizations occurred afterward. This finding aligns with similar observations in other studies [120], given the longer duration of the latter period. However, considering the relatively low number of emergency department visits and readmissions despite the high number of red and red+ alerts (n = 59) during the early postoperative phase, remote follow-up via a mobile application may serve as an effective triage and counseling system during these critical initial days, acting complementarily to known risk factors [121].

In terms of postoperative weight outcomes, the cohort did demonstrate satisfactory progression during the 6-month follow-up period, even though subgroup analysis did not reveal any particular association between patient alert profile and TWL or EWL outcomes. This lack of significance might stem from the short postoperative follow-up available; however, observed reductions in weight are consistent with reports from other studies focusing on the same time span [122]. Another plausible explanation is that mobile applications structured in a questionnaire format may not effectively promote increased activity and thus potentiate weight loss. This could also explain the controversies in currently existing studies comparing remote follow-up via digital application platforms to standard practice. Specifically, weight loss outcomes are equivalent in two studies using a questionnaire-based system [95,123], while the single RCT on the topic [98] indicates that significant weight loss can be expected with the integration of interactive applications oriented towards dietary and activity surveillance.

Patient adherence to postoperative follow-up is a crucial aspect of bariatric surgery care. Numerous risk factors for non-adherence have been identified [124], and evidence suggests that adequate adherence is essential for achieving initial weight loss [125][98]. In our study, the overall adherence rate was 67.5%, with adherence peaking during the early postoperative period and gradually declining thereafter. This adherence rate is comparable to rates associated with conventional follow-up [126], indicating successful compliance with the mobile application's use. Patient satisfaction, as measured by the Mobile Application Usability Questionnaire (MAUQ), was also high, with a median score of 9.3 out of ten, indicating satisfaction with its ease of use.

### 4.5.4 Limitations of the study

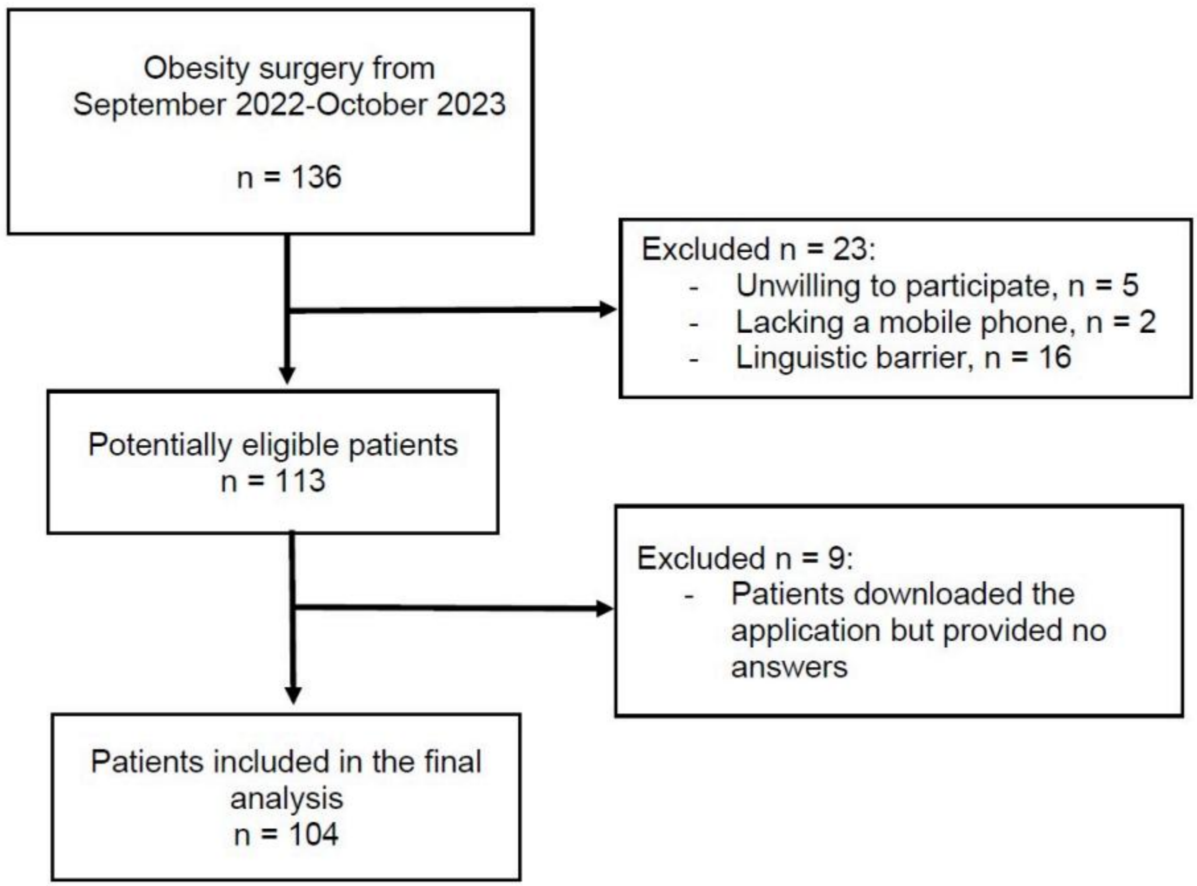
This study has several limitations. Firstly, it is a single-center observational study, which, despite being conducted prospectively, is susceptible to selection bias. Although efforts were made to include patients from diverse socioeconomic backgrounds and a digital coordinator was employed to enhance patient inclusivity, some patients were excluded due to language barriers or lack of access to a mobile phone. Secondly, the follow-up period of 6 months may have been too short to adequately assess differences in outcomes such as weight loss. Additionally, comparative analyses may have been affected by confounding bias, as adjustments for confounding factors were not feasible with the available dataset. Finally, it is worth noting that in the present study, adherence to other postoperative measures, such as vitamin supplementation or lifestyle changes, was not monitored.

## 4.6 Conclusion

In conclusion, this study underscores the potential of remote patient follow-up using a questionnaire-based mobile application with a three-tiered alert system in the postoperative care of bariatric surgery patients, enabling real-time monitoring. The significant association between patient alert profile and emergency department visits, hospital readmissions, and postoperative morbidity indicates the application's ability to identify at-risk patients and potentially reduce unnecessary healthcare resource utilization. High adherence rates and patient satisfaction further support the feasibility and acceptance of the mobile application. Overall, remote follow-up via mobile application offers a promising approach to enhancing the management of bariatric surgery patients, providing a proactive supplement to traditional practices.

## 4.7 Figures and Tables

**Figure 1.** Patient selection flowchart.



| Type of alert | Phase | Notification | Action |
|---|---|---|---|
| Orange | Preoperative | - Patient would like information to help stop smoking | An e-mail with all orange alerts of the last 24 hours will be sent to the medical staff in the morning |
| | | - Patient feels quite bad the day before surgery | |
| | Postoperative | - Patient does not understand discharge info | |
| | | - Patient has moderate pain and is taking painkillers (VAS between 6 and 7) | |
| | | - Patient has one of the following conditions: worsening cough, chest pain, shortness of breath, swollen/painful leg, dizziness, temperature > 38.5 C | |
| | | - Patient experiences problem with wound | |
| | | - Patient's wound is not dressed and not kept clean | |
| | | - Patient doesn't understand the recovery exercises | |
| | | - Patient's activity level is half of what it was before surgery and patient is in pain | |
| | | - Patient is not feeling well | |
| | Late postoperative (31 days postoperatively) | - Patient has abdominal pain or tenderness in the shoulders | |
| | | - Patient experiences pain when eating | |
| | | - Patient is experiencing one or more of the following symptoms: heartburn, nausea/vomiting, abdominal pain, difficulty eating/swallowing, dumping syndrome symptoms, other (unspecified) complaints | |
| | | - Patient has lost more than 10% of weight | |
| | | - Patient is not able to follow guidelines around time to eat a meal | |
| | General questions (asked at prespecified time points) | - Patient is experiencing one or more of the following symptoms: diabetes, high blood pressure, fast heart rate, breathing problems, heart problems, kidney failure, sleep apnea, joint condition(s), high cholesterol, other (non-specified) | |
| | | - Patient experiences pain when eating | |
| | | - Patient suffers from a decrease in quality of life | |
| Red | Preoperative | - Patient feels terrible the day before surgery | An e-mail will immediately be sent to the medical staff |
| | Postoperative | - Patient experiences a lot of pain and is taking painkillers (VAS between 8 and 9) | |
| | | - Patient has wound separation or gaping wound | |
| | | - Patient didn't drink today | |
| | Late postoperative (31 days postoperatively) | - Patient has been vomiting for 3 days | |
| Red+ | Postoperative | - Patient has two or more of the following conditions: chest pain, shortness of breath, swollen/painful leg | The patient will be presented with a notification to immediately contact the medical staff or present to the Emergency Department |
| | | - Patient experiences severe pain and is taking painkillers (VAS of 10) | |

**Table 1**. List of alerts and notifications generated by the application depending on patients' answers.

VAS = Visual Analog Scale of pain

| | | Number of patients n (%) |
|---|---|---|
| Sex | *Male* | 19 (18.3) |
| | *Female* | 85 (81.7) |
| Age (years)* | | 35.6 ± 12 |
| Preoperative BMI | | 41.5 (21.4-64.8) |
| Comorbidities | *Smoking* | 15 (14.4) |
| | *Alcohol consumption* | 6 (5.8) |
| | *Hypertension* | 24 (23.1) |
| | *Sleep apnea* | 41 (39.4) |
| | *Diabetes* | 18 (17.3) |
| | *GERD* | 17 (16.3) |
| Previous abdominal surgery | | 36 (34.6) |
| Previous bariatric surgery | | 10 (9.6) |
| Postoperative Morbidity | *Total* | 24 (23) |
| | ≤ *Clavien-Dindo grade II* | 20 (83.3) |
| | > *Clavien-Dindo grade II* | 4 (16.7) |
| Types of Surgery | *Sleeve gastrectomy* | 20 (19.2) |
| | *Roux-en-Y gastric bypass* | 67 (64.4) |
| | *SASI-S* | 7 (6.7) |
| | *Conversion to bypass* | 10 (9.7) |
| Length of Hospital stay (days) | | 2 (1-7) |
| Number of alerts | *Orange* | 1027 (91.8) |
| | *Red* | 74 (6.6) |
| | *Red+* | 18 (1.6) |
| | *Total* | 1119 |
| Emergency department visits | | 12 (11.5) |
| Readmissions | | 8 (7.7) |

**Table 2.** Baseline patient parameters and characteristics. * Values presented as mean and standard deviation.

| | 1 month | 3 months | 6 months |
|---|---|---|---|
| Postoperative BMI | 37.8 (28.7-59.5) | 33.5 (24.7-51.3) | 31.2 (22.5-46.1) |
| Total weight loss (kg) | 10.6 (-1.4-25.5) | 22.7 (1.2-35.3) | 27 (7.2-58.9) |
| %TWL | 9.2% (-1.2% - 17%) | 18.4% (1.2%-35.3%) | 22.8% (7.5%-39.8%) |
| %EWL | 22.8% (-2.6%-53.4%) | 46.2% (8.6%-102.6%) | 57.9% (26.8%-124.5%) |

**Table 3.** Follow-up data on weight loss. Data are presented as median (range). TWL%= Total weight loss (percentage), EWL%= Excess weight loss (percentage),

| Type of alert | Orange alerts < 10 | Orange alerts ≥ 10 | Red alerts | Red+ alerts | p-value |
|---|---|---|---|---|---|
| Number of patients | 53 | 21 | 22 | 8 | |
| Total number of alerts | 194 | 324 | 318 | 280 | |
| Age* | 36.6±11.6 | 39.5±12.6 | 31.7±11.8 | 32.3±10.4 | 0.08 |
| ED visits, n (%) | 3 (5.7) | 0 | 5 (22.7) | 4 (50) | 0.002 |
| Readmission, n (%) | 2 (3.8) | 0 | 3 (13.6) | 3 (37.5) | 0.008 |
| Morbidity | 3 (5.7) | 5 (23.8) | 10 (45.5) | 6 (75) | <0.001 |
| %TWL at 6 months | 23.1% (15.5%-38.9%) | 21.9% (13.4%-35.5%) | 22.7% (13%-39.8%) | 25.2% (13%-39.8%) | 0.25 |
| %EWL at 6 months | 57.9 (30.8-82.3) | 56.7 (26.8-124.5) | 53.9 (31.8-91) | 55.2 (32.1-81.5) | 0.31 |

**Table 4.** Outcomes of patients depending on the type of alert profile. *values presented as means with standard deviation.

| | Early postoperative period (≤7 days) | Late postoperative period (>7 days) | p-value |
|---|---|---|---|
| Total alerts | 439 | 680 | <0.001 |
| Orange alerts | 380 (86.5) | 646 (95) | |
| Red alerts | 45 (10.3) | 30 (4.4) | |
| Red+ alerts | 14 (3.2) | 4 (0.6) | |
| ED visits, n (%) | 2 (1.9) | 10 (9.6) | 0.03 |
| Readmission, n (%) | 1 (0.9) | 7 (6.7) | 0.07 |

**Table 5.** Alert profile and patient outcomes in the first postoperative week as opposed to the later postoperative period.

# Chapter 5

# 5 Integrating Artificial Intelligence and Dynamic Digital Follow-Up for Enhanced Prediction of Postoperative Complications in Bariatric Surgery [3]

## 5.1 Abstract

**Introduction.** Traditional risk models, such as POSSUM and OS-MS, have limited accuracy in predicting complications after bariatric surgery. Machine learning (ML) offers new opportunities for personalized risk assessment by incorporating artificial intelligence (AI). This study aimed to develop and evaluate two ML-based models: one using preoperative clinical data and another integrating postoperative data from a mobile application.

**Methods.** A prospective study was conducted on 104 bariatric surgery patients at Saint-Pierre University Hospital (September 2022–July 2023). Patients used the "Care4Today" mobile app for real-time postoperative monitoring. Data were analyzed using ML algorithms, with performance evaluated via cross-validation, accuracy, F1 scores, and AUC. A preoperative model used demographic and surgical data, while a postoperative model incorporated symptoms and mobile app-generated alerts.

**Results.** A total of 104 patients were included. The preoperative model, utilizing Extreme Linear Discriminant Analysis, achieved an accuracy of 75% and an AUC of 64.7%. The postoperative model, using logistic regression with six selected features, demonstrated improved performance

with an accuracy of 77.4% and an AUC of 71.5%. A user interface was developed for clinical implementation.

**Conclusion.** ML-based predictive models, particularly those integrating dynamic postoperative data, improve risk stratification in bariatric surgery. Real-time mobile health monitoring enhances early complication detection, offering a personalized, adaptable approach beyond traditional static risk models. Future validation with larger datasets is necessary to confirm generalizability.

# 5.2 Introduction

## 5.2.1 Limitations of traditional risk prediction models

Several risk score-based models such as the Physiological and Operative Severity Score for the enumeration of Morbidity and Mortality (POSSUM) and the Obesity Surgical Mortality Risk (OS-MS), have been used to predict complications after bariatric surgery [127,128]. At the present, however, their predictive accuracy remains limited, with AUC values of 0.66 and 0.62, respectively [129], justifying the need to develop improved models.

## 5.2.2 The promise of machine learning and mobile integration

Artificial intelligence (AI) offers now new solutions in this setting by enabling personalized risk assessments through machine learning (ML) and artificial neural networks (ANN). These models have shown effectiveness in predicting early postoperative complications in bariatric surgery. [130,131] Furthermore, their modular nature allows integration with other technologies, like smartphone applications, for real-time monitoring and dynamic patient-physician interactions [132], enabling rapid risk assessment and personalized interventions.

### 5.2.3 Study objectives

The objective of this study was to develop and to evaluate two distinct ML-based risk assessment models relying on 1) preoperative parameters, using standard clinical and demographic data, and 2) postoperative parameters by incorporating patient's data collected through a mobile application follow-up.

## 5.3 Materials and Methods

### 5.3.1 Study design and patient inclusion criteria

Consecutive adult patients undergoing bariatric surgery at Saint-Pierre University Hospital from September 2022 to July 2023 were considered eligible for inclusion in this study. After signing a written informed consent form, patients who agreed to participate were instructed to download the "Care4Today" mobile application, which enables real-time remote patient follow-up during the perioperative period. The indications for bariatric surgery were a BMI greater than 40, or greater than 35 in the presence of obesity-related comorbidities. Exclusion criteria included unwillingness to participate, incomplete follow-up (less than 60 days), lack of a mobile phone, or linguistic barriers that precluded the use of the mobile application.

This study was approved by the institutional ethics committee (Protocol number: B0762022220903).

### 5.3.2 Mobile application-based postoperative follow-up

Postoperative remote digital follow-up was performed using the "Care4Today monitoring" mobile application, developed by Q1.6, in addition to standard office-based consultations. This application enables remote postoperative follow-up by asking patients a set of predefined questions centered around various aspects of postoperative patient care, such as nutrition, wound care, pain management, and patient well-being, starting from one day preoperatively to 60 days postoperative, which corresponded to their second postoperative office-based consultation. The objective of this mobile application is to serve as a communication tool between Health Care Professionals (HCPs) and patients, facilitating post-discharge patient surveillance. The application itself utilizes a questionnaire framework that was designed by five local expert bariatric surgeons and is formatted as a decision tree. Depending on patients' responses, an alert may be generated and transmitted via daily emails, direct email, or directly to the healthcare provider dashboard depending on the severity of the patients' symptoms. A three-tiered alert system was utilized by color coding alerts into orange alerts (mild symptoms and complaints), red alerts (symptoms with significant health implications), and red+ alerts (symptoms that warrant immediate medical attention). In order to expand patient inclusivity and facilitate communication between patients and physician through the application, a digital coordinator was involved to ensure that each patient understood and effectively utilized the application, as well as to promptly communicate any alerts to the medical staff. Median office-based patient follow-up was 63 days (range 28 to 369 days).

### 5.3.3 Database construction and variables of interest

Clinical details of patients were prospectively collected and entered into a standardized database for further tabulation. Pertinent clinical data included comprehensive information on each patient's medical history and specific details related to their bariatric surgery. This encompassed patient demographics, preoperative BMI, details of prior surgeries, presence of obesity-related comorbidities, type of surgical intervention; Roux-en-Y gastric bypass (RYGB), single anastomosis stomach-ileal bypass with sleeve gastrectomy (SASI-S), or conversion to RYGB following previous bariatric procedures, as well as any complications and postoperative symptoms reported during follow-up visits or via the mobile application. Furthermore, real-time data were collected through the mobile application dashboard, capturing responses to predefined questions, frequency and types of alerts generated per patient per day.

### 5.3.4 Data preprocessing and encoding methods

To facilitate data handling and processing, raw data from the project database were transformed in preparation for analysis. Null and missing values were imputed by replacing numerical values with the mean and categorical values with the mode, ensuring data robustness. Additionally, ordinal and categorical data were converted into numerical representations using the "one-hot encoding" technique [133].

### 5.3.5 Model training and cross-validation

Following data analysis, cleaning, and preprocessing, a comparative analysis of machine learning (ML) models was conducted for predicting postoperative complications according to pre- and postoperative collected variables. The first provides a general tool to assess the global surgical risk, while the second aimed to quantify the specific surgical risk.

To validate the predictive model, a cross-validation approach was used. This technique is essential for evaluating the model's performance on different partitions of the training data, thus ensuring a robust evaluation of the model's performance [134]. The Synthetic Minority Oversampling Technique (SMOTE) algorithm was also used, which serves to increase the number of observations of the minority class with synthetic examples [135,136]. This approach aimed to address the class imbalances observed in the complication outcome data.

### 5.3.6 Machine learning algorithms used

A comparison between fifteen ML classification models was launched (Table 1). These models were specifically selected for the present study, as they are easy to train with limited data. The Pycaret tool, a Python v 2.3 library that enables training and evaluation, was utilized to provide a reusable pipeline for deploying the best-found model.

### 5.3.7 Performance metrics and dimensionality reduction

The predictive performance of the 15 ML models investigated was assessed based on metrics such as cross validation accuracy, precision and recall (measured as cross validation F1 scores) and cross validation area under the curve (AUC), and the total number of input parameters (variables and possible values for each one). In the case of a large number of input features, dimensionality reduction was performed to allow for a model that is easier to manipulate and use. To achieve this, the 'SelectKBest' feature selection method from scikit-learn python library, with Principal Component Analysis (PCA) for dimensionality reduction was used [137]. Furthermore, the t-distributed stochastic neighbor embedding (T-SNE) method was employed to illustrate model classification data on a 2-dimensional diagram after dimensionality reduction, to verify the accuracy and correctness of the final models.

# 5.4 Results

## 5.4.1 Patient characteristics and postoperative symptoms

Overall, 104 patients were included in the study sample, of whom 85 (81.7%) were female and 19 (18.5%) were male, with an average age of 35.6±12 years (Table 2). The median preoperative BMI was 41.5 (21.4-64.8) kg/m². Fifteen patients (14.4%) reported smoking history, 18 (17.3%) had a history of gastroesophageal reflux disease, and 71 (68.3%) exhibited obesity-related comorbidities such as hypertension (n=6, 5.8%), sleep apnea (n=24, 23.1%), and diabetes (n=41, 39.4%). Previous surgical history was noted in a minority of these patients (n=36, 34.6%), with the majority undergoing RYGB (n=67, 64.4%), followed by sleeve gastrectomy (n=20, 19.2%).

The total number of patients reporting postoperative symptoms was 52 (64.2% of the entire cohort), among whom pain was the chief complaint (45.7% of patients), followed by vomiting (8.6%), constipation (6.2%), and other isolated complaints including generalized malaise, odynophagia, nausea, or dyspnea.

## 5.4.2 Complication types and frequency of alerts

The morbidity rate in the cohort was 20.2%, with six cases of intractable vomiting requiring hospitalization (either readmission or prolongation of initial stay) for intravenous fluid replacement, three cases of postoperative dysphagia lasting longer than 30 days, two cases of anastomotic strictures, three cases of severe pain requiring in-hospital pain management, two cases of dumping syndrome, one case of pancreatitis, one internal hernia, one biliary fistula, one pulmonary embolism, and one case of surgical site infection. No deaths were reported, with 3 patients (3.7%) requiring readmission.

Global morbidity rate  according to Clavien-Dindo (CD) classification [138] was 20.2%, with a total of 141 alerts transmitted by the application during the follow-up period (supplementary material). Complications were minor (CD<III) in 16 (76.2%) patients and major (CD≥III) in 5 (23.8%). Accordingly, a total of 1119 alerts were transmitted during the follow-up period, the majority being orange alerts (n=1027, 91.8%), followed by red alerts (n=74, 6.6%), and red+ alerts (n=18, 1.6%).

The total patient cohort was divided into a training (n=72, 70%) cohort and a validation (n=32, 30%) cohort. Cross-validation across 5 folds verified the predictive capacity of the final models.

### 5.4.3 Preoperative predictive model: performance and features

After the training of the models, the best adapted predictive model used the Extreme Linear Discriminant Analysis model with inputs being patient demographics (age, sex, BMI, comorbidities), the type of scheduled bariatric operation and the previous history of abdominal surgery. The model displayed an accuracy of 75%, an F1 score of 43% and an AUC of 64.7%.

### 5.4.4 Postoperative predictive model: optimization and results

The model applied in this setting initially incorporated all available input variables (namely, answers to mobile application questions and generated alerts), utilizing the logistic regression method and displaying an accuracy of 83.8%, an F1 score of 46.1% and an AUC of 62.7%.

However, this model was found to be cumbersome and difficult to deploy due to its large number of input features. To address this, we employed the 'SelectKBest' feature selection method from sklearn with Principal Component Analysis (PCA) for dimensionality reduction. We found that the optimal tradeoff between usability and predictive accuracy was achieved with only 6 features (presence and type of symptoms, answers to smartphone application questions "Do you experience vomiting?", "Do you experience abdominal pain?", "Do you experience pain while eating?", "How much did you drink today?", total number of orange and red alerts), using logistic regression, and achieving an accuracy of 77.4%, an F1 score of 46.2% and an AUC of 71.5%.

### 5.4.5 User interface for clinical deployment

A graphical user interface was constructed to facilitate the use of the predictive models (Figure 2). This interface allows for a choice between the preoperative or postoperative models, with each one utilizing different input features to output a distinct probability associated with the likelihood of postoperative complications. A prototype is deployed in the English language and is available for review on https://barisk.deepilia.com/.

## 5.5 Discussion

### 5.5.1 Benefits of dynamic, AI-driven risk assessment

This study demonstrates the potential of an integrated AI-driven approach to risk assessment in bariatric surgery, combining baseline clinical data with dynamic postoperative follow-up data from a mobile application. By leveraging ML, our approach enables a more personalized and adaptable risk prediction, reflecting real-time changes in a patient's postoperative status. Unlike traditional static models, this dynamic risk assessment adapts to postoperative progression, potentially enabling timely interventions for complications arising in the postoperative period.

In designing and optimizing the ML models involved in this study, a careful review of known risk factors associated with postoperative complications following bariatric surgery was conducted, so as to optimize model output. Baseline patient demographics such as sex, age, BMI and the presence of comorbidities such as hypertension, diabetes and smoking have been consistently linked to increased complication rates [139,140]. In addition, the type of operation performed has also been found to play a significant role, with RYGB ostensibly associated with worse outcomes [141]. Exploratory analysis within the current dataset did not reveal any clear associations between these variables and the presence of postoperative complications. However, this may have been due to the small total number of included patients, which increases the risk of a type II statistical error. Nevertheless, these variables were included in the generic ML model as input features was mainly because of their simplicity and ease of application in the generic predictive model.

### 5.5.2 Comparative analysis of preoperative and postoperative models

Between the two models evaluated (in the preoperative and postoperative settings), the postoperative model, which incorporates data from the "Care4Today" application, proved to be more the robust, achieving an accuracy of 77.4% and an AUC of 71.5% even after dimensionality reduction. This highlights the enhanced predictive accuracy that comes with incorporating dynamic, from patient monitoring. Such a model potentially offers tangible clinical benefits, allowing for continuous, patient-centered follow-up that specialist physicians can use to refine risk assessments throughout the postoperative period.

### 5.5.3 Clinical implications for bariatric surgery follow-up

This feature is particularly valuable in bariatric surgery, where complications may evolve over time and require early detection to prevent escalation.

In contrast, the preoperative model—using only traditional demographic and clinical data—showed a predictive performance associated with an accuracy of 75%. While simpler and potentially useful for generalist physicians in preoperative patient counseling, this model lacks the adaptability and precision offered by dynamic, app-based follow-up. Similar studies have achieved higher accuracy through more complex models. For instance, Sheikhtaheri et al. [130] applied an ANN model to predict complications following one-anastomosis gastric bypass, achieving 90.9% accuracy by augmenting baseline clinical features with biochemical, sonographic, endoscopic, and intra-operative data, implying that more extensive data inputs could improve predictive power in specific clinical settings. Findings from the present study suggest that the primary limitation of the preoperative model is its tendency to generate false negatives, likely due to limited training and dataset diversity. Ensuring a diverse training dataset is crucial for enhancing the model's generalizability.

### 5.5.4 Limitations of the study and considerations for improvement

The present study has some notable limitations that need to be acknowledged. First and foremost, the models developed herein were not externally validated. This is currently impossible due to the lack of implementation of the "care4today" mobile applications in other bariatric surgery programs at different institutions. Secondly, the small size of the training dataset presents several limitations, including the risks of overfitting, underfitting, and high variance in model performance. Additionally, the small dataset hampers the model's ability to capture the full variability of the data and accurately detect outliers or anomalies. Furthermore, the dataset was imbalanced, necessitating the use of SMOTE to address this issue. While SMOTE helps mitigate class imbalance by generating synthetic samples, it may also introduce noise and affect the natural distribution of the data. Consequently, the model's performance and generalizability might be impacted, and results should be interpreted with caution. Finally, it should be noted that all complications were grouped together irrespective of severity. Thus, the model currently lacks the capability to specifically detect the risk of severe complications.

## 5.6 Conclusion

In conclusion, our findings suggest that AI-driven models, particularly those utilizing postoperative app-based follow-up, can enhance risk assessment in bariatric surgery. This dynamic approach, combining ML with mobile health technology, demonstrates the benefits of incorporating evolving patient data for accurate risk estimation, providing an alternative to static, traditional risk scores.

### 5.6.1 Figures and Tables

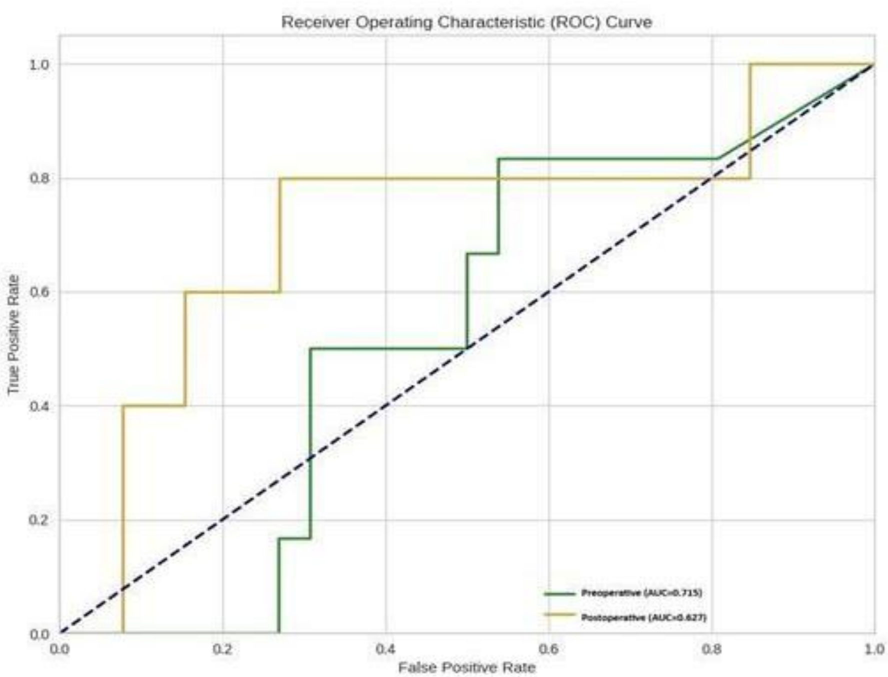



**Figure 1.** Receiver operator curves for the predictive efficacy of each of the two trained models in the postoperative setting.

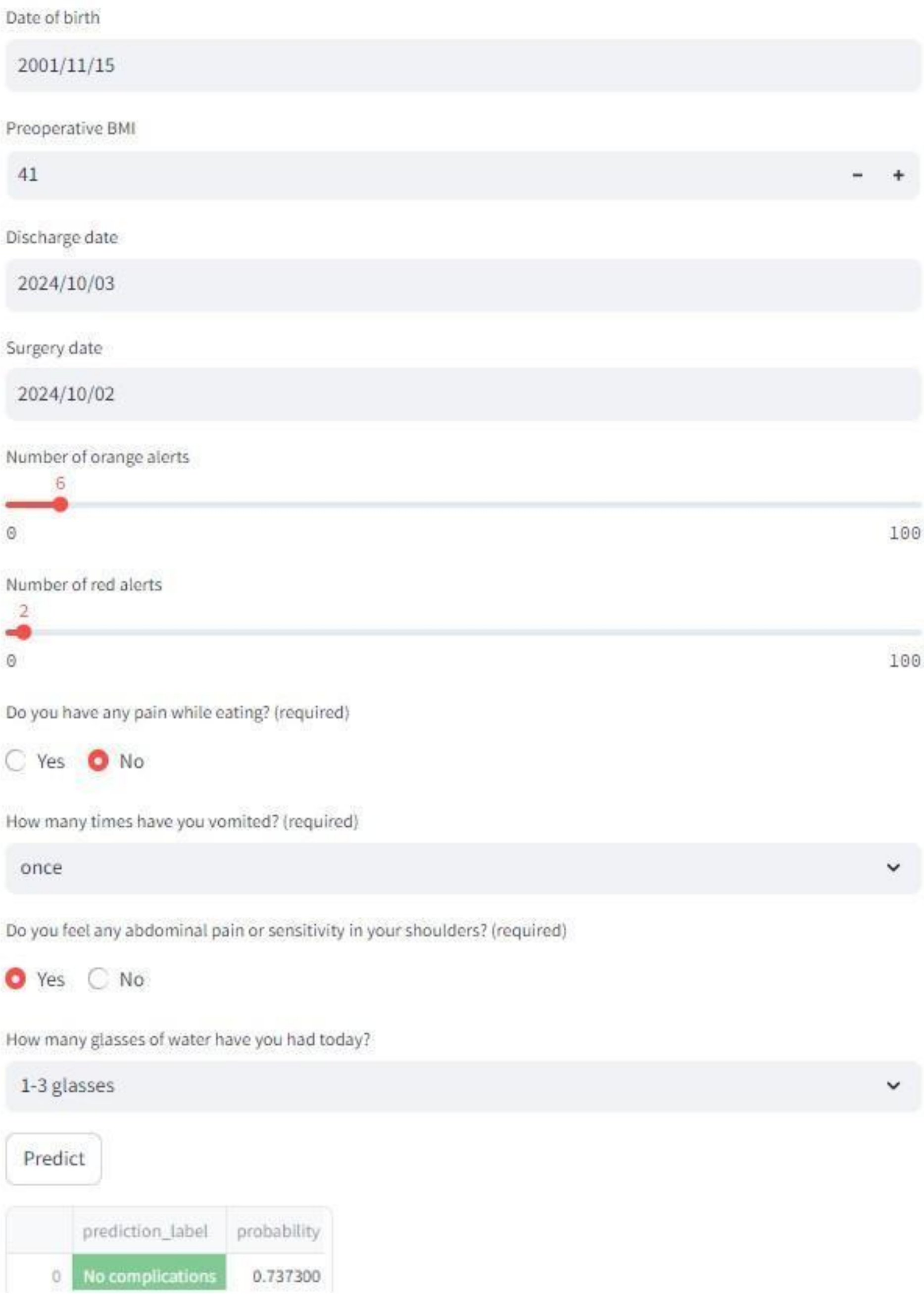



**Figure 2.** Illustration of the deployment of the models through a pilot web-based user interface.

| Model | Description |
|---|---|
| **Extreme Gradient Boosting (XGBoost)** | Supervised learning algorithm based on decision trees, optimized for performance and speed. Uses gradient boosting to improve accuracy. |
| **K Neighbors Classifier (KNN)** | Classifier based on supervised learning that assigns to a data point the most frequent class among its K nearest neighbors. |
| **Random Forest Classifier** | A set of decision trees used for classification, reducing variance by bagging compared to a single decision tree. |
| **Dummy Classifier** | A simple classifier that does not perform any real learning and serves as a reference point for comparing other models. |
| **Light Gradient Boosting Machine (LightGBM)** | A fast and efficient version of gradient boosting, using a histogram-based algorithm to process large data sets. |
| **Logistic Regression** | A regression model used for binary classification, estimating the probability that a feature belongs to a specific class. |
| **Gradient Boosting Classifier** | A boosting algorithm that sequentially builds a set of weak decision trees to improve accuracy. |
| **Extra Trees Classifier** | A variant of Random Forest that uses random divisions to reduce variance. |
| **Decision Tree Classifier** | A predictive tree model that associates observations with conclusions about the target value. |
| **AdaBoost Classifier** | A boosting technique that adjusts the weights of learning instances to focus on difficult cases. |
| **Ridge Classifier** | A variant of linear regression with L2 regularization, adapted to correlated explanatory variables. |
| **Quadratic Discriminant Analysis (QDA)** | A classifier that assumes a Gaussian distribution and estimates the variances for each class. |
| **Linear Discriminant Analysis (LDA)** | A dimension reduction and classification technique that maximizes class separability. |
| **Linear Kernel (used in support vector machines)** | A linear method for calculating similarity in support vector machines, suitable for large datasets. |
| **Naive Bayes** | A class of probabilistic classifiers based on Bayes' theorem, with an assumption of naive dependence between features. |

**Table 1.** Descriptive table of the machine learning models used in the comparisons.

| Input features | Number of patients n, (%) |
|---|---|
| **Age** (years) | 35.6 ±12 |
| **Sex** | |
| *Male* | 19 (18.3) |
| *Female* | 85 (81.7) |
| **BMI** (kg/m$^2$) | 41.5 (21.4-64.8)* |
| **Comorbidities** | |
| *Smoking* | 15 (14.4) |
| *Hypertension* | 6 (5.8) |
| *Sleep apnea* | 24 (23.1) |
| *Diabetes* | 41 (39.4) |
| *Gastroesophageal reflux* | 18 (17.3) |
| **Previous surgical history** | 36 (34.6) |
| **Type of intervention** | |
| *Sleeve gastrectomy* | 20 (19.2) |
| *RYGB* | 67 (64.4) |
| *SASI-S* | 7 (6.7) |
| *RYGB conversion* | 10 (9.7) |
| **Total number of alerts** | 1119 |
| *Orange alerts* | 1027 (91.8) |
| *Red alerts* | 74 (6.6) |
| *Red+ alerts* | 18 (1.6) |
| **Postoperative complications** | |
| *Postoperative pain* | 3 (2.9) |
| *Postoperative vomiting* | 7 (6.7) |
| *Dysphagia* | 3 (2.9) |
| *Anastomotic stricture* | 2 (1.9) |
| *Other* | 6 (5.8) |
| **Postoperative morbidity** | 21 (20.2) |

**Table 2.** Patient-related characteristics utilized as input features in each of the evaluated complication risk assessment models. ED = Emergency Department. * Value represents median (range).

# Chapter 6

# 6 General Discussion and Conclusion

## 6.1 Introduction

### 6.1.1 Context and challenges in bariatric surgery

Bariatric surgery has emerged as one of the most effective interventions for the management of severe obesity, offering long-term benefits in terms of weight loss and improvement of obesity-related comorbidities such as type 2 diabetes, hypertension, and sleep apnea [12,25]. However, like any surgical procedure, it is not without risks, particularly in the early postoperative period, when complications can appear rapidly after hospital discharge [26].

These challenges underscore the need for more structured and responsive postoperative monitoring systems that not only ensure patient safety but also promote recovery, reduce complications, and support long-term therapeutic success.

This thesis addresses these issues through a multidisciplinary exploration of how digital health innovations, specifically mobile health (mHealth) technologies and artificial intelligence (AI), can be leveraged to optimize postoperative care pathways in bariatric surgery. Echoing the call for innovation in surgical follow-up raised by Lim et al. [26] and reinforced by recent systematic reviews [142–147], this work provides both conceptual and empirical insights into how mHealth tools can bridge existing gaps in continuity of care, patient engagement, and complication management.

### 6.1.2 Contributions of digital tools (mHealth) in postoperative care

The practical implementation of a structured digital follow-up model, leveraging the *Care4Today* mobile application, has demonstrated multiple benefits in the postoperative management of bariatric patients. At the core of this system is a dynamic, three-tiered alert mechanism (orange, red, red+), which enables real-time identification of early warning signs and allows healthcare professionals to intervene before complications escalate. The strong correlation observed between red+ alerts and emergency department visits reinforces the clinical relevance of this tool for risk stratification and proactive intervention [2].

This shift from a reactive to a preventive care model aligns with the evolving paradigm of digitally supported surgical care. As highlighted by Heuser et al [142] and Versteegden et al. [143], the use of mHealth technologies in bariatric surgery significantly improves patient monitoring by fostering continuous engagement, enhancing communication with care teams, and facilitating early detection of complications.

Traditional postoperative care often relies on scheduled, face-to-face consultations that, while essential, may fail to capture subtle symptom progression or early signs of complications that arise between visits. This episodic model of care introduces a critical vulnerability during the transition from hospital to home. In contrast, mobile health (mHealth) applications offer a new paradigm, where patients can report symptoms on a daily basis, remain in close contact with healthcare professionals, and receive timely, tailored feedback after discharge. This shift ensures that the postoperative period is no longer a blind spot but a time of active monitoring and support.

This is an advanced system for tracking symptoms. These digital platforms also empower patients to become more engaged actors in their recovery journey. As demonstrated in our study and supported by the literature, individuals using mHealth tools tend to report higher satisfaction levels and improved adherence to postoperative instructions. In our cohort, the average satisfaction score reached 9.3 out of 10, with a response rate of 67.5%, reflecting both usability and perceived value of the technology. These platforms thus go beyond simply filling in the gaps in traditional monitoring; they reconfigure the very nature of follow-up, fostering a more responsive, personalized, and patient-centered care pathway.

A major innovation lies in the integration of AI-based predictive models into these digital systems. Our results show that the inclusion of real-time, patient-specific monitoring data enhances the performance of postoperative risk prediction tools: the model's Area Under the Curve (AUC) increased from 64.7% in the preoperative phase to 71.5% postoperatively. These findings echo those of Yang et al. [144] and Wild et al. [145], who have similarly documented the benefits of combining digital monitoring with predictive analytics to improve surgical outcomes. However, improved prediction alone is not sufficient, clinical usability remains essential. Our approach emphasizes the importance of model explainability, high-quality data collection, and continuous human oversight to ensure that AI supports rather than supplants clinical judgment.

Central to this digital transformation is the role of the **digital health coordinator**: a human interface who ensures the meaningful integration of technology into care routines. This role is not merely administrative; it includes guiding patients in the use of the application, interpreting real-time data, and escalating alerts when necessary. In doing so, the coordinator helps maintain and even strengthen the therapeutic alliance between patient and provider. Rather than replacing human relationships, technology can reinforce them, enabling a more efficient, safe, and humane approach to postoperative care.

Finally, mHealth applications, particularly when combined with AI and embedded in a structured clinical workflow, represent a major advancement in postoperative follow-up. They bridge the hospital-home gap, support both patients and professionals, and lay the groundwork for a more intelligent, connected, and compassionate model of surgical recovery.

## 6.2 Integration of artificial intelligence in monitoring

### 6.2.1 Development of predictive models in this study

In this research, we evaluated the role of predictive tools based on AI, as well as the potential benefits of integrating mHealth apps into postoperative monitoring in bariatric surgery. Although our results did not reach statistical significance, several systematic reviews and meta-analyses suggest an encouraging trend: greater weight loss, both overall and in excess, as well as a reduction in the number of emergency room visits in patients using digital follow-up tools.

For example, Yang et al. [145] observed improved weight loss and postoperative follow-up outcomes with the use of adapted digital tools. Similarly, Wild et al. [145] described a reduction in emergency consultations among patients receiving support via mHealth platforms. Mangieri et al. [146] confirm these observations by evidence that patients monitored using mobile apps show better adherence to postoperative recommendations. Finally, Versteegden et al [143] emphasize the beneficial role of mHealth technologies in improving RM after bariatric surgery. These findings underline the importance of setting up digital care pathways for postoperative monitoring.

According to our retrospective analysis, the intervention group experienced a significant decrease in emergency visits, suggesting that mobile apps can improve patient management by enabling early detection of complications and avoiding clinical deterioration. These results, which show a significant reduction in unnecessary hospitalizations and increased patient satisfaction due to better adherence to postoperative protocols, are in agreement with previous work [142].

### 6.2.2 Performance and impact of app-based data

As our research shows, AI enhances the potential of mHealth applications. Through AI-powered predictive analytics, it becomes possible to identify high-risk patients earlier, refine clinical decisions and optimize the use of medical resources [47].

As part of this study, two predictive models based on AI were developed to estimate the risk of postoperative complications in patients who had undergone bariatric surgery.

The first model, built from preoperative data (clinical and demographic), achieved 75% accuracy, with an AUC of 64.7%, demonstrating moderate but encouraging discriminatory power for use ahead of surgery [2].

The second model, incorporating data from digital monitoring via the Care4Today mobile application, performed even better, with an accuracy of 83.8% in its initial version. After optimization, reducing the number of variables to six key parameters, the final model showed an accuracy of 77.4% and an AUC of 71.5%, indicating an acceptable ability to identify patients at risk [2].

### 6.2.3 Correlation between alerts and postoperative complications

In addition, analysis of the volume and nature of alerts generated by the application shows a significant link between alert profile and the occurrence of complications. Of the 1119 alerts recorded, the majority were "orange", representing benign symptoms. However, patients who received "red+" alerts had a significantly higher rate of postoperative complications, with an almost threefold increase in the risk of morbidity, readmission or emergency room visit [2].

These results confirm that the three-tiered alert system implemented not only enables reactive follow-up, but also early detection of at-risk patients, reinforcing the relevance of using digital tools integrated into the care pathway.

## 6.3 Clinical outcomes of the study

### 6.3.1 Reduction in emergency visits and readmissions

The results of our study are consistent with an increasing number of studies demonstrating the value of digital technologies in post-operative follow-up after bariatric surgery. Several studies have shown that mobile applications can improve patient adherence to medical recommendations, facilitate early detection of complications, and reduce emergency department use without clear benefit [89,142].

A recent meta-analysis also found a trend towards better weight loss outcomes and fewer emergency room visits among patients using a digital health app, although the differences were not statistically significant [2].

These data support the idea that mHealth tools are a valuable complement to conventional monitoring, particularly in sensitive periods such as the return home.

At the same time, the use of AI in surgery is developing rapidly. In bariatric surgery, ML-based models have demonstrated their ability to predict certain postoperative events with greater accuracy than traditional clinical scores, which are often limited in their predictive value [34]. The integration of AI into real-time monitoring systems, such as the one developed in our project, thus represents a promising step towards more personalized, responsive and potentially safer medicine for at-risk patients.

### 6.3.2 Improved patient adherence to follow-up

Furthermore, other studies point out that mobile apps can help patients better follow behavioral recommendations after surgery, which could promote long-term sustainable weight loss. For example, Mangieri et al. [146] observed that users of mHealth apps were more compliant with dietary and physical activity guidelines [147]. have also reported a reduction in unnecessary visits to healthcare facilities among patients who have used these digital tools.

Despite these encouraging results, a number of challenges remain. In particular, there are concerns about data confidentiality, the risk of bias associated with digital divide, and the difficulties of integrating digital tools into existing clinical practices. It is therefore becoming essential to develop quality standards for mHealth applications, while accompanying their deployment with appropriate training for HCPs [54].

For the future, research priorities should include large-scale multicenter trials with extended follow-up, integrated approaches combining connected objects and mobile apps for more comprehensive real-time monitoring, and clear regulatory frameworks to enhance trust and adoption of these technologies by patients and caregivers [54].

### 6.3.3 Added value of the three-level alert system

One of the major contributions of this project lies in the implementation of a real-time digital monitoring system, enabling continuous, personalized monitoring of patients after bariatric surgery. Using a Digital Application, patients are asked daily to answer targeted questions about their state of health, generating graduated alerts according to the severity of symptoms reported. This system facilitates proactive communication between the patient and the healthcare team, while enabling rapid action to be taken in the event of signs of complications. This interactive, structured monitoring model goes beyond traditional telemonitoring approaches to create a true care dynamic focused on anticipation rather than reaction.

A second innovative aspect is the integration of AI into the system. By exploiting the data collected by the application, the ML models developed in this study can predict the risk of postoperative complications, by combining clinical and behavioral variables. This hybrid approach, combining digital field tools mHealth and advanced algorithmic analysis, is fully in line with the logic of personalized and preventive medicine. It offers a concrete response to the challenges of hospital overload and resource optimization, while improving patient safety and experience.

## 6.4 Study limitations

### 6.4.1 Methodological constraints and lack of external validation

However, there are a number of limitations to this study that should be highlighted. Firstly, the predictive models developed could not be validated externally. This limitation is mainly due to the fact that the Care4Today mobile application has not yet been systematically deployed in other centers practicing bariatric surgery. Furthermore, even in the centers where it is used, we do not yet have access to a shared multicenter database. This lack of data sharing currently makes it impossible to cross-validate models on external cohorts. This lack of external validation limits the scope of the results. Furthermore, the relatively small sample size used to train the models is another weakness: it increases the risk of overlearning (where the model learns the specific data too well without being able to generalize) or, on the contrary, underlearning, which reduces the accuracy of predictions. Furthermore, the limited amount of data makes it difficult to detect anomalies or atypical cases, which can bias results and limit their applicability to other clinical contexts.

### 6.4.2 Challenges for clinical implementation

Another challenge was the imbalance in the distribution of cases in the database, which necessitated the use of the SMOTE (Synthetic Minority Over-sampling Technique) method. While this technique allows for better class balancing by creating synthetic data, it can also introduce noise and alter the natural distribution of the data, which can impact the reliability of the model. Finally, it is important to note that all postoperative complications have been grouped together, without distinction of severity. As a result, the model is not yet capable of specifically identifying patients at risk of severe complications, which limits its clinical use at this stage.

## 6.5 Future Perspectives

The promising results observed in the early use of mobile health (mHealth) technologies during bariatric surgery recovery open new avenues for future research and clinical innovation. To build on these findings, future studies should adopt robust, prospective designs, ideally multicenter and controlled, to assess the long-term impact of digital follow-up strategies across diverse healthcare settings and populations. These studies should aim to extend follow-up periods beyond the typical 90-day window to capture sustained outcomes relating to weight loss, complication rates and patient well-being.

The integration of wearable devices, such as smartwatches and biosensors, for real-time tracking of physiological parameters like heart rate, oxygen saturation, physical activity, and sleep quality, is a key area of interest. This could facilitate the earlier detection of deviations from recovery norms and enhance overall clinical responsiveness. Furthermore, combining this data with hospital records and patient-reported outcomes via mHealth apps could provide a fuller, more dynamic picture of each patient's postoperative journey.

Artificial intelligence (AI) and predictive analytics also warrant further exploration, as do other topics. Machine learning models trained on multimodal data could improve the early identification of risk factors and help to tailor postoperative interventions. However, future research should not only focus on predictive performance. This should include things like AUC scores. It should also focus on explainability, usability, and integration into existing clinical workflows.

Researchers must also study the psychological and behavioral dimensions of digital follow-up. Digital tools facilitate symptom reporting. But their capacity to support behavioral change, reduce anxiety, and increase patient empowerment remains underexplored. Investigating features such as motivational coaching, gamification and personalized feedback could improve long-term adherence to dietary, physical activity and medication regimens.

Equity in digital health access must also be addressed. Future research should evaluate strategies to improve usability and adoption among older adults, individuals with limited digital literacy, and those from underserved communities. This includes testing simplified user interfaces, multilingual platforms, and enhanced onboarding processes supported by human guidance.

Finally, economic and organizational outcomes should be central to the focus. Longitudinal studies assessing cost-effectiveness are needed to determine whether digital follow-ups reduce unnecessary consultations, emergency visits or readmissions, and whether they contribute to the more efficient use of healthcare resources. Investigating healthcare providers' experiences, including perceived workload and responsiveness to digital alerts, will also be essential to ensure that these innovations support, rather than burden, clinical teams.

In summary, future research should adopt a multidisciplinary, patient-centered approach that evaluates not only clinical safety and efficacy but also psychological, economic, and systemic outcomes. This will be key to validating the full potential of mHealth and AI-driven tools in transforming bariatric surgery follow-up into a smarter, safer, and more humane process.

## 6.6 Conclusion

This dissertation contributes to a growing body of evidence that digital innovation has the capacity to redefine postoperative care. In the specific context of bariatric surgery, a procedure increasingly performed in outpatient settings, the first 90 days following the intervention remain a high-risk period marked by possible complications, patient anxiety, and fragmented follow-up. Traditional care models, which rely on a limited number of face-to-face consultations, often leave patients feeling unsupported during this vulnerable time [54].

To address this gap, we have developed and tested a hybrid digital model that integrates mobile health (mHealth) technology, artificial intelligence (AI), and human coordination. The implementation of an interactive mobile application allowed patients to report daily symptoms, while a three-tiered alert system guided the clinical response. Over the course of the study, 1,119 alerts were generated—91.8% were classified as mild (orange), 6.6% as moderate (red), and 1.6% as severe (red+), the latter showing a strong correlation with emergency visits [1]. These results demonstrate that continuous digital surveillance can identify subtle clinical deterioration earlier than traditional models.

The added value of AI lies in its ability to process daily data inputs in real time and generate risk scores that are both personalized and dynamic. The postoperative predictive model developed in this study achieved an area under the curve (AUC) of 71.5% and an accuracy of 77.4%, which is a significant improvement on preoperative models that relied on static baseline variables (AUC 64.7%) [2]. This confirms the importance of integrating real-time, patient-generated data into clinical decision-making systems. Research has shown that using AI tools with relevant, long-term data can improve how we assess risk and make sure we take action early [144,145].

However, technology alone is not enough. At the heart of this digital care model is the human factor: the digital health coordinator. This role has become a linchpin of success, far from being a passive interface. They help patients use the app, explain clinical instructions, interpret alerts, and facilitate prompt communication with healthcare teams. This model preserves and reinforces the therapeutic alliance by offering patients reassurance and maintaining continuity of care, even at a distance. This helps coordinators to reduce the effects of digital exclusion, especially for those who are less familiar with technology. The results are clear: a daily response rate of 67.5% and a satisfaction score of 9.3/10 show that the digital platform is acceptable, usable and valuable [1].

These findings have several broader implications. Firstly, this hybrid digital model can be scaled up to cover areas beyond bariatric surgery. As healthcare systems move towards shorter hospital stays and outpatient procedures, structured remote follow-up becomes essential, and mHealth solutions paired with AI and human mediation offer a way to provide safer, more flexible care that respects clinical guidelines and individual patient needs.

Secondly, the model demonstrates the efficient use of healthcare resources. By enabling the early detection of complications, reducing unnecessary emergency consultations and adjusting the intensity of follow-ups based on risk profiles, digital monitoring enables clinical attention to be allocated more efficiently.

Thirdly, this model highlights the need for systemic transformation. Despite their clinical value, the use of digital tools and the role of the coordinator are not formally recognized or reimbursed within current healthcare frameworks. This disconnect between technological innovation and funding mechanisms poses a significant obstacle to large-scale implementation [3]. A transition towards value-based care, where reimbursement is tied to clinical outcomes, patient satisfaction and continuity of care, would provide the structural foundation necessary to effectively and equitably scale these solutions [4].

More broadly, the hybrid model of digital postoperative monitoring developed in this thesis holds significant promise for application in ambulatory surgery, a domain experiencing rapid growth across Europe. In Belgium, over 60% of common surgical interventions are now performed without overnight hospitalization, a trend driven by the need to reduce hospital stays and optimize resource allocation [148]. However, this shift has exposed a structural gap in postoperative continuity of care. The short length of stay associated with ambulatory procedures often leaves patients with minimal direct follow-up, increasing the risk of unrecognized complications and preventable readmissions.

In this context, mHealth technologies, when paired with AI and supported by a digital health coordinator, can serve as a strategic lever to reorganize care pathways in an ethical and efficient manner. These tools make it possible to offer real-time, risk-adjusted monitoring, without increasing the burden on hospitals. They help prioritize clinical attention where it is most needed and maintain a strong therapeutic connection between patients and providers, even after discharge. As emphasized in recent reflections on the digital transformation of surgical care, such systems enable a shift toward proactive and patient-centered follow-up models [1]. However, to scale up these approaches sustainably, public health policies must adapt, particularly by recognizing digital tools and coordination roles within reimbursement frameworks. This alignment between innovation and funding is essential to make digital follow-up not only possible, but standard practice in modern ambulatory surgery.

Finally, this work advocates for a deeply ethical and inclusive vision of digital health. Tools must be designed with accessibility in mind, accounting for linguistic diversity, cognitive barriers, and unequal access to technology. Human accompaniment is not an optional complement; it is an ethical imperative to ensure that digital transformation does not exacerbate health disparities but rather becomes a lever for equity and inclusion.

In conclusion, the digital monitoring model explored in this thesis offers more than a technical upgrade to postoperative care, but it proposes a new paradigm: One in which technology amplifies clinical vigilance, enhances human connection, and adapts care to individual needs. It is a model that aligns with the imperatives of modern healthcare: efficiency, personalization, accessibility, and compassion.

Looking ahead, the integration of mHealth applications, AI, and human coordination represents not just a promising innovation, but a necessary evolution in surgical care. Future efforts should focus on large-scale validation, economic evaluation, and policy reform to support widespread adoption. Only then can we fully realize a care model that is intelligent, inclusive, and profoundly humane.

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