Chapter

Current and Potential Applications of Artificial Intelligence in Metabolic Bariatric Surgery

Athanasios G. Pantelis

Abstract

Artificial intelligence (AI) is an umbrella term, which refers to different methods that simulate the process of human learning. As is the case with medicine in general, the field of bariatric metabolic surgery has lately been overwhelmed by evidence relevant to the applications of AI in numerous aspects of its clinical practice, including prediction of complications, effectiveness for weight loss and remission of associated medical problems, improvement of quality of life, intraoperative features, and cost-effectiveness. Current studies are highly heterogeneous regarding their datasets, as well as their metrics and benchmarking, which has a direct impact on the quality of research. For the non-familiar clinician, AI should be deemed as a novel statistical tool, which, in contradistinction to traditional statistics, draws their source data from real-world databases and registries rather than idealized cohorts of patients and is capable of managing vast amounts of data. This way, AI is supposed to support decision-making rather than substitute critical thinking or surgical skill development. As with any novelty, the clinical usefulness of AI remains to be proven and validated against established methods.

Keywords: artificial intelligence, machine learning, deep learning, data mining, decision trees, bariatric surgery, metabolic surgery, obesity, diabetes mellitus, obesity-related health problems, surgical safety, effectiveness, quality of life

1. Introduction

Artificial intelligence (AI) is an umbrella term that incorporates concepts such as supervised and unsupervised machine learning (ML), deep learning (DL), and reinforcement learning [1]. In essence, AI is the simulation of human learning by a machine (computer). Learning, in turn, is the procedure of acquiring information (input), which, after retention and processing, may lead to adjustment of behavior under given temporospatial circumstances or optimization of the chances of achieving specific goals (output). Each type of AI differs from the others in the extent of intervention by the operator, i.e., the degree of autonomy of the machine.

AI subtypes have certain integral components: an algorithm, specific datasets (training, validation, test), input (predictors), and output (outcomes), as well as performance indices of the algorithm for each dataset (sensitivity, specificity, F1 score, area under the receiver operator curve—AUROC, area under the precision-recall curve—AUPRC, and so on). Depending on the degree of autonomy of the AI algorithm, the operator (human researcher, data scientist) has variable knowledge of and interference to the aforementioned components. For instance, in *supervised ML,* the training data are labeled, and the possible outcomes are known *a priori*. This type of AI is used in cases of classification (in the case of categorical outcomes—i.e., disease or no disease, TNM staging for neoplasia, Clavien-Dindo staging for postoperative complications, etc.) or regression (in the case of numerical outcomes—i.e. weight, height, body mass index, etc.). Examples of supervised ML algorithms are decision trees (DT), random forest (RF), k-nearest neighbors (knn), linear and logistic regression (LR), support vector machines (SVMs), etc. On the other hand, in *unsupervised ML*, outcomes are unknown; therefore, they are subject to discovery with the aid of the AI algorithm itself. Unsupervised ML problems are divided into clustering (inherent grouping of data) and association (rules that define the relationship between predictors and outcomes). Besides, *reinforcement learning* is based on continuous training of the algorithm with the method of "trial-and-error" and is implemented in the case of highly chaotic systems such as cost analysis, with Markov models being typical examples [2].

Deep learning (DL) is the most autonomous subtype of AI. DL utilizes large amounts of real-world data (big data) and is structured on the basis of neural networks of three or more layers (input layer, output layer, one or more hidden intermediate layers). The layered architecture of DL algorithms resembles that of neurons in the central nervous system, hence the characterization "neural (or neuronal) networks." Characteristic examples are artificial neural networks (ANN), convolutional neural networks (CNNs), long-short term memory networks (LSTMNs), recurrent neural networks (RNNs), multilayer perceptrons (MLPs), etc. [2]. **Figure 1** is a

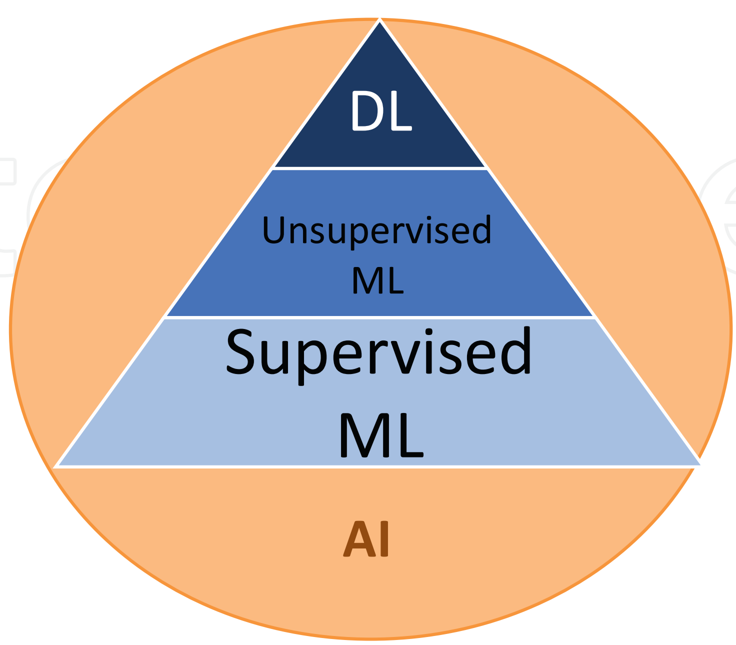

Figure 1.
Schematic representation of the hierarchy of artificial intelligence algorithms. The more one moves to the top of the pyramid, the more autonomous the algorithm becomes and the less intervention is exerted by the researcher. AI — artificial intelligence, ML — machine learning, DL — deep learning.

schematic representation of the different subtypes of AI, with the degree of autonomy of each one.

Recently there has been documented an exponential increase of literature investigating the application of various AI algorithms in healthcare [3]. It is within this context that our team recently attempted to trace the applications of artificial intelligence and machine learning in bariatric metabolic surgery (BMS) [4]. Based upon this study, this chapter is organized in seven sections, in concordance with the respective disciplines of BMS for which there have been relevant publications concerning applications of AI. The last two sections are devoted to the future perspectives of AI in BMS, as well as the methodological limitations and ethical barriers that should be considered when applying AI in BMS, in analogy to every biomedical scientific field.

2. AI applications in basic science relevant to bariatric metabolic surgery

Basic science and research are the cornerstones of evolution in medicine. Popular basic science applications on which AI may be applied include but are not limited to genome-wide sequencing (WGS), whole slide imaging (WSI), and all the omics (genomics, transcriptomics, proteomics, metabolomics, but also radiomics and multi-omics). Regarding the discipline of BMS in particular, metabolomics is a field of increased interest and intensive research, for the purpose of characterizing the metabolic milieu of patients living with obesity as well as for studying the long-term postoperative interactions between BMS and the metabolism [5–7].

In one of the first attempts to implement AI methods in BMS, Cortón et al. studied the gene expression profile in omental adipose tissue procured by women who were submitted to bariatric surgery and simultaneously suffered from polycystic ovarian syndrome (PCOS) [8]. More specifically, the researchers implemented data mining, a method that combines traditional statistics, machine learning and database systems, and retrieved abnormal expression of genes that participate in insulin and Wnt signaling, oxidative stress, inflammation, immune function, and lipid metabolism. Additionally, they conducted hierarchical clustering, a type of unsupervised ML, in order to retrieve co-expressed genes in female patients with PCOS and consequently detect specific patterns of gene expression.

More recently, Chaim et al. calculated beta cell function through assessment of NO production by means of electro-sensor complex (ESC) data and statistical network, a set of DL algorithms [9]. Subjects consisted of patients living with obesity who were candidates for MBS. In another study, Macartney-Coxson et al. used genome-wide DNA methylation data and compared traditional statistics with combinatorial algorithms in the identification of methylation loci [10]. Study samples included subcutaneous and omental adipose tissue that had been harvested from obese individuals, before and after BMS. Besides, Candi et al. performed a metabolomics analysis of visceral adipose tissue harvested from individuals who had undergone bariatric surgery and identified three kinds of metabolotypes: healthy controls (normal weight), healthy obese, and pathological obese [11]. Consequently, they implemented RF analysis, an unbiased supervised classification technique, in order to differentiate among the three groups, but also retrieve the most important predictive metabolites for each category, with lipids playing a cardinal role with this respect. In another metabolomics-oriented study, Narath et al. used an untargeted approach that yielded 177 features [12]. Consequently, they processed the data with RF in order to detect short- and long-term metabolic changes following Roux-en-Y gastric bypass (RYGB).

The most important finding was that short-term changes in metabolites (1–3 weeks postoperatively) do not necessarily match long-term effects (up to 1 year).

Future research should focus on reconciling metabolic surgery, metabolomics, and deep learning. So far, application of DL in metabolomics has manifested several methodological limitations, including high computational cost, lack of external validation, non-calculation of isotopic peaks during sample analysis with spectroscopy, overfitting secondary to low sample size, reduced predictive ability upon application to asymmetrical datasets, poor applicability of outcomes from experimental animal models to human metabolomics, etc. [13]. On the other hand, the exponentially increasing numbers of patients who undergo BMS offer an excellent substrate for obtaining biological fluids (whole blood, plasma, serum, feces, urine) and tissues (gastric, adipose, liver) for further metabolomic analysis. The implementation of ML, and most importantly DL, could potentially assist in unraveling the roles of the myriads of metabolites through untargeted metabolomic analyses, distinguish between causes and effects, and gain clinical usefulness both for prediction and diagnosis. With this regard, one may distinguish the emerging role of data analysists as key members of the multidisciplinary BMS team.

3. AI and surgical safety: predicting and preventing complications following bariatric metabolic surgery

Bariatric operations have a favorable safety profile, with an overall morbidity less than 5% and mortality less than 0.5%, as it has been documented over time by different investigators, based on data from large databases and comprehensive meta-analyses [14–20]. Most importantly, this holds true even for special populations, such as patients suffering from diabetes [21] or at the extremes of age [22, 23]. Even during the COVID-19 pandemic, not only has bariatric surgery proven its endurable safety, but it may also have a protective effect for one of the most vulnerable population groups against the adverse sequelae of SARS-CoV-2 [24, 25], as shown in a series of publications by the GENEVA collaborative group regarding 7704 patients from 42 countries [26–30]. Due to the fact that complications and deaths following BMS are rare events, their evaluation from a statistical perspective is challenging. Thanks to artificial intelligence algorithms, it is now possible to incorporate and analyze data from big databases and cohorts of patients, with the advantage of yielding reliable results from imbalanced datasets, as well as having access to real-word conditions rather than idealized simulations, as is the case with randomized controlled trials. Besides, the concept of implementing AI algorithms in order to quantify and predict postoperative outcomes, with the intention to enhance clinical practice and improve decision-making, is gaining popularity within surgical literature [31–33].

Cao et al. pioneered research in prediction of serious complications after BMS by implementing machine learning [34], as well as deep learning methods [35], in a Scandinavian bariatric database (SOReg) comprising more than 40,000 bariatric patients. In their extensive analyses, they compared multiple machine and deep learning algorithms (as well as combinations of algorithms, *aka* ensembles), respectively, and they found that the latter had better predictive accuracy, along with the fact that ensemble algorithms had better performance than baseline ones. Additionally, in order to overcome the obstacle of imbalanced data secondary to the low occurrence of complications, they applied the synthetic minority oversampling technique (SMOTE). SMOTE is a method of artificially augmenting underrepresented groups (such as patients with postoperative complications) and thus yield data eligible for classification. In a similar manner, Razzaghi et al. developed predictive models for bariatric surgery risks with imbalanced data by applying SMOTE on different classification algorithms, such as RF, bagging, and AdaBoost [36]. As a source of data, they utilized the Premier Healthcare Database, which gathers data from more than 700 hospitals across the United States. Again, their work showcased that ensemble classification was superior to isolated ML algorithms. Charles-Nelson followed a different strategy: in order to document the 30-day readmission rate, which is a reflection of short- and intermediate-term complications, they applied Formal Concept Analysis (FCA), a data mining technique, in a cohort of 196,323 bariatric patients according to the main principal diagnoses code at readmission [37]. Their most important finding was heterogeneity of severity of complications across different bariatric procedures.

There are two studies regarding prediction of complications after specific operations. Wise et al. applied a DL algorithm (ANN) on a cohort of 101,721 patients from the Metabolic and Bariatric Surgery Accreditation and Quality Improvement Program (MBSAQIP) who had undergone laparoscopic sleeve gastrectomy (LSG), in order to predict 30-day postoperative morbidity [38]. As compared with logistic regression, the ANN algorithm was more accurate in predicting postoperative complications, based upon easily obtainable demographic and clinical factors. Similarly, Sheikhtaheri et al. applied Clinical Decision Support System (CDSS) to predict morbidity after one-anastomosis gastric bypass (OAGB) across five hospitals over a 4-year period [39]. The predictive performance of the model at the 10-day, 1-month, and 3-months intervals was favorable.

Regarding specific complications, Dang et al. developed the BariClot tool, a forward regression predictive model, in order to stratify individuals undergoing BMS according to their 30-day risk for venous thromboembolic (VTE) events [40]. Their data were retrieved from the MBSAQIP and included patients who had undergone either RYGB or LSG. As compared with established predictive tools for VTE, such as the Michigan Bariatric Surgery Collaborative or the Caprini score, BariClot demonstrated enhanced predictive accuracy, as documented by the relevant AUROCs (0.5817 vs. 0.5533 vs. 0.6023, respectively). Moreover, Nudel et al. developed and validated three different machine/deep learning models (ANN, X-Gradient Boosting, logistic regression) in order to predict not only VTE, but also leaks after BMS, again based on a MBSAQIP cohort of 436,807 patients [41]. AI models outperformed traditional LR in detecting both leak and VTE in a statistically significant manner.

Finally, AI has also been implemented for predicting long-term morbidity after BMS, including the development of gallbladder disease and formation of gallstones [42], nutritional deficiencies [43], nonalcoholic fatty liver disease (NAFLD) [44], and fractures [45]. The implemented AI algorithms were ANN [42], SVM [44], and Bayesian networks [43, 45].

4. AI as a tool for predicting effectiveness of bariatric surgery

Undoubtedly, the main and utmost priority of any bariatric operation is weight loss. It has been long established that any bariatric intervention is more effective and durable in maintaining weight loss than optimal conservative treatment and lifestyle modifications [46–53]. Data that support this statement stem from both observational and randomized controlled studies. Although the latter are prospective in nature and thus can establish causality, they may be accompanied by publication bias. On the contrary, observational studies contain raw data as they are collected according to healthcare providers' registrations and patient testimonials. As such, they can serve as an invaluable source of prediction, provided they undergo appropriate analysis with AI tools. Nevertheless, despite the accumulated experience and evidence with bariatric surgery and its effectiveness, to date there is no accurate tool for weight loss prediction, and most clinical models tend to overestimate the bariatric outcome of the most commonly performed procedures [54].

In one of the first relevant attempts, Lee et al. developed a predictive model back in 2007 with the use of a data mining technology through LR and ANN [55]. They found that ANN yields a better predictive accuracy for weight reduction at 2 years as compared with traditional methods, with the best predictors of successful weight loss being OAGB (vs. LAGB), high preoperative triglyceride level, and low glycated hemoglobin (HbA1c) level. Similarly, Giraud-Carrier et al. developed a predictive model with the use of a data-mining-based software available online [56]. The data mining process included problem formulation (prediction of the type of bariatric procedure and quality of its outcome); domain and data understanding (71,849 patients with >350,000 visits across 125 centers); data preparation and preprocessing (aka determination of input or predictors, i.e., physician ID, gender, age, ethnicity, employment status, smoking behavior, state of origin, BMI prior to surgery, surgery performed, and BMI at 12 months postoperatively); model building (multinomial logistic regression and decision tree C4.5); prediction of surgical procedure; prediction of success (classification into poor, fair, good, very good, and excellent if BMI reduction at 12 months was ≤5, 5–10, 10–15, 15–20, and >20, respectively). Although these studies were performed at an era when experience on bariatric surgery was more limited, the armamentarium of procedures was significantly different, benchmarking was inadequate, and definition of weight loss was not according to current standards (%TWL or %EBMIL or %EBMIL), the study designs showed a dynamic potential. More recent attempts have implemented different methodology (i.e., a rule-based semantic approach, [57]) or different input data (i.e., preoperative patient liking for sweet beverages, [58]) in order to predict bariatric surgery outcomes in general.

Other studies have focused on specific bariatric operations. For instance, Piaggi et al. found that ANN models could successfully predict weight loss in women treated with laparoscopic adjustable gastric banding (LAGB), although this method tends to be abandoned nowadays [59]. On the other hand, Celik et al. in a very recent study applied neural network Bayesian regularization, a DL algorithm, in patients who had undergone LSG and predicted excess and total weight loss (%EWL and %TWL, respectively) based on gastric remnant volumes (antrum and body were deemed as different compartments) [60]. Regarding RYGB, Wise ES *et al.* implemented an ANN model to predict excess weight loss by means of % reduction in BMI loss (%EBMIL) at 3 months and 1 year postoperatively [61]. On a more advanced level, Choudhury et al. implemented a Markov model so as to predict which modality of weight loss was more effective for patients with end-stage renal disease awaiting renal transplant [62]. Not surprisingly, RYGB was found to be more effective than aggressive diet and exercise with this regard.

5. AI as a tool for diagnosing and predicting resolution of obesity-associated medical problems after bariatric metabolic surgery

Apart from weight loss, MBS is associated with the alleviation of the long-term effects of associated medical problems (or comorbidity, as they were collectively referred to until recently), namely type 2 diabetes mellitus (T2DM), hypertension (HTN), nonalcoholic fatty liver disease (NAFLD), and nonalcoholic steatohepatitis (NASH), obstructive sleep apnea (OSA), dyslipidemia, end-stage renal disease (ESRD), depression, etc. Most importantly, some of these health problems have been recognized as dedicated indications for MBS, irrespective of BMI [63]. The rationale of this is supported by high-quality evidence on the superiority of surgical management vs. intensive medical therapy [64, 65]. Regarding T2DM in particular, the evidence is solid and stems from cohorts with long-term perspective surveillance [66–69], to the point that they have substantially contributed to the establishment of the concept of metabolic surgery in clinical practice [70, 71].

The advent of AI has introduced novel methods of predicting long-term remission of obesity-associated medical problems based on real-world data. In a recent comprehensive relevant study, Cao et al. compared three different AI models (Gaussian Bayesian Network – GBN, CNN, and traditional linear regression) in predicting 5-year remission of T2DM, dyslipidemia, HTN, OSA, and depression from data extracted from the large SOReg database concerning 6542 patients [72]. Among the examined algorithms, GBN showed excellent performance in predicting long-term remission of T2DM (AUC 0.942) and dyslipidemia (AUC 0.917), good performance for HTN (AUC 0.891) and OSA (AUC 0.843), and fair performance in predicting depression (AUC 0.750). On the other hand, van Loon et al. devised the Metabolic Health Index (MHI) to objectively quantify metabolic health, in analogy to BMI as an index for quantifying weight, and consequently developed an ordinal logistic regression model in order to quantify severity of comorbidity in a 6-grade scale [73]. As a scaffold, they used 4778 data records from 1595 patients and high-yield predictors included age, estimated glomerular filtration rate (eGFR), HbA1c, triglycerides, and potassium.

Regarding specific conditions, T2DM has been the most studied obesity-associated health problem with regard to AI algorithms so far. Lee et al. ran a series of multi-centric studies with the aim to investigate the effectiveness of BMS in T2DM resolution, as well as to predict short- and long-term T2DM remission after BMS [74–76]. Their analysis was performed by means of back propagation neural networks (BPN), a type of ANN, and important predictors of T2DM remission included younger patient age, shorter T2DM duration, higher weight, wider waist, higher C-peptide levels, and bypass operation (vs. restrictive one). A few years later, another group investigated the role of the advanced-Diabetes Remission (ad-DiaRem) score in improving the prediction of T2DM remission following RYGB [77, 78]. DiaRem is a valid prediction score for T2DM remission that relies on variables such as age, HbA1c, treatment with insulin, treatment with oral hypoglycemics other than metformin and classifies patients into five subgroups according to their probability of remission [79–81]. Ad-DiaRem has two additional parameters (diabetes duration and number of glucose-lowering agents). The group of Aron-Wisnewsky, Debédat et al. analyzed Ad-DiaRem with the use of machine learning and devised a 1-year algorithm with enhanced predictive accuracy as compared with the original score, which yielded a corrected classification for 8% of those misclassified with DiaRem [77]. The same team used

ML methods to extend the predictive accuracy to 5 years post-RYGB, with the correct re-classification rate reaching 33% [78]. Consequently, AI can be implemented not only as a novel method, but also in order to improve established clinical tools.

At a more advanced level, Aminian et al. utilized ML in order to predict long-term end-organ complications owing to T2DM (in particular all cause-mortality, coronary artery events, heart failure, and nephropathy) in patients who did or did not undergo metabolic surgery [82]. A total of 2287 T2DM patients who had undergone metabolic operations were matched with 11,435 non-surgical diabetic patients. Analysis was performed by means of multivariable regression and random forest and data were uploaded by patients through user-friendly web-based and smartphone applications in an Individualized Diabetes Complications (IDC) risk score environment for clinical use. This is one of the most useful applications of ML in clinical practice so far. In another sophisticated study, Pedersen et al. combined clinical data (treatment with insulin, use of insulin-sensitizing agents, baseline HbA1c levels, and baseline serum insulin levels) with eight single-nucleotide polymorphisms (SNPs) and processed the data with ANN [83]. The addition of the SNPs significantly improved the predictive ability of the algorithm.

Nonalcoholic fatty liver disease (NAFLD)/nonalcoholic steatohepatitis (NASH) constitutes another entity of particular interest in the context of obesity. NAFLD/NASH represents the most common chronic liver disease worldwide nowadays, for the treatment of which BMS seems to play a pivotal role as it seems to offer sustainable resolution [84–86]. Back in 2013, Sowa et al. examined several ML algorithms (among which LR, knn, SVM, decision trees, RF) to determine noninvasive assessment of fibrosis in NAFLD based on serum parameters (transaminases, hyaluronic acid, and cell death markers) and compared their combined effect with the gold standard of liver biopsy, which was performed intraoperatively during BMS [87]. The combination of these parameters with RF had a better diagnostic accuracy than each single parameter. More recently, Uehara et al. constructed a noninvasive algorithm for predicting NASH in a Japanese population of patients living with morbid obesity [88]. The most important predictors (alanine aminotransferase—ALT, C-reactive protein—CRP, homeostasis model assessment insulin resistance—HOMA-IR, and albumin) were selected by means of rule extraction technology.

6. AI as a means of improving quality of life assessment following bariatric metabolic surgery

Quality of life (QoL) after BMS is a parameter with increasing interest in literature because it is perhaps more patient-related and less of a technicality, as compared with safety, effectiveness, and resolution of associated health problems. There are several scores for evaluating QoL after BMS and their applicability has been implemented after various procedures [89–92]. In the realm of AI, the group of Cao et al. has conducted two studies based on the SOReg with the use of CNN, Gaussian Bayesian Network (BN), and LR for predicting 5-year health-related QoL after BMS [72, 93]. GBN showed better predictive accuracy as compared with the other methods. In another publication, BN was implemented for a network meta-analysis of studies referring to QoL after BMS [94]. The analysis involved 26,629 patients in total and 11 different procedures.

7. AI for evaluating intraoperative aspects of bariatric metabolic surgery

One of the advantages of laparoscopic surgery (and video-assisted surgery in general) is the continuous recording of the procedure. In the digital era, these recordings can be transformed into captions, which subsequently may be stored, transferred, processed, etc. Another usage that has recently been highlighted is technical skill assessment. In comparison to crude measures of surgical performance, such as operative time, postoperative outcomes, and complications, video-assisted operative evaluation offers better opportunities for constructive feedback and progressive improvement of technique. The rating may be performed by human peers and supervisors, but lately ML has shown promising results in objective assessment of surgical skills [95].

In the field of BMS specifically, Twinanda et al. have pioneered AI techniques in laparoscopic videos with two discrete applications: retrieval of a specific fraction of the video (i.e., suturing of an anastomosis) and prediction of remaining time. In the former example, the researchers used Fisher kernel encoding, a precursor of deep learning techniques for managing large-scale object categorization, and applied it on 49 bypass and seven LSG videos [96]. In the latter case, remaining operative time in 170 RYGB videos was predicted by RSDNet, a DL-based algorithm that depends only on visual data for training rather than manual annotations [97]. Other pioneers in computer vision analysis of operative steps are Hashimoto et al., who implemented DNN to analyze LSG videos [98]. In this case, laparoscopic videos were segmented into seven steps: port placement, liver retraction, liver biopsy, gastrocolic ligament dissection, stapling of the stomach along the greater curvature, bagging specimen, and final inspection of the staple line. AI could extract quantitative data from video with an accuracy of >85%, a feature that allows quantification of operative capacity and objective evaluation for the purposes of both training and self-development. Similarly, Derathé et al. utilized annotated spatial and procedural data and processed them with SVM in order to predict surgical exposure [99].

In a totally different approach, Heremans et al. implemented ANN-based automated detection of food intake after neuromodulation by analyzing heart rate variability in electrocardiograms [100]. This is another example of intraoperative application of AI in a different kind of surgery for weight loss (neuromodulation).

8. Cost analysis of bariatric metabolic surgery with the use of AI

We are living in an era that cost-effectiveness is paramount in medicine for every intervention, either conservative or surgical. It has been estimated that the cost of BMS is approximately 14,000 euros and 3600 euros annually ever after. In comparison, the cost for the non-surgical treatment of T2DM is about 12,200 euros per annum [101].

Cost analyses are considered dynamic systems that are affected by various, often non-predicable parameters. Many cost analyses studies are based on Markov models. Markov models are stochastic models designed for systems that change over time (i.e., dynamic ones) and change their parameters randomly. Using decision analysis with the implementation of a Markov process, Borisenko et al. calculated that the annual savings for a cohort of bariatric patients from the SOReg was 66 million euros, whereas over a lifetime bariatric surgery produced savings of 9332 euros [102, 103].

Similarly, Faria et al. compared different bariatric interventions and calculated that RYGB saves an average of 13,244 euros per patient as compared with best medical management [104].

9. AI: hope or hype? methodological, ethical, medicolegal issues, and patient perspectives

AI is a relatively novel clinical tool, as such the healthcare provider should be cautious before adopting its methods and incorporating them into clinical routine. The following limitations are uniform across medicine, not BMS alone, and prompt the implementation of a solid frame in the context of which AI may yield its most beneficial aspects in clinical practice. Extensive analysis of AI limitations is beyond the scope of this chapter; therefore, we will attempt to outline the most important aspects of them.

One of the advantages of AI is the management of large amounts of data, but at the same time this is a prerequisite to obtain reliable outcomes. As such, data quantity is one issue. Data quality is another, and this can be achieved only when source data (i.e., registries or electronic health records—EHRs) are comprehensive and inclusive. In other words, all patients should have access to health services irrespective of socioeconomic status, and health services on their part should promote continuity of care instead of segmentation. The third important component is model interpretation, especially when it comes to deep learning, given that sometimes the relations between inputs (predictors) and outcomes are not obvious. Next, model generalizability and interoperability are paramount for implementing AI algorithms across different health systems and contexts, and these can be ensured only when the three former methodological requirements are met. Finally, AI researchers must ensure model security, i.e., avoid "contamination" of data. This is a potential issue even after meticulous training of data [105]. To address these potential sources of bias, several strategies have been proposed. Among them, oversampling minority groups in training datasets, creating flags for certain high-risk groups, and formulating baseline predictions at presentation of illness (i.e., in the case of BMS, before surgery) are the most feasible ones [106].

The usage of AI as a decision-making tool may also have medicolegal sequelae. In this case, one should take into consideration all the parameters, i.e., agreement between AI recommendation and standard of care, accuracy of AI prediction, physician action (acceptance or rejection of the AI decision), and patient outcome. Different combinations may lead to different legal outcomes, i.e., no injury of the patient and no liability of the surgeon, injury but no liability, or both injury and liability [107]. Consequently, on the one hand, healthcare providers should know how to interpret AI algorithm outcomes and recruit their clinical judgment above all; on the other hand, they should have an active role in shaping their liability issue through their professional societies and legislation-forming organizations.

Is the role of the surgeon threatened by the advent of AI? Are surgeons transforming from leaders to simple operators of what a machine has decided for a patient? Definitely not. AI should be deemed as a tool that is intended to assist surgeons in their daily workflow and ease their work with the intent to help them focus on what is important, i.e., physician-patient relationship. Additionally, AI offers a real opportunity for individualized interventions and precision medicine, not only at the time of operations, must (even most importantly) during the postoperative period and follow-up.

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What impact does AI make on patients themselves? According to a recently published survey, it depends on the context. Fifty-five percent of participants were very or somewhat comfortable with AI making chest X-ray diagnosis, but the respective percentage for making cancer diagnosis dropped to 31.2% [108]. Consequently, the role of the surgeon remains central to continuum of healthcare provision, while discussing all diagnostic and therapeutic options with the patient is indispensable.

As it has been stressed out by Bellini et al., AI has contributed to substantial progress in decision-making, quality of care, and precision medicine, but several legal and ethical issues need to be addressed before its widespread application in clinical practice [109].

10. Conclusions

AI is gaining more and more ground to clinical practice, as it has been documented not only by our research [4], but also that of other investigators within the same context [109]. The clinician is not required to understand how AI algorithms work but should be cautious when interpreting AI-based outcomes and decision by evaluating its source data and metrics. For reasons of simplicity, AI should be considered a novel statistical tool with the advantage of yielding data from large, real-world registries of patients rather than restricted cohorts as the ones used in the context of randomized trials. Given the specialized nature of processing these data, specialists such as data scientists could assume new roles in the multidisciplinary team of managing bariatric patients.

Conflict of interest

The author declares no conflict of interest.

Author details

Athanasios G. Pantelis
4th Department of Surgery, Bariatric Metabolic Surgery Unit, Evaggelismos General Hospital of Athens, Athens, Greece

*Address all correspondence to: ath.pantelis@gmail.com

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