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Prediction of Excess Weight Loss after Laparoscopic Roux-en-Y Gastric Bypass: Data from an Artificial Neural Network

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Abstract

Introduction—Laparoscopic Roux-en-Y Gastric Bypass (LRYGB) has become the gold standard for surgical weight loss. The success of LRYGB may be measured by excess body-mass index loss (%EBMIL) over 25 kg/m², which is partially determined by multiple patient factors. In this study, artificial neural network (ANN) modeling was used to derive a reasonable estimate of expected postoperative weight loss using only known preoperative patient variables. Additionally, ANN modeling allowed for the discriminant prediction of achievement of benchmark 50% EBMI at one year postoperatively.

Methods—Six-hundred and forty-seven LRYGB included patients were retrospectively reviewed for preoperative factors independently associated with EBMI at 180 and 365 days postoperatively (EBMI₁₈₀ and EBMI₃₆₅, respectively). Previously validated factors were selectively analyzed, including age; race; gender; preoperative BMI (BMI₀); hemoglobin; and diagnoses of hypertension (HTN), diabetes mellitus (DM), and depression or anxiety disorder. Variables significant upon multivariate analysis ($P < .05$) were modeled by “traditional” multiple linear regression and an ANN, to predict %EBMI₁₈₀ and %EBMI₃₆₅.

Results—The mean EBMI₁₈₀ and EBMI₃₆₅ were 56.4%±16.5% and 73.5%±21.5%, corresponding to total body weight losses of 25.7%±5.9% and 33.6%±8.0%, respectively. Upon multivariate analysis, independent factors associated with EBMI₁₈₀ included black race (B=−6.3%, $P < .001$), BMI₀ (B=−1.1%/unit BMI, $P < .001$) and DM (B=−3.2%, $P < .004$). For EBMI₃₆₅, independently associated factors were female gender (B=6.4%, $P < .001$), black race (B=−6.7%, $P < .001$), BMI₀ (B=−1.2%/unit BMI, $P < .001$), HTN (B=−3.7%, $P = .03$) and DM (B=−6.0%, $P < .001$). Pearson r^2 values for the multiple linear regression and ANN models were .38 (EBMI₁₈₀) and .35 (EBMI₃₆₅), and .42 (EBMI₁₈₀) and .38 (EBMI₃₆₅), respectively. ANN-prediction of benchmark 50% EBMI at 365 days generated an area under the curve of 0.78±0.03 in the training set (n=518), and 0.83±0.04 (n=129) in the validation set.

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Conclusions—Available at <https://redcap.vanderbilt.edu/surveys/?s=3HCR43AKXR>, this, or other ANN models may be used to provide an optimized estimate of postoperative EB MIL following LRYGB.

Keywords

bariatric; obesity; gastric bypass; outcomes

Introduction

The incidence of morbid obesity continues to rise, and patients are increasingly turning to surgical weight loss management. Bariatric surgery, while not the first line treatment of obesity, is one of the most effective means of achieving substantial and sustained weight loss. A highly effective bariatric procedure, the Roux-en-Y gastric bypass operation is frequently performed in the U.S [1–3], as it is considered to have the best balance of comorbidity resolution and excess weight loss against complications [4]. The laparoscopic approach to this operation has reduced associated morbidity as well as length of hospital stay [3]. The laparoscopic Roux-en-Y gastric bypass (LRYGB) operation involves exclusion of the stomach, leaving only a fundal pouch to which a cut segment of jejunum (“Roux-limb”) is anastomosed [5, 6]. A biliopancreatic limb with a distal jejunojejunal anastomosis is created as well, allowing for weight loss by multiple mechanisms [4, 6, 7].

The weight loss expectations vary widely among candidates. Some patients may aim to lose a modest amount of body weight to alleviate comorbidities, while others may envision a more significant amount of weight loss. To this effect, the development of a tool to provide a reasonable estimate of postoperative excess body-mass index loss (EBMIL, excess defined as over 25 kg/m²) may be of benefit to surgical candidates and their physicians [8].

There are myriad factors validated in previous studies as independent predictors of weight loss after LRYGB. Some of these factors are related to the technical aspects of the operation itself (i.e., length of the Roux limb), intraoperative findings (i.e. degree of liver fibrosis on intraoperative biopsy), or socioeconomic factors. Preoperative demographic and medical factors have also been identified, including female gender, black race, age at surgery, preoperative weight loss, immediately preoperative BMI (BMI₀), diagnoses of hypertension (HTN); diabetes mellitus (DM); depression and anxiety, and iron stores. These have all been externally validated as independent correlates to EBMIL, and were collectively chosen as a panel of comprehensive and easily quantifiable and obtainable variables for review in this study [1, 9–18].

Artificial neural networks (ANN) are advanced, continually adapting computational systems taught to identify complex non-linear relationships among variables correlated with an outcome. Selected independent variables are chosen as the input layer, and an ANN algorithm provides an output layer (dependent variables) [19–23]. The ANN is initially trained using these layers, which are processed through training nodes, and can subsequently be used to predict future outcomes. Its advantages are its ability to continuously adapt its algorithm to new patient information and its superior prognostic ability relative to standard multiple linear regression models. In this study, we aim to devise a web-based tool to predict

EBMIL after LRYGB first by identification of independent preoperative predictors of postoperative weight loss in our cohort, with subsequent imputation of those variables into an ANN-based model.

Methods

This was a single-institution retrospective cohort study conducted at Vanderbilt University Medical Center, a large bariatric referral center in Nashville, TN. Using the Vanderbilt University Synthetic Derivative, a de-identified mirror of the electronic medical record, 1,621 patients from 2004–2013 were identified via CPT code search (43644, Laparoscopy, surgical, gastric restrictive procedure with gastric bypass and Roux-en-Y gastroenterostomy [roux limb 150 cm or less]) as having undergone LRYGB for bariatric purposes. As all data is scrubbed of patient identifiers, this protocol was approved by the Institutional Review Board with waiving of informed consent. Patients were excluded if they did not have sufficient information in the chart, had an initial BMI < 35 kg/m², or had clearly spurious values which called the data integrity into question (Figure 1). Six-hundred and forty-seven patients were identified for inclusion, and their demographics were exported to the Research Electronic Data Capture (REDCap) program hosted at Vanderbilt University [24].

Demographics and previously identified independent clinical preoperative predictors of EBMIL were chosen for review. These included age at surgery; race; gender; BMI₀; preoperative weight loss; previous diagnosis of HTN, DM, depression or anxiety; and hemoglobin as a surrogate for iron stores. Attribution of comorbidities was based upon having an associated ICD-9 diagnosis documented no later than five days postoperatively. The hemoglobin measurement used was taken as the preoperative value temporally closest to the day of surgery, up to one year prior. The value used to determine whether the patient lost weight preoperatively was the most recent BMI documented between 6–12 months prior to the day of surgery. The primary endpoints were %EBMIL at 180 ± 30 days and 365 ± 45 days postoperatively (EBMIL180 and EBMIL365, respectively). %EBMIL was defined as $100\% * (BMI_0 - BMI_{post-surgery}) / (BMI_0 - 25 \text{ kg/m}^2)$ [8].

A bivariate linear regression analysis was performed to assess the influence of each variable on EBMIL180 and EBMIL365. Variables for each endpoint that demonstrated a bivariate association ($P < 0.1$) with EBMIL were entered into a multivariate analysis using the method of least squares, to determine independent association with EBMIL180 and EBMIL365 ($P < 0.05$). The groups of preoperative variables significant on multivariate analysis represented variables considered in the multiple linear regression models, and as the input layers for ANN180 and ANN365, respectively (Figure 2). The ANN model used was a three-node back-propagation ANN with k -fold validation. Each node was assigned a training value of 0.333, and the model was trained with 3 iterations. The neural network algorithms for ANN180 and ANN365 were derived from 80% of the 647 patients (training set); 20% of the patients were randomly withheld in ANN derivation to comprise a necessary validation set. A full mathematical description of the ANN model has been reviewed previously [19, 21].

Using both the multiple linear regression prediction expressions and the ANN algorithms, actual EBMI vs. predicted EBMI plots were generated, using Pearson r^2 values of the linear regression lines as the primary measure of goodness of fit. A receiver-operating characteristic (ROC) curve was also generated to assess the ability of ANN365 to predict the achievement of benchmark 50% EBMI [25]. Measures of central tendency were expressed as mean \pm standard deviation. Area under the curve (AUC) values for ROC curves were expressed as AUC \pm standard error. Bivariate, multivariate and ANN analysis was performed using JMP Statistical Software (Cary, NC) and GraphPad Prism (La Jolla, CA). $P < 0.05$ was used to denote statistical significance.

Results

Patient characteristics from the 647 patient cohort are summarized in Table 1. The mean age of the cohort was 47.4 ± 11.0 years. 14.4% were of black race, and 79.6% were female. Among all patients, the average EBMI180 was $56.4\% \pm 16.5\%$, and EBMI365 was $73.5\% \pm 21.5\%$. These values corresponded to total body weight losses of $25.7\% \pm 5.9\%$ and $33.6\% \pm 8.0\%$, respectively. Of note, only 299 patients had BMI values 6–12 months preoperatively. This was due to a combination of poor chart maintenance, decentralized preoperative care as well as a rather stringent six month window chosen for acceptable values, as BMI values beyond one year or within six months were felt more likely to erroneously reflect the preoperative weight trajectory.

Results of the bivariate and multivariate analyses for EBMI180 and EBMI365 are reported in Table 2 and Table 3, respectively. Bivariate analysis of EBMI180 revealed associations with black race ($B = -10.9\%$, $P < .001$), BMI₀ ($B = -1.2\%$ /unit BMI, $P < .001$), HTN ($B = -4.7\%$, $P = .003$), DM ($B = -5.6\%$, $P < .001$) and hemoglobin ($B = 1.5\%$, $P = .006$). Independent predictors of EBMI180 were black race ($B = -6.3\%$, $P < .001$), BMI₀ ($B = -1.1\%$ /unit BMI, $P < .001$) and DM ($B = -3.2\%$, $P < .004$). Results of the bivariate analysis of EBMI365 revealed associations with female gender ($B = 8.0\%$), black race ($B = -12.6\%$), BMI₀ ($B = -1.4\%$), HTN ($B = -8.9\%$) and DM ($B = -8.9\%$), all at $P < .001$. Independent correlates with EBMI365 were female gender ($B = 6.4\%$, $P < .001$), black race ($B = -6.7\%$, $P < .001$), BMI₀ ($B = -1.2\%$ /unit BMI, $P < .001$), HTN ($B = -3.7\%$, $P = .03$) and DM ($B = -6.0\%$, $P < .001$).

Plots representing actual EBMI vs. multiple linear regression-predicted EBMI at both 180 and 365 days postoperatively are shown in Figures 3A and 3B. For EBMI180 and EBMI365, the Pearson r^2 values of the linear regression lines, a measure of goodness of fit of the model, were .38 and .35, respectively. Plots representing actual EBMI vs. ANN-predicted EBMI at both 180 and 365 days postoperatively are shown in Figures 3C and 3D. For EBMI180 and EBMI365, the Pearson r^2 values of the linear regression lines were .42 and .38, respectively. At both 180 and 365 days postoperatively, the ANN model was more accurate in predicting loss of excess BMI, with a greater Pearson r^2 and lower root-mean-square error.

Using the ANN algorithm an ROC curve was generated to assess the ability of ANN365 to predict achievement of benchmark 50% EBMI. In the cohort, 87% (564/647) of the

patients successfully achieved this goal. The ROC curves obtained from training and validation sets of ANN365 analysis in prediction of 50% EBMI are shown in Figure 5; areas under the curve (AUC) for the training set and validation set were 0.78 ± 0.03 and 0.83 ± 0.04 , respectively.

Discussion

ANNs are excellent model systems for prediction of postoperative outcomes, and have been used in general surgery and surgical oncology, among other specialties [22, 26–35]. In bariatric surgery, ANN modeling has been used sparingly. The largest of the few published bariatric ANN studies reported outcomes of laparoscopic adjustable gastric banding in Italy. Using 172 patients, weight loss was predicted on the basis of results from the Minnesota Multiphasic Personality Inventory-2 test of psychopathology, BMI₀ and age [21].

We selected the procedure of LRYGB as it represents the gold standard for weight loss. Its role in reduction of BMI, improving comorbidities and decreasing polypharmacy has been well-established [2, 6]. Surgical weight loss is reserved only for those of extreme obesity, with a BMI greater than 40 kg/m^2 , or greater than 35 kg/m^2 with at least one associated weight-related comorbidity, required for candidacy. LRYGB patients have a higher rate of medical and psychiatric comorbidities than the general population, and these additional comorbidities may have significant contributions to the success of these patients in postoperative weight loss. While variance in surgical success can only be partially attributed to preoperative comorbidities, they were nonetheless used along with demographics to develop a robust predictive tool derived from a cohort of over 600 patients, for estimation of EBMI after LRYGB.

Determination of those variables to examine for this model necessitated thorough review of the literature to identify preoperative predictors of EBMI after LRYGB. A patient-centered tool for weight loss estimation after bariatric surgery, reported in 2014, found age and preoperative BMI (BMI₀) as the most significant predictors of sustained postoperative weight loss [1]. Race has also been shown to predict weight loss, as Coleman *et al.* recently reported prospective data showing that black race is associated with impaired weight loss in LRYGB [11]. It is a universally accepted recommendation to attempt weight reduction prior to LRYGB. The influence of preoperative weight loss on postoperative weight loss, however, has not been well established. In one study, modest preoperative weight reduction was correlated with sustained weight loss 3–4 years after bypass [12], however, its effect on more immediate weight loss has been somewhat ambiguous. A 2012 systematic review of preoperative predictors of weight loss after bariatric surgery identified seven studies that showed a positive association between preoperative and postoperative weight loss, one showed a negative association, and six did not show an association [14].

Various medical conditions have been reported to have an independent association with postoperative weight loss. Psychiatric disease, particularly depression and anxiety disorders, are common, and are negatively associated with postoperative weight loss in bariatric surgery [14]. In 2014, Still *et al.* reported observational cohort data in which HTN and DM were considered as measures associated with decreased weight loss [9]. Hemoglobin A1C

also had an inverse correlation with weight loss, suggesting that postoperative weight loss is associated with optimal glycemic control [9]. For simplicity, our analysis only considered presence or absence of HTN or DM, and not the extent of disease. Diminished iron stores have demonstrated significance in impairing weight loss after bariatric surgery [9]. For this study, hemoglobin values were chosen as a surrogate for iron stores, as more sensitive measures such as serum ferritin, serum iron, and total iron binding capacity were not sufficiently available [17]. Collectively, the preoperative clinical variables studied is by no means exhaustive, but rather represents a selected set of parameters that in conjunction with behavioral changes may govern the success of the operation [12].

In our cohort, risk factors for impaired EBMIL180 and EBMIL365 on multivariate analysis were found to be black race, higher BMI₀ and DM; male gender and HTN were risk factors only for impaired EBMIL365. Using these variables, multiple linear regression functions were obtained for endpoints EBMIL180 and EBMIL365. Pearson r^2 values for these models were .38 and .35, for EBMIL180 and EBMIL365, respectively (Figure 3A and 3B). The corresponding Pearson r^2 values for the ANN models were .42 and .38 for EBMIL180 and EBMIL365, respectively (Figure 3C and 3D), values that fit the data more closely than the corresponding multiple linear regression model. As the ANN model was superior, its training set algorithm was used to predict 50% EBMIL365, a benchmark sometimes used to herald a successful operation, via generation of an ROC curve (Figure 4).

Although the ANN model was algorithmically sophisticated, the input factors were easy to quantify. Using only demographics, BMI and basic knowledge of the patient's medical history, one can easily make an independent determination of estimated EBMIL180 and EBMIL365. This ANN model can be used as a web-based weight loss prediction calculator accessible to patients (currently available at <https://redcap.vanderbilt.edu/surveys/?s=3HCR43AKXR>; Figure 5), or plausibly incorporated as a platform within an electronic medical record accessible to health care providers. Further, ANNs offer the flexibility to adapt continually to newly input patient data, and to optimize the model's overall prognostic ability. To the authors' knowledge, this is the first implementation of neural network modeling for prediction of postoperative weight loss.

This study has several limitations. There is the drawback inherent in the accuracy and bias of data collected retrospectively rather than prospectively. The cohort in this study was also biased by inclusion of only those patients who attended six and twelve month follow-up appointments at Vanderbilt University, perhaps representing a more closely monitored, adherent and motivated group of patients. This study also currently lacks external validity, as the patient cohort underwent institution-specific preoperative and postoperative preparation and follow-up protocols, although somewhat standardized due to the institution's designation as a Bariatric Surgery Center of Excellence since 2005. Furthermore, the 647 patients were operated on by a relatively small number of bariatric surgeons. In addition, while patients customarily attended 6 and 12 month follow-up appointments, the regularity of these visits beyond this time frame was inconsistent preventing accurate data collection beyond one year. As it is known that weight loss may continue to occur after one year, this study does not allow for the estimation of sustained weight loss. It is our hope that as ANNs are integrated into routine clinical care, this

limitation will be overcome. Finally, while ANNs have improved prognostic accuracy, the model does not conveniently express the relative contribution of each variable in predicting the outcome, as opposed to a multiple linear regression analysis. Thus, a “black box” approach in deriving the output variable from input variables is necessitated [21].

In summary, successful postsurgical weight loss is partially dependent on multiple preoperative patient factors. Our cohort demonstrated black race, higher BMI₀, DM, HTN and male gender as independent markers for a less successful operation. Using these predictors, an ANN model allows for development of a patient-centered tool with which to obtain an optimized estimate of postoperative EBMI_L at 6 and 12 months. This model can be readily translated to a web-based platform as a novel patient-centered tool; alternatively, it may assist bariatric surgeons either as a preoperative screening tool or a means to provide realistic expectations to their patients.

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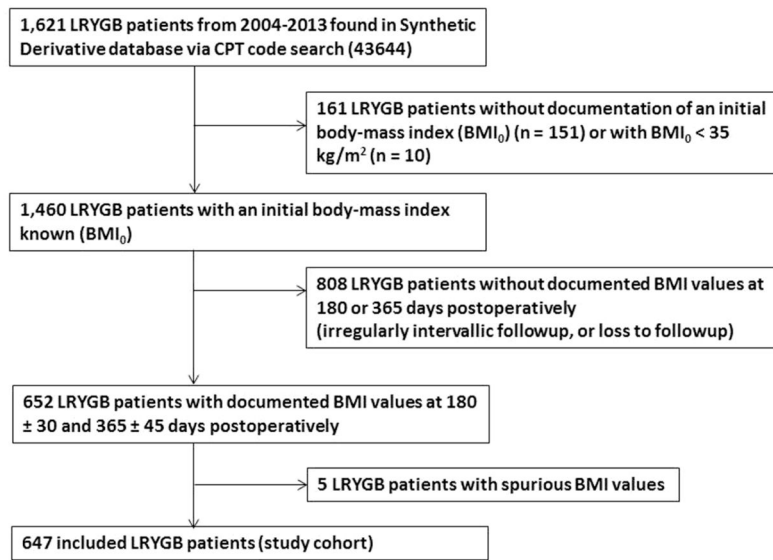


Figure 1.
Derivation of the 647 patient study cohort

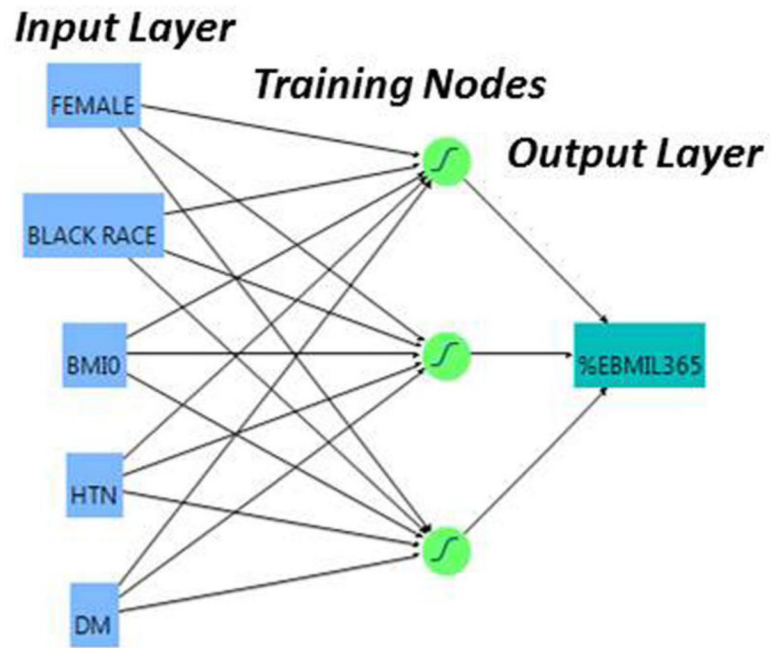


Figure 2. Diagram of the 3-node artificial neural network for prediction of excess body-mass index loss at one year postoperatively (EBMIL365).

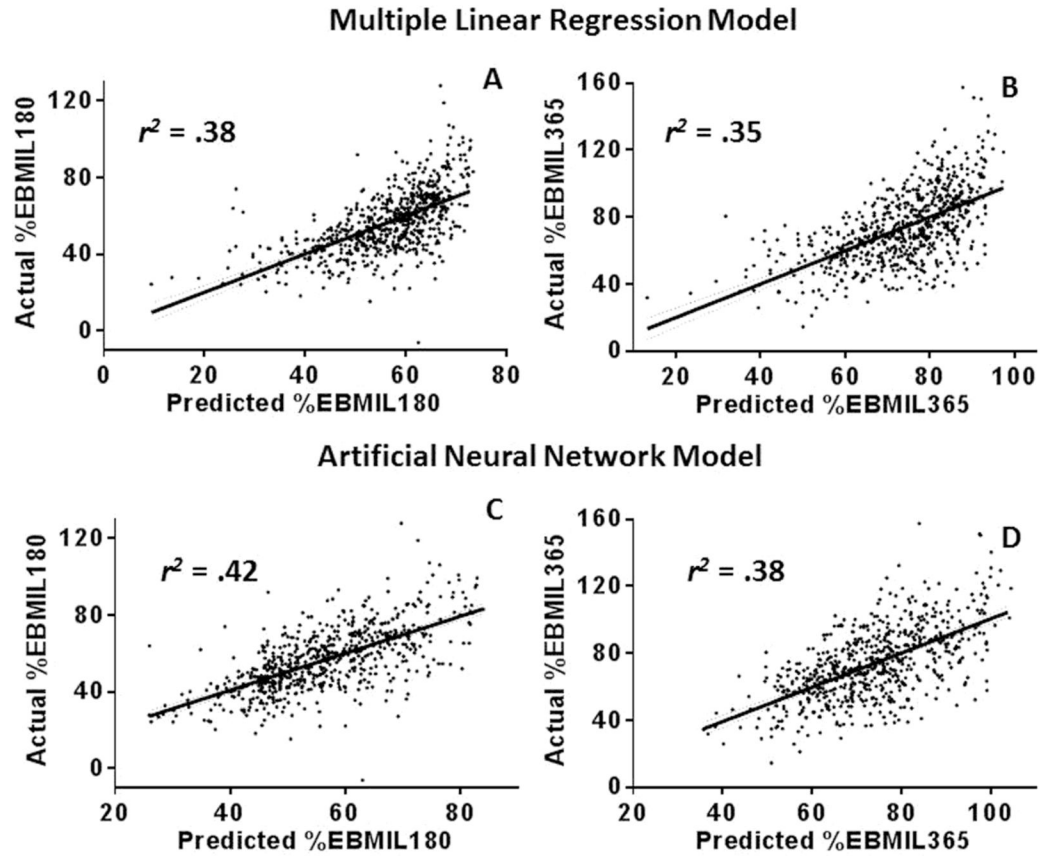


Figure 3.

Actual vs. predicted EB MIL plots for both models, at 180 and 365 days postoperatively
A- Plot of actual vs. multiple linear regression-predicted EB MIL180; $r^2 = .38$, root-mean-square error (RMSE) = 13.0. **B-** Plot of actual vs. multiple linear regression-predicted EB MIL365; $r^2 = .35$, RMSE = 17.4. **C-** Plot of actual vs. artificial neural network-predicted EB MIL180; $r^2 = 0.42$, root-mean-square error (RMSE) = 12.6. **D-** Plot of actual vs. artificial neural network-predicted EB MIL365; $r^2 = .38$, RMSE = 16.9. Linear regression lines with 95% confidence bands are included on all plots (dashed lines).

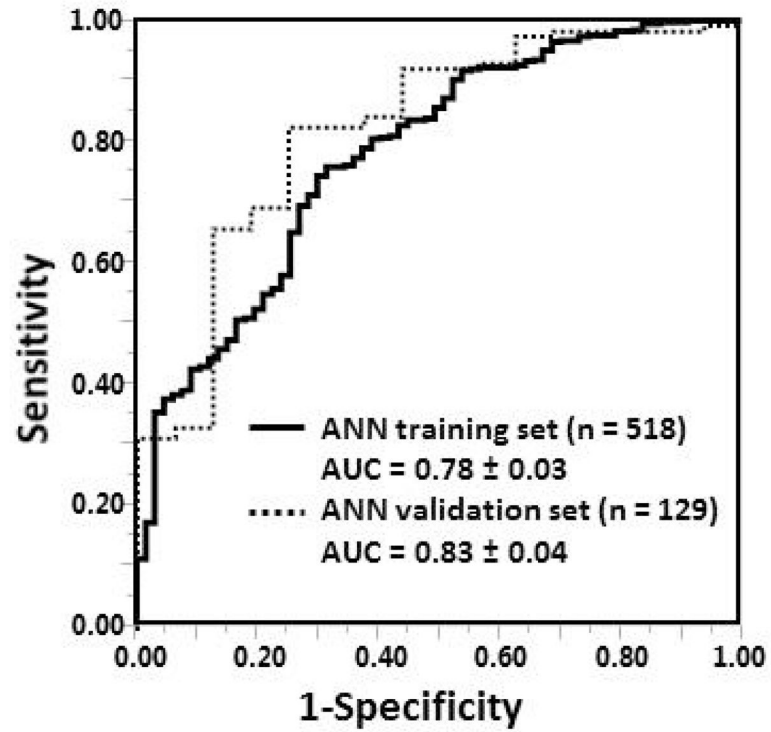


Figure 4. Receiver-operating characteristic curve for the 518 patient ANN training cohort (AUC = 0.78 ± 0.03 ; solid line), and the 129 patient ANN validation cohort (AUC = 0.83 ± 0.04 ; dashed line) for the model to predict benchmark 50% EBML365

Weight Loss Estimator for Laparoscopic Roux-en-Y Gastric Bypass Patients

Please enter all information below. You will then be provided with an estimation of postoperative weight loss.

1)	Please enter "1" if female, "0" if male <small>* must provide value</small>	1
2)	Please enter "1" if African-American/Black race; otherwise, enter "0" <small>* must provide value</small>	0
3)	Please enter your height (in inches), at the time of surgery <small>* must provide value</small>	66
4)	Please enter your weight (in pounds) prior to surgery <small>* must provide value</small>	233
5)	Preoperative Body-Mass Index	37.6
6)	Please enter "1" if you have a current diagnosis of high blood pressure. If not, enter "0" <small>* must provide value</small>	1
7)	Please enter "1" if you have a current diagnosis of diabetes. Of not, enter "0" <small>* must provide value</small>	0
8)	Total Weight Loss (in pounds), 180 days postoperatively	60
9)	Total Weight Loss (in pounds), 365 days postoperatively	78
10)	Estimated Body Weight (in pounds) at 180 days postoperatively	173
11)	Estimated Body Weight (in pounds) at 365 days postoperatively	155
12)	Estimated Body-Mass Index, 180 days postoperatively	28
13)	Estimated Body-Mass Index, 365 days postoperatively	25
14)	Estimated Percent Total Body Weight Loss, 180 days postoperatively	26
15)	Estimated Percent Total Body Weight Loss, 365 days postoperatively	34
16)	Estimated Percent Excess Body-Mass Index Loss, 180 days postoperatively	79
17)	Estimated Percent Excess Body-Mass Index Loss, 365 days postoperatively	97

Figure 5.
 Demonstration of web-based weight loss estimation tool
 The ANN-derived algorithm is available for use at “<https://redcap.vanderbilt.edu/surveys/?s=3HCR43AKXR>”.

Table 1

Preoperative Clinical Characteristics of the Study Population

Variable	Patients Analyzed	Patients with Trait (categorical) Mean \pm SD (continuous)
Age at Surgery	647	47.4 \pm 11.0 years
Female Gender	647	515/647 (79.6%)
Black Race	647	93/647 (14.4%)
BMI ₀	647	47.0 \pm 8.5 kg/m ²
Hypertension	647	506/647 (78.2%)
Diabetes Mellitus	647	331/647 (51.2%)
Depression Disorder	647	56/647 (8.7%)
Anxiety Disorder	647	97/647 (15.0%)
Hemoglobin	609	13.4 \pm 1.2 g/dL
Preop. Wt. Loss	299	160/299 (53.5%)
%EBMIL180	647	56.4% \pm 16.5%
%EBMIL365	647	73.5% \pm 21.5%

SD- standard deviation; %*EBMIL180*- %excess body-mass index loss (over 25 kg/m²) at 180 days postoperatively; %*EBMIL365*- %excess body-mass index loss (over 25 kg/m²) at 365 days postoperatively

Table 2

Bivariate and Multivariate Analysis of Factors Associated with Excess Body-Mass Index Loss, 180 days postoperatively

Variable	Bivariate Analysis		Multivariate Analysis	
	B (95% CI)	P	B (95% CI)	P
Age (yrs)	-0.03% (-0.14, 0.09)	.64	-	-
Female Gender	1.6% (-1.6, 4.7)	.95	-	-
Black Race	-10.9% (-14.4, -7.3)	<.001	-6.3% (-3.3, -9.3)	<.001
BMI ₀	-1.2% (-1.3, -1.0)	<.001	-1.1% (-1.0, -1.2)	<.001
Hypertension	-4.7% (-7.8, -1.6)	.003	-1.8 (-4.4, 0.8)	.17
Diabetes Mellitus	-5.6% (-8.1, -3.1)	<.001	-3.2% (-5.3, -1.0)	.004
Depression Disorder	-0.6% (-3.8, 2.6)	.72	-	-
Anxiety Disorder	-0.6% (-4.2, 3.0)	.75	-	-
Hemoglobin	1.5% (0.4, 2.5)	.006	0.2% (-0.7, 1.0)	.67
Preop. Wt. Loss	0.9% (-3.0, 4.7)	.66	-	-

B- Units of %EBMIL180/unit variable (e.g. -0.03% EBML180/year) *Italics* indicate variables included in multivariate analysis; **Bold** indicates variables included in multiple linear regression and artificial neural network models ($P < .05$). Multivariable model was a standard least squares fit, $n = 609$, constant = 110.9%, $r^2 = .38$, $F = 75.2$, $P < .001$.

Table 3

Bivariate and Multivariate Analysis of Factors Associated with Excess Body-Mass Index Loss, 365 days postoperatively

Variable	Bivariate Analysis		Multivariate Analysis	
	B (95% CI)	P	B (95% CI)	P
Age (yrs)	-0.1% (-0.2, 0.06)	.22	-	-
Female Gender	8.0% (3.9, 12.1)	<.001	6.4% (3.0, 9.8)	<.001
Black Race	-12.6% (-17.2, -8.0)	<.001	-6.7% (-10.6, -2.8)	<.001
BMI ₀	-1.4% (-1.5, -1.2)	<.001	-1.2% (-1.4, -1.1)	<.001
Hypertension	-8.9% (-12.8, -4.9)	<.001	-3.7% (-7.2, -0.3)	.03
Diabetes Mellitus	-8.9% (-12.2, -5.7)	<.001	-6.0% (-8.8, 3.2)	<.001
Depression Disorder	-1.9% (-4.0, 7.8)	.40	-	-
Anxiety Disorder	-1.0% (-5.6, 3.7)	.69	-	-
Hemoglobin	0.9% (-0.4, 2.3)	.18	-	-
Preop. Wt. Loss	0.7% (-4.4, 5.7)	.79	-	-

B- Units of %EBMIL365/unit variable (e.g. -0.1% EBML365/year) *Italics* indicate variables included in multivariate analysis; **Bold** indicates variables included in multiple linear regression and artificial neural network models ($P < .05$). Multivariable model was a standard least squares fit, $n = 647$, constant = 137.1%, $r^2 = .35$, $F = 69.9$, $P < .001$.