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Mapping the obesity problems scale to the SF-6D: results based on the Scandinavian Obesity Surgery Registry (SOReg)

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Abstract

Background *Obesity Problem Scale* (OP) is a widely applied instrument for obesity, however currently calculation of health utility based on *OP* is not feasible as it is not a *preference-based measure*. Using data from the *Scandinavian Obesity Surgery Registry (SOReg)*, we sought to develop a mapping algorithm to estimate *SF-6D utility* from *OP*. Furthermore, to test whether the mapping algorithm is robust to the effect of surgery.

Method The source data *SOReg* (*n* = 36 706) contains both *OP* and *SF-36*, collected at pre-surgery and at 1, 2 and 5 years post-surgery. The *Ordinary Least Square (OLS)*, *beta-regression* and *Tobit regression* were used to predict the SF-6D utility for different time points respectively. Besides the main effect model, different combinations of patient characteristics (age, sex, Body Mass Index, obesity-related comorbidities) were tested. Both internal validation (split-sample validation) and validation with testing the mapping algorithm on a dataset from other time points were carried out. A multi-stage model selection process was used, accessing model *consistency, parsimony, goodness-of-fit* and *predictive accuracy*. Models with the best performance were selected as the final mapping algorithms.

Results The final mapping algorithms were based on OP summary score using OLS models, for pre- and post-surgery respectively. Mapping algorithms with different combinations of patients' characteristics were presented, to satisfy the user with a different need.

Conclusion This study makes available algorithms enabling crosswalk from the *Obesity Problem Scale* to the *SF-6D* utility. Different mapping algorithms are recommended for the mapping of pre- and post-operative data.

Keywords Mapping · Quality of life (QOL) · Obesity-problem scale (OP) · SF-6D · Obesity · Health utility · Cross-walk

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Introduction

Obesity is associated with significant mortality, reduced *quality of life* and increased risk of developing diseases such as diabetes mellitus, cardiovascular disorders and cancers [1–3]. Europe has the world's second highest obesity rate (women 25%, men 22%) after North America (women 30%, men 24%) [4]. Management of obesity involves variety of treatment options: the first-line *lifestyle modification*, includes diet, physical activity, and behavioral therapy [5, 6]. This may be supplemented with adjunct *pharmacotherapy* [5, 7]. When these conventional treatments are partially efficacious in achieving sustained weight loss, *bariatric surgery* will be introduced [5, 7].

To make treatments comparisons, *cost-utility analysis* are required, particularly by reimbursement agencies and national advisory bodies such as the *National Institute for*



Health and Clinical Excellence (NICE) in the UK [8], the Dental and Pharmaceutical Benefits Agency in Sweden [9] which put a request on health utility data to be collected in clinical studies. Health utility is often obtained through a preference-based measure (PBM) [10, 11]. The most commonly used PBM are EQ-5D [1], SF-6D [2], and Health Utilities Index (HUI) [3]. For obesity, the most commonly applied PBM is SF-6D [2].

However, not all clinical studies contain a PBM. Similarly, in obesity studies, quite often only none-preference-based-measures (NPMB) were used [12], such as Obesity Problem Scale (OP), Obesity and weight-loss Quality of life, and weight-related symptom measure (WRSM). The OP scale has been mostly applied in Scandinavia [13], but recently, has been recognized by the American Society for Metabolic and Bariatric Surgery [14]. When in the absence of PBM, it may be possible to map utility values indirectly from a NPBM as a solution [15].

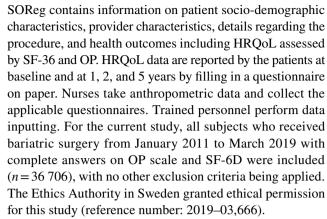
Mapping is a relative new research area with most papers published after 2000 [16, 17]. For obesity, mapping algorithms have been estimated from Moorehead-Ardelt II questionnaire (MA-II) to SF-6D and EQ-5D [18], from Weight on Quality of Life-Lite to SF-6D [19]. However, to the best of our knowledge, currently there is no mapping algorithm for OP. In the Scandinavian Region, as both SF-36 and OP have been applied in the Swedish Obesity Subjects trial between 1987 and 2001 [20], as well as in the large national register for bariatric surgery in Sweden, the Scandinavian Obesity Surgery Registry since 2007 [20-22], which enables constructing a mapping algorithm from OP to SF-6D utility index. As the OP mainly measures the impact of obesity on psychosocial function [23], and the obesity level will be significantly reduced after bariatric surgery [24], we assume that the relationship between OP and SF-46 might be different for pre- and post-surgery.

The aim of the study is to provide a mapping algorithm to estimate SF-6D utility values from the *Obesity Problem Scale*, which can be used to estimate utilities in subsequent analyses, such as economic evaluations reliant on data sets that include only Obesity Problem Scale. Additionally, we explored different mapping models and to test whether the mapping algorithm was robust to the effect of bariatric surgery.

Method

Data source and study population

The Scandinavian Obesity Surgery Registry (SOReg) is a national research and quality registry for bariatric surgery in Sweden (>97% national coverage), and is validated regularly and has been shown to have high data quality [21].



The development and validation of the mapping algorithm followed guidelines from ISPOR [25] and TRIPOD checklist [26] (Supplementary material Table S8). For internal cross-validation, data at each wave (baseline, 1-, 2- and 5-year follow-ups) were randomly split into two parts: 80% of the data were used as a training dataset for building models, and the remaining 20% were used as a validation dataset, thus resulting in totally eight datasets (training and validation datasets at each time point (baseline, 29,365 and 7342; 1-year, 27,125 and 5425; 2-year, 13,911 and 3478; 5-year, 5945 and 1488) (Supplementary material, Table S3. No significant differences in patient characteristics were found between the training and validation datasets. To know if the performance of the mapping algorithm differs between preand post-surgery, we also tested the mapping algorithm from one wave on datasets from all time points. For example, for baseline data, validations were carried out on baseline, 1-, 2-, and 5-year data, respectively. The mapping model with the best predictive performance was selected as the final model.

Health outcomes measure

Short Form-36 (SF-36/RAND) and SF-6D

SF-36 measures HRQoL in eight domains (social functioning, physical function, role-physical, bodily-pain, general health, vitality, social functioning, role-emotional and mental health) [27, 28], and the SF-36-v1 has been applied in the SOReg. The *short form six-dimensions (SF-6D)* was developed to derive a preference-based score from the SF-36 [29] or its 12-item version (SF-12) [30], using a *standard gamble* method. The six SF-6D domains include pain, mental health, physical functioning, social functioning, role limitations, and vitality, and each is described into four to six functional levels. The SF-6D utility scores in the current study were calculated using the UK tariff [29] since there is a local tariff in Sweden. Details regarding SF-6D domains and relevant SF-36 items could be found in the supplemental material (S1 and S2).



Obesity problem scale

Obesity problem scale (OP) is a validated disease-specific instrument, which assesses the impact of obesity on psychosocial functioning [20, 23]. The instrument comprises eight items (private gatherings at home; private gatherings at a friend's/relative's home; going to restaurants; participation in community activities; holidays away from home; trying on and buying clothes; bathing in public places; intimate relations) on a four-point scale (significant difficulties; some difficulties; limited difficulties; no difficulties). Based on responses on the OP dimensions, an OP summary score can be calculated ranging from 0 to 100, with a higher score indicating more psychosocial dysfunction [20].

Statistical methods for mapping

Descriptive analyses were used to examine the sample characteristics and the responses to the SF-6D and OP measures (proportions for discrete variables, mean and standard deviation, plus median and inter quart range for continuous variables).

We applied multivariate analysis to predict the values of the SF-6D utility score from OP summary score and items, with and without other covariates. Besides the commonly used Ordinary Least Square (OLS) method, both betaregression (accounting for the fact that the SF-36 utility score is bounded between 0 and 1) [31] and Tobit regression (accounting for the fact that SF-6D index were centred at 0.301 and 1) [32] were used. In beta regression, to decide whether or not including a link function and which link function to use, we computed AIC and BIC for those with and without link functions, based on Model 1 (Supplementary materials Tables S9). Model with Cauchit link function performed the best, and was applied in all beta-regression analyses in the study. In order to make comparisons across OLS, Tobit and Beta regression, as well as for easily interpreting the results, both transformed OP summary score $\left(\frac{100-OP_{\text{raw}}}{100} \times \frac{(N-1)+0.5}{N}, (N=500)\right)$ and transformed SF-6D index $\left(SF - 6D_{\text{raw}} \frac{(N-1)+0.5}{N} (N = 500)\right)$ were used, as betaregression does not allow the value of the dependant variable and variable used in the link function to be 0 or 1 [33].

Both transformed SF-6D index and OP summary score ranged between 0 and 1, with a higher value indicating better health.

Five sets of modes were tested, OP as the main effect (Model 1); including age and sex (Model 2); including age, sex and BMI (model 3); including age, sex and comorbidities (Model 4); including age, sex, BMI and comorbidities (Model 5). All the models were run on the baseline, 1, 2, and 5 years follow-up datasets, respectively.

Two types of independent variables were constructed for the OP measure: Type A is a simple additive model, where the transformed OP summary score was used as the independent variable. In Type B modelling, the item responses for each OP dimensions were used as independent variables and three dummy variables (reference: "no difficulty") were created for levels "not so bothered", "mostly bothered" and "definitely bothered", respectively. As there are eight OP dimensions, totally 24 dummy variables were included in the models.

Model selection

Model goodness-of-fit was assessed using adjusted/pseudo R² statistics in ordinary least squares (OLS)/Beta regression, Bayesian information criteria (BIC), and Alkaike information criteria (AIC) statistics. Lower BIC and AIC values would indicate a better fitting model. To examine the predictive performance of the model, the differences between the predicted and observed SF-6D value at the individual level were used to compute the mean absolute error (MAE) and root-mean-square error (RMSE). Smaller error values were indicative of better-performing models. All analyses were conducted using R.4.0.2 [34].

Results

Patient characteristics

Patient's characteristics were reported in Table 1. More than 76% of the patients were female, and the mean age was 41 at the baseline. About 10% of the patients were current smokers. Mean BMI was 42 at the baseline, and decreased to 29 at follow-ups. In general, the presence of obesity-related comorbidities (sleep apnoea, hypertension, diabetes, dyslipidaemia and depression) has decreased overtime, lowest at 1-year follow-up, followed by 2- and 5-year follow-ups.

Patient-reported health outcomes

Details regarding reporting on OP and SF-6D were reported in Table 2. HRQoL improved after surgery, with the highest improvements observed at 1-year follow-up, followed by 2and 5-year follow-ups. The SF-6D index was close to normal distribution at the baseline but left-skewed at the followups (Supplementary material Figure S1 and S2). There were moderate (0.4–0.59) and high correlations (\geq 0.6) between the SF-6D index and OP summary score at all time wave, as well as with most of the OP dimensions (Supplementary material Table S4).



Table 1 Socio-demographic characteristics, at baseline, 1, 2 and 5 years follow-ups

	Baseline $(n = 36,706)$	(9	1 year $(n=27,125)$		2 year $(n = 17,389)$		5 year $(n=7437)$	
	и	%	u	%	u	%	n	%
Age								
18–35 yrs	11,994	32.7	7448	27.5	3966	22.8	1179	15.9
36-45 yrs	11,168	30.4	9908	29.7	4876	28.0	1810	24.3
46-55 yrs	9655	26.3	7877	29.0	5405	31.1	2426	32.6
56-65 yrs	3662	10.0	3468	12.8	2817	16.2	1664	22.4
+ 59	227	9.0	266	1.0	325	1.9	358	4.8
Mean (SD)	41.02 (11.2)		42.73 (11.18)	44.59 (11.22)	47.92 (11.17)			
Median (Q1, Q2)	41 (32, 49)		43 (34, 51)		45 (37, 53)		48 (40, 56)	
Sex								
Men	8637	23.5	6439	23.7	4032	23.2	1662	22.3
Women	28,069	76.5	20,686	76.3	13,357	76.8	5775	T.TT
Educational level								
Missing	22,450	61.2	15,909	58.7	8920	51.3	3802	51.1
Less than 9 school	7627	20.8	5999	22.1	4565	26.3	1954	26.3
0 17 school years	1588	73	1203		044	7 7	717	9.5
on in selection years	0001	÷ :	777	ļ.	ţ.	t. 1	+ -	0.0
More 12 school years	5041	13.7	4014	14.8	2960	17.0	1267	17.0
Smoking								
Yes	3746	10.2	5669	8.6	1592	9.2	755	10.2
No	22,670	61.8	16,812	62.0	10,293	59.2	4469	60.1
Don't know	3992	10.9	2824	10.4	2270	13.1	910	12.2
Occationally	5626	15.3	4414	16.3	3013	17.3	1272	17.1
Quit before operation	029	1.8	406	1.5	221	1.3	31	0.4
BMI								
Mean(SD)	41.57(5.63)		28.55(4.56)		28.41(4.65)		29.86(4.93)	
Median(Q1, Q2)	40.8(37.7, 44.6)	27.9(25.3, 31.1)	27.8(25.1, 30.9)	29.3(26.3, 32.6)				
Sleep aponea								
Missing	2	0.0	206	0.8	333	1.9	222	3.0
No	32,913	7.68	26,046	0.96	16,556	95.2	7039	94.6
Yes	3791	10.3	873	3.2	500	2.9	176	2.4
Hypertension								
No	27,554	75.1	22,321	82.3	13,911	80.0	5643	75.9
Yes	9150	24.9	4598	17.0	3145	18.1	1572	21.1
Diabetes								
Missing	2	0.0	206	8.0	333	1.9	222	3.0



lable I (continued)	ed)							
	Baseline $(n = 36,706)$	(90	1 year $(n=27,125)$		2 year $(n=17,389)$	(6	5 year (n=7437)	
	п	%	n	%	n	%	n	%
No	32,003	87.2	25,709	94.8	16,154	92.9	6744	7:06
Yes	4701	12.8	1210	4.5	902	5.2	471	6.3
Dyslipidemia								
Missing	2	0.0	206	0.8	333	1.9	222	3.0
No	33,213	90.5	25,440	93.8	16,018	92.1	6719	90.3
Yes	3491	9.5	1479	5.5	1038	0.9	496	6.7
Depression								
Missing	2	0.0	206	0.8	333	1.9	222	3.0
No	30,707	83.7	23,257	85.7	14,521	83.5	5959	80.1
Yes	2997	16.3	3662	13.5	2535	14.6	1256	16.9
Year								
2011	5625	15.3	4721	17.4	3582	20.6	2991	40.2
2012	5426	14.8	4439	16.4	3047	17.5	2189	29.4
2013	5399	14.7	4373	16.1	3199	18.4	1628	21.9
2014	4886	13.3	3865	14.2	2738	15.7	578	7.8
2015	4462	12.2	3734	13.8	2165	12.5	19	0.3
2016	4142	11.3	2697	6.6	1871	10.8	17	0.2
2017	3225	8.8	2245	8.3	778	4.5	7	0.1
2018	2522	6.9	1046	3.9	9	0.0	7	0.1
2019	1019	2.8	5	0.0	3	0.0	1	0.0



Table 2 Reporting of Obesity problem scale (dimension, summary score) and SF-6D index score, at baseline, 1, 2 and 5 years follow-ups

	Dascinic $(n-30,100)$	(an/	1 year $(n=27,125)$	',125)	2 year $(n=17,389)$	(,389)	5 year (n = /43/)	/45/)
	n	%	n	%	u u	%	n	%
Obesity problem scale dimensions	ns							
Private gatherings in my own home (OP1)	ome (OPI)							
No difficulties	7723	21.0	20,841	76.8	12,840	73.8	5029	9.29
Limited difficulties	7846	21.4	3978	14.7	2633	15.1	1266	17.0
Some difficulties	13,276	36.2	1736	6.4	1429	8.2	608	10.9
Significant difficulties	7861	21.4	570	2.1	487	2.8	333	4.5
Private gatherings in a friend's or relative's home (OP2)	or relative's home (O	22)						
No difficulties	4924	13.4	19,773	72.9	12,158	6.69	4675	62.9
Limited difficulties	5020	13.7	4303	15.9	2703	15.5	1308	17.6
Some difficulties	13,036	35.5	2344	8.6	1872	10.8	1036	13.9
Significant difficulties	13,726	37.4	705	2.6	929	3.8	418	5.6
Going to a restaurant (OP3								
No difficulties	6563	17.9	19,362	71.4	12,337	70.9	5055	68.0
Limited difficulties	7811	21.3	4427	16.3	2753	15.8	1229	16.5
Some difficulties	14,045	38.3	2703	10.0	1776	10.2	888	11.9
Significant difficulties	8287	22.6	633	2.3	523	3.0	265	3.6
Going to community activities, courses etc. (OP4)	courses etc. (OP4)							
No difficulties	6647	18.1	20,869	76.9	12,887	74.1	2086	68.4
Limited difficulties	7759	21.1	3964	14.6	2645	15.2	1253	16.8
Some difficulties	13,596	37.0	1714	6.3	1367	7.9	778	10.5
Significant difficulties	8704	23.7	578	2.1	490	2.8	320	4.3
Vacations away from home (OP5)	5)							
No difficulties	6344	17.3	20,615	76.0	12,656	72.8	5084	68.4
Limited difficulties	6378	17.4	3614	13.3	2412	13.9	1120	15.1
Some difficulties	13,446	36.6	2121	7.8	1625	9.3	862	11.6
Significant difficulties	10,538	28.7	775	2.9	969	4.0	371	5.0
Trying on and buying clothes (OP6)	196)							
No difficulties	1555	4.2	18,101	2.99	10,729	61.7	3947	53.1
Limited difficulties	1810	4.9	4506	16.6	2886	16.6	1335	18.0
Some difficulties	7317	19.9	3349	12.3	2564	14.7	1380	18.6
Significant difficulties	26,024	70.9	1169	4.3	1210	7.0	775	10.4
Bathing in public places (beach, public pool, etc.) (OP7)	public pool, etc.) (O	(24						
No difficulties	2367	6.4	12,576	46.4	4062	45.5	3219	43.3
Limited difficulties	2413	9.9	4485	16.5	2539	14.6	1198	16.1
Some difficulties	7585	20.7	5861	21.6	3697	21.3	1575	21.2
	24 341	8 99	4203	155	3244	18.7	1445	101



Table 2 (continued)

	Baseline $(n = 36,706)$		1 year $(n=27,125)$,125)	2 year $(n=17,389)$	(68	5 year $(n=7437)$	
	n	%	n	%	n	%	n	%
Intimate relations (OP8)								
No difficulties	4909	13.4	15,013	55.3	9189	52.8	3795	51.0
Limited difficulties	9099	15.3	4637	17.1	2778	16.0	1278	17.2
Some difficulties	12,711	34.6	4711	17.4	3176	18.3	1373	18.5
Significant difficulties	13,480	36.7	2764	10.2	2246	12.9	991	13.3
OP summary score								
Mean (SD)	65.11 (26.06)		18 (21.86)		20.37 (24.32)	23.61 (26.74)		
Median (Q1, Q2)	70.8 (50, 83.3)		8.3 (0, 29.2)		12.5 (0, 33.3)		12.5 (0, 41.7)	
Transformed OP summary score								
Mean (SD)	0.35 (0.26)		0.82 (0.22)		0.8 (0.24)		0.76 (0.27)	0.35 (0.26)
Median (Q1, Q2)	0.29 (0.17, 0.5)		0.92 (0.71, 1)		0.87 (0.67, 1)		0.87 (0.58, 1)	0.29(0.17, 0.5)
Mean (SD)	0.66 (0.13)		0.80 (0.14)		0.78 (0.15)		0.75 (0.15)	
Median (Q1, Q2)	0.65 (0.57, 0.75)		0.84 (0.71, 0.89)	(68	0.82 (0.67, 0.89)		0.79 (0.63, 0.89)	
Transformed SF-6D index								
Mean (SD)	0.66 (0.13)		0.80 (0.14)		0.78 (0.15)		0.75 (0.15)	
Median (Q1, Q2)	0.65 (0.57, 0.75)		0.84 (0.71, 0.89)	(68	0.82 (0.67, 0.89)		0.79 (0.63, 0.89)	



Initial model development

Results for model goodness of fit and prediction accuracy for the initial model development at each time point (baseline, 1, 2, 5-year follow-up) are reported in Table 3, details can be found in Supplementary materials, for OLS (Table S5A and S5B), for Tobit regression (S6A-S6B) and beta regression (S7A and S7B). Four main issues were investigated: whether using OP summary score or item as a predictor? Whether including other covariates such as age, sex, BMI and comorbidity? Whether using a separate mapping algorithm for pre- and post-surgery? Whether using OLS, Tobit or beta regression?

OP summary score or item as predictor (Type A or B model)

Across the OLS, Tobit and beta regression, the application of OP dimensions instead of the OP summary score did not increase the model performance, as it had little impact on goodness-of-fit and prediction power. Furthermore, for OLS models, inconsistency was found for the dimension *bathing in public places* (*beach*, *public pool*, *OP7*), with positive coefficients at baseline.

Inclusion of age, sex BMI and comorbidity as predictors

Conclusions from beta regression and Tobit regression were similar to OLS models, that the inclusion of age, sex, BMI and comorbidity variables increased model performance: in terms of goodness-of-fit, an increased R² and decreased AIC and BIC across Mode 1 to 5 for each wave of data; in terms

of prediction power, decreased MAE and RMSE for model validations were also observed across Model 1 to 5.

OLS, Tobit or beta regression

Results for the goodness of fit and prediction power are presented in Table 3 In terms of goodness of fit, OLS yielded lowest AIC and BIC values for mapping algorithm from baseline and 2-year follow-up, while Beta regression gave the lowest AIC and BIC values for mapping algorithm from 1- and 5-year follow-ups. In terms of prediction power, results were similar for OLS and Tobit models, both yielded lower MAE and RAE values and higher RMSE and RRSE values relative to beta regressions at almost all time points; The performance of OLS and Tobit models were rather similar, both yielded better results than beta-regression.

Comparison between Pre- and post-surgery algorithms

Coefficients for pre- and post-surgery algorithms showed different patterns: coefficients for the OP summary score differed between baseline (0.26) and follow-ups (0.32). Coefficients for age groups were rather stable across all the models. The coefficient for male was higher than the coefficient for female at follow-ups, but not at baseline. At baseline, coefficients for BMI were significant; however, at follow-ups, not all coefficients for BMI were significant. Coefficients for comorbidities were relatively stable from baseline to 2-year follow-up, with depression associated with the largest effect, followed by sleep apnoea and diabetes.

Table 3 Comparison of model goodness of fit and prediction accuracy, transformed SF-6D index^a and OP Summary Score ^b used

											00																	-	_	_	Tot	obit Mod	id																		Deta	negressi	00					-			\neg
		Mappin			ed on					based on			pping alg			,			algorithe		on	-		g algorid		d on				ithm base		Т			rithm bas					porithm bo			Mag		orithm ba	sed on	Т			ithm bas		Т		g algorith		on		tapping al			\neg
	_		baselin			_			oliow-up		_		2-year fo				_		follows			_		baseline						ow-up data					low-up da		_			stew-up o		_			ine data		_			ow-up da		_		ar follow-				Syear f			_
	MI	M2	M		84	MS.	MI	M2	M3	M4	MS	MI	M2	M2	M4	MS	MI	M2	MG	564	MS	MI	M2	MG	M	M	M1				M MS						AS .	MI I	M2	MG	M4	MS	MI	M2	M3 1	W4 1	MS	M3 M	2 h	13 N	64 M	5 M	1 M2	MG	564	MS	MI	M2	ма	M4	MS
Goodness of fit																																\neg																													_
AC DC		0 468								-22049 -21945		-18957 - -18934 -							-7621 -7552							96 -466 88 -465					1916 -239 1812 -237				4253 -15 4170 -14			6444 -					46500 -4					25079 -25 25047 -25					957 -209 927 -209					-8453 -8392			
Validation	40.0	19 1000	0, 40	73 ~	219	7274	12007	*****	-20-911	-31903	-31900	-28924		-18373	-20070	-10200	-7820	-788	-7333	-782	1780		400	7 -482	-	-	720	8 72.00	28 228	143 238	12.2	372 -24	1430 -21	1220 -	4270 -24	1880 -24			0430	-8102	-0.283	4,744	1000		-	48.00		13007 -23	200 -91	-93	1424 -323	200	200		2000	2 -20881	4372	4000	-8076	4011	-0.243
MAE Training data (80%)		7 0.0					0.093			0.090			0.098						0.100				0.00	7 0.00		96 00					099 00				0.096		1093	0.301 (0.087			0.006		0.095 0					100 01		0.00			0.103			
Validating data (20%)		5 0.00				0.086	0.094			0.090			0.098				0.101		0.100				0.08			9A 00					090 00				0.096 0			0.301 0					0.085					0.096 0					100 0.1					0.103			
Questine		7 0.00								0.087		0.088									0.09					86 0.0					0.0				0.093 0			0.093 0				0.093	280.0	980.0	0.006	0.086	0.065	0.091 0					0.0					0.092			
1-year 2-year		0.00					0.093			0.090		0.095							0.099		0.09					96 0.0					089 0.0				0.094 0			0.100 0				0.095	0.105	0.104	0.104 6	0.104 0	0.303	0.095 0					997 0.0 100 0.3					0.102			
S-year		3 0.30								0.096		0.100							0.100							00 0.0					095 0.0				0.099 0			0.101 0					0.107					0.102 0					103 0.1					0.103			
AMSE																																																													
Training data (80%) Validating data (20%)		9 0.10				0.108				0.115		0.123					0.125	0.125	0.124	0.12	0.12					06 0.1					115 01				0.122 0			0.125 0					0.106					0.120 0					124 0.1 124 0.1				0.127	0.126	0.126	0.123	0.123
Questine	0.30	9 0.1	09 0	08 0	108	0.108	0.111	0.111	0.112	0.110	0.111	0.111	0.112	0.117	0.111	0.116	0.118	0.11	0.119	0.11	0.11	0.309	0.10	9 0.30	18 0.1	08 0.1	0.1	11 0.1	111 0.1	113 0.1	111 0.1	112 0.	112 0	112 (0.118 0	112 0	117	0.118 0	0.117	0.120	0.115	0.117	0.108	0.108	0.108 (0.107 0	0.307	0.116 0	116 0	121 0	118 0.1	120 0.	114 0.1	4 0.12	6 0.11	6 0.124	0.118	0.116	0.119	0.115	0.116
1-year 2-year		0 0.12								0.115		0.119									0.11					18 0.1 21 0.1					115 01				0.118 0 0.122 0			0.122 0					0.125					0.120 0					120 0.1					0.123			
5-year		7 0.1								0.119		0.122									0.12					24 0.1					124 01				0.126 0			0.124 0					0.127					0.125 0								5 0.125		0.126			
AAC																																																													
Training data (90%) Validating data (20%)		0.80								0.796		0.803							0.772		0.74					97 0.7					794 0.7 795 0.7				0.799 G		772	0.775 0	0.770	0.770	0.729	0.728	0.819					0.840 0					125 0.E	0.82	6 0.90	0.806		0.793			
Baseline	0.82	0.80	18 0.	17 0	320	0.810	0.823	0.823	0.834	0.824	0.829	0.828	0.829	0.858	0.831	0.859	0.858	0.852	0.877	0.85	0.86	0.820	0.81	8 0.81	6 0.5	10 0.5	0.8	27 0.8	827 0.8	829 0.8	329 O.S.	835 0.	831 0	832 (0.863 0	335 O	.863	0.861 0	0.856	0.876	0.855	0.870	0.816	0.812	0.811	0.807 0	0.806	0.861 0.	863 0	890 O.	881 0.5	891 0.	149 0.5	0.90	6 0.86	8 0.919	0.866	0.858	0.874	0.861	0.870
1-year		2 0.8								0.796		0.924					0.833	0.827	0.927	0.80	0.80	0.842				04 0.0					794 0.7 768 0.7				0.818 O			0.829 0					0.873					0.840 0								6 0.827		0.849			
2-year 5-year	0.79	6 0.7	93 0.	93 0	276	0.775	0.777	0.770	0.770	0.771	0.771	0.774	0.770	0.771	0.7/1	0.772	0.776	0.271	0.800	0.74	0.74	0.225	0.75	9 0.83	3 0.3	76 0.7	75 0.7	77 0.7	769 0.1	769 0.7	766 0.7	743 0.	772 0	267 (0.768 0.	740 0	740	0.773 0	0.768	0.768	0.776	0.777	0.824	0.821	1.822 (0.812 0	0.814	0.796 0	790 O	790 O.	774 0.7	774 0.	796 0.7	0.82	1 0.77	4 0.772	0.296	0.792	0.792	0.775	0.774
3259																																																													
Training data (80%) Validating data (20%)		0.80								0.835		0.846									0.79	0.849	0.84	7 0.84	0.0	40 0.1	20 02				835 0.8 831 0.8	235 O.	846 0	244 (0.844 0 0.826 0	820 0	921	0.823 6	0.819	0.819	0.792	0.791	0.842				0.833	0.866 0	866 0	0 332	852 0.8 850 0.8	952 0.	857 0.8 844 0.8					0.829			
Saceline	0.84	0.9	64 0.1	42 0	328	0.836	0.856	0.857	0.862	0.855	0.857	0.857	0.858	0.877	0.858	0.878	0.870	0.871	0.887	0.87	0.88	0.846	0.84	4 0.84	2 0.5	28 0.5	36 0.8	61 0.8	961 0.8	867 0.8	861 0.8	863 0.	860 0	862 (0.881	863 0	992	0.873 0	0.974	0.889	0.874	0.889	0.829	0.837	0.836	0.831 0	0.830	0.893 0	296 0	915 0	913 0.9	921 0:	177 0.8	0.92	2 0.89	7 0.942	0.878	0.876	0.888	0.880	0.889
1-year		6 0.8								0.924		0.858									0.84	0.865	0.80	3 0.80	2 0.5	49 03	47 0.8	18 0.8	255 0.7	854 0.8	825 0.8 818 0.8	835 0.	258 O	355 (0.855	325 O	926	0.863 0	0.000	0.860	0.841	0.841	0.885				0.876	0.868 0	866 0	265 0	852 0.8	952 0.	0.0	0.86	6 0.85	2 0.852	0.873	0.970	0.870	0.857	0.857
2-year 5-year										0.817		0.843									0.82					15 0.0					918 0.8 903 0.8												0.867				0.858	0.856 0	854 0 839 0	854 O.	937 0.8 925 0.6	925 O	154 O.B 139 O.B	0.85	6 083	0.835	0.856	0.853	0.854	0.937	0.838
																																,																													
																													Type 2 m	nodelling	with OP d	dimensio	ons as pr	edictors																											
Goodness of fit	4835	2 482	04 40	97 4	1774		11.475	31550	21220	-32342	22222	10346	10330	16036	1000	10033	2010	70.5	2/2	807			1700	1 4770	2 486	20 481	201 222	07 734	411 22	240 24	172 -241	ard as	707 1		eron 11	221 10	and .	6528 -	****	£224	£300	cent	46022 4	10017	2062 6	7701 6	rand :	25220 -25	207 30	000 30	200 200	erel 10	140 311	2077	2 2124	3 31366	4330	-8222	2025	8368	8313
aic ac	-4813	8 -481	27 -42	25 -41	1475 -	12549	11267	21342	31108	-32055	-32000	-19052	29074 -	-18672	-29417	-19229	-7736	-7741	-7453	-783	-778	47295	-6725	4 -4740	11 -477	22 -479	05 -230	99 -231	163 -221	978 -231	1886 -238	847 -14	1589 -14	1608 -1	4248 -14	1951 -14	1884	6254 -	6160	-6098	-6460	-6423	46708 -	6690 -	6781 -4	7002 -4	17079	35023 -35	047 -34	797 -35	558 -355	514 -30	353 -209	5 -2051	7 -2107	3 -20991	-8036	-8025			
Validation																																					_																								
Training data (80%)	0.08	5 0.00	85 Q.I	185 G	.085	0.085	0.092	0.092	0.092	0.089	0.099	0.096	0.096	0.096	0.093	0.093	0.100	0.091	0.099	0.09	6 0.09	0.085	0.06	5 0.00	15 0.0	es 0.0	84 0.0	92 0.0	391 0.	091 07	088 0.0	088 0	096 0	095 (0.095 0	092 0	1092	0.099 0	990.0	0.098	0.095	0.095	0.085	0.085	0.085 (0.085	0.064	0.092 0	091 0	091 0	0.0 980	089 0.0	296 0.0	5 0.09	5 0.09	0.093	0.099	0.098	0.098	0.096	0.095
Validating data (20%)										0.090		0.097									0.09					82 0.0					009 00				0.095 0			0.100					0.084					0.092 0								0.093		0.098			
Baseline 1-year		1 0.1								0.086		0.087							0.093		0.09					64 0.0 08 0.1					086 00				0.092 0			0.091 0					0.085					0.088 0					0.0 880					0.092			
2-year	0.11	1 0.1	11 0.	09 0	308	0.107	0.095	0.095	0.095	0.092	0.092	0.097	0.096	0.096	0.093	0.093	0.101	0.300	0.100	0.00	0.09	0.110	0.11	0.10	0.3	00 0.1	0.0	95 0.0	094 0.0	094 0.0	092 0.0	092 0.	096 0	095	0.095 0	092 0	.092	0.100 0	990.0	0.099	0.096	0.096	0.105	0.105	3.304 (0.103 0	0.302	0.095 0	095 0	095 0	092 0.0	092 03	296 0.0	0.095	5 0.09	0.093	0.098	0.098	0.098	0.096	0.095
S-year awsr	0.30	9 0.1	09 0.	08 0	106	0.105	0.099	0.098	0.098	0.095	0.095	0.098	0.098	0.098	0.095	0.095	0.100	0.300	0.099	0.00	0.09	0.308	0.10	0.00	7 0.1	06 0.1	0.0	29 0.0	398 0.5	0.0	095 0.0	094 0.	098 0	098 (0.098 0	095 0	1.094	0.099 0	990.0	0.099	0.095	0.095	0.105	0.105	0.304 (0.103 0	0.302	0.099 0	098 0	098 0	0.0	096 0.1	299 0.0	0.09	0.00	6 0.096	0.099	0.098	0.098	0.096	0.094
Training data (80%)	0.10	6 0.10	06 0.	06 0	106	0.105	0.117	0.117	0.117	0.114	0.114	0.121	0.121	0.121	0.118	0.118	0.124	0.124	0.127	0.12	0.11	0.306	0.10	6 0.10	6 0.1	06 0.1	05 0.1	17 0.1	117 0.	117 0.1	114 01	114 0.	121 0	121 (0.121 0	118 0	118	0.124 0	0.124	0.123	0.120	0.119	0.106	0.106	1.106	0.106	0.306	0.118 0	118 0	118 0	116 0.1	116 0.	122 0.1	0.12	2 0.11	9 0.119	0.126	0.125	0.125	0.122	0.121
Validatine data (20%)		0.10			103	0.103				0.114	0.114	0.121	0.121	0.120	0.117	0.117	0.124	0.122	0.124	0.12	0.12	0.334	0.10	4 0.10	4 0.1	03 0.1	03 0.1	17 0.1	117 0.7	117 0.1	114 0.1	114 0.	121 0	121 (0.120 0.	117 0	117	0.124	0.123	0.123	0.121	0.121	0.105	0.104	0.304 (0.104	0.303	0.118 0	117 0	117 0	115 0.1	115 0.	122 0.1	0.12	1 0.11	8 0.118	0.125	0.124	0.124	0.122	0.122
Baseline		9 0.1								0.109		0.110									0.11					05 0.1 26 0.1					110 01				0.116 0			0.115 0					0.106					0.113 0					112 0.1					0.117			
2-year	0.13	0.13	30 0.	28 0	127	0.126	0.122	0.121	0.121	0.118	0.118	0.121	0.121	0.121	0.118	0.117	0.123	0.122	0.122	0.11	0.11	0.130	0.13	0 0.13	18 0.1	27 0.1	26 0.1	22 0.1	122 0.1	121 0.1	118 0.1	118 0.	121 0	121	0.121 0	117 0	117	0.123	0.122	0.122	0.119	0.119	0.125	0.125	0.124 (0.123 0	0.122	0.123 0	123 0	122 0	120 0.1	120 0.	122 0.1	0.12	2 0.11	9 0.119	0.123	0.122	0.122	0.119	0.119
Syear	0.12	9 0.12	29 0.	28 0	127	0.126	0.127	0.126	0.126	0.123	0.122	0.126	0.125	0.125	0.121	0.121	0.124	0.124	0.123	0.12	0.12	0.129	0.12	9 0.12	8 0.1	26 0.1	26 0.1	JS 0.1	27 02	126 0.1	123 0.1	123 0.	126 0	125	0.125 0	122 0	121	0.124 0	0.124	0.123	0.120	0.120	0.127	0.127	0.127	0.125	0.125	0.129 0	128 0	128 0	126 0.1	125 0.	128 0.1	0.12	7 012	4 0.124	0.125	0.125	0.125	0.122	0.121
Training data (90%)	0.90	5 0.80	04 0.1	102 0	798	0.796	0.812	0.810	0.809	0.789	0.789	0.792	0.789	0.791	0.766	0.766	0.768	0.764	0.764	0.73	0.72	0.804	0.80	9 0.80	2 0.7	98 0.7	96 0.8	12 0.5	808 G.	808 0.	797 0.7	788 0.	789 0	286 (0.788 Q	764 0	764	0.764	0.761	0.761	0.722	0.732	0.803	0.802	0.800	0.797 0	0.796	0.815 0	813 0	812 0	295 0.7	795 0.	791 0.7	0.79	0 0.77	0 0.771	0.762	0.759	0.760	0.729	0.729
Validating data (20%)	0.79	2 0.71	99 0.	22 0	792	0.781	0.810	0.807	0.807	0.789	0.729	0.784	0.782	0.778	0.754	0.754	0.764	0.763	0.761	0.74	0.74	0.791	0.79	9 0.75	18 0.7	92 03	91 0.8	0.0	805 0.8	805 0.7	787 0.7	797 0.	791 0	229 (0.775 0.	751 0	751	0.761 0	0.758	0.758	0.729	0.738	0.791	0.789	0.788 6	0.792 0	0.781	0.811 0	908 0	808 Q	792 0.7	793 0.	284 0.7	0.77	7 0.75	6 0.756	0.755	0.753	0.754	0.741	0.729
Baseline 1-year		9 0.80								0.815		0.819							0.850		0.85					95 0.7 61 0.1					818 0.8 787 0.2				0.809			0.844 0					0.855					0.833 0 0.814 0					131 O.S 114 O.S					0.854			
1-year 2-year	0.85	8 0.81	58 0.	55 0	.943	0.839	0.790	0.797	0.788	0.764	0.764	0.790	0.788	0.798	0.763	0.764	0.903	0.800	0.800	0.77	0.77	0.857	0.85	7 0.85	3 0.5	41 0.0	127 0.7	99 0.7	785 0.7	785 0.7	761 0.7	762 0.	797 0	785 (0.795 0	761 0	761	0.799 0	0.796	0.797	0.772	0.772	0.835	0.824	0.833 (0.822 0	0.921	0.791 0.	788 0	799 0	768 0.7	769 0.	790 0.7	0.78	7 0.76	7 0.768	0.794	0.792	0.793	0.773	0.774
5-year	0.82	7 0.83	27 0.1	25 0	309	0.806	0.765	0.760	0.761	0.728	0.727	0.763	0.759	0.761	0.725	0.735	0.767	0.763	0.764	0.72	0.72	0.826	0.93	5 0.83	2 0.5	08 0.8	03	26 0.7	/59 G.7	760 0.7	728 0.7	222 0.	761 0	257 (0.759 0.	725 0	.734	0.764 0	0.760	0.760	0.734	0.723	0.805	808.0	3.804	0.790	0.789	0.769 0	763 0	765 Q	247 0.3	747 0.	765 0.7	0.76	0.74	5 0.745	0.761	0.758	0.759	0.740	0.729
ARSE Training data (80%)	0.03	6 0.8	w 0	22 4	800	0.010	0.000	0.040	0.847	0.828	0.838	0.836	0.834	0.034	0.013	0.011	0.015	0.81	0.017	6.78	0.78	0.00	0.83		2 00	19 03		F1 04		047 0	829 0.8		#3¢ #		0.835 0	#13 O	912	0.815 0	0.013	0.013	6.787	0.784	0.827	0.836		1821 6	0.830	0.858 0		eer 0	440 0.0		H2 0.8	0.00	0 083	2 0.834		0.820	0.831	0.700	0.708
Validating data (20%)	0.81	5 0.80	13 0.	112 0	308	0.806	0.844	0.842	0.842	0.924	0.825	0.826	0.824	0.820	0.798	0.797	0.819	0.811	0.816	0.80	0.79	0.815	0.81	3 0.81	2 0.5	0.0	0.0	44 0.8	842 0.8	842 0.8	924 O.S	825 0.	926 0	824 (0.819 0	298 0	.797	0.819 0	0.815	0.816	0.800	0.799	0.817	0.815	3.834	902.0	0.908	0.849 0	848 0	949 Q	833 0.8	134 0.1	132 0.8	0.821	6 0.80	0.806	0.825	0.922	0.823	0.810	0.908
Baseline	0.82	0.83	22 0.1	21 0	817	0.816	0.549	0.850	0.856	0.848	0.851	0.949	0.850	0.872	0.849	0.872	0.857	0.851	0.871	0.85	0.87	0.924	0.83	2 0.83	1 0.5	17 0.1 75 0.1	116 0.8	12 0.8	153 0.7	459 Q.P	852 0.8 828 0.8	ass 0.	851 C	353 (0.875 O.	253 0	976	0.859 0	198.0	0.873	0.860	0.874	0.825	0.824	0.822 (0.819	0.817	0.867 0	869 0	885 0	224 0.5	991 0.	0.9	5 0.90	2 0.87	8 0.913 0 0.841	0.870	0.972	0.883	0.884	0.992
1-year 2-year										0.929		0.834															52 0.8	36 0 0	933 0.6	834 0.0	912 0.0	812 0	924 0	822 (0.031 0	910 0	910	0.020 0	n 836	0.036	0.815	0.015	0.872														0.860				
5-year	0.84	0.0	47 0:	146 0	822	0.830	0.823	0.819	0.819	0.797	0.796	0.920	0.816	0.818	0.794	0.794	0.816	0.81	0.817	0.71	0.78	0.847	0.84	6 0.84	15 0.5	31 0.1	129 0.8	25 0.9	421 07	821 03	800 0.7	798 0.	822 0	\$18 (0.819 0	796 0	795	0.816	0.812	0.813	0.790	0.788	0.834	0.833	0.834	0.822 0	0.821	0.822 0	230 O	931 0	813 0.5	913 01	20 0.0	7 0.82	9 0.83	0 0.810	0.923	0.820	0.821	0.801	0.800

$${}^{a}SF - 6D_{transformed} = SF - 6D_{raw} \times \frac{(N-1)+0.5}{N} (N = 500)$$

$${}^{b}OPS_{transformed} = \frac{100-OPS_{raw}}{100} \times \frac{(N-1)+0.5}{N}, (N = 500)$$



Hypertension and dyslipidaemia had a very low impact. At the 5-year follow-up, only depression was significant.

Final mapping algorithm

Based on the above findings, we conclude that using OP summary score as the main predictor, including age, sex, BMI and comorbidities, using OLS model, and separate analyses for pre- and post- surgery. For comorbidities, sleep apnoea, diabetes and depression were included as those were with significant coefficients and also confirmed by the clinicians as the most important obesity-related comorbidities. We include BMI into the algorithm for pre-surgery prediction, but exclude BMI for post-surgery prediction as it led to inconsistency (higher BMI was not associated with lower SF-6D index). We ran Model 1 to 5 for baseline data, and Model 1, 2 and 4 for post-surgery data (Table 4). As beta regression was not used for deriving the final mapping algorithms, it was not necessary to use the transformed SF-6D and OP summary score. Therefore, we ran OLS model with the raw OP summary score (ranged 0-100, with a higher value indicating worse health) as the predictor and raw SF-6D index (ranged 0–1, with a higher value indicating better health). We recommend Model 5 for mapping with pre-surgery data, and Model 4 for post-surgery data. When not all information of predictors are available, one may choose any algorithm from Model 1–4 for pre-surgery data, and Model 1 or 2 for post-surgery based on their own need or preferences.

Discussion

This study explored mapping algorithms from OP to SF-6D index using a large patient register. Conceptual overlap between the source measure and the target PBM should be considered before mapping can be undertaken [35]. The OP has been developed as a condition-specific instrument to measure the impact of obesity on psychosocial function [23]. Although the focus of OP was on mental health and role function mental, dimensions such as *Vacations away from home, Trying on and buying clothes, Bathing in public places (beach, public pool, etc.), and Intimate relations* would also indicate the impact of obesity on physical health and pain. Therefore, we considered that there was a reasonable overlapping between OP and SF-6D, which was also indicating by the R^2 in the mapping algorithm (0.3).

One important finding of our study was that the mapping algorithm should be different for data collected before and after bariatric surgery, which is in line with a recent study [36]. We found that the effect of the OP summary score increased while the effect of gender decreased after surgery and that the effect of BMI disappeared after the surgery.

Possible explanation could be that pre-surgery patients were associated with very high BMI, and the there were remained effects of BMI on SF-6D utility even after controlling for OP; However, patients who underwent bariatric surgery lost weight significantly [24], and those with higher preoperative BMI tend to lose a higher percentage of their total weight [37], thus all the effects of BMI were picked up by OP already. This finding suggests that mapping algorithm might differ at baseline and follow-ups for bariatric surgery, and one should be cautious to merge pre-operative and postoperative data to construct mapping algorithms, or to use follow-up data to examine the prediction power of mapping algorithm based on baseline data, or vice versa. To the best of our knowledge, this is the first evidence showing that clinical interventions may affect the crosswalk between an NPBM and a PBM among patients received bariatric surgery. Further research using data from other disease/intervention populations is needed to assess its generalizability.

We have chosen a simple additive model (with the OP summary score as the main predictor) for constructing the final mapping algorithm. This model assumed that the dimensions of the OP were equally important, and all levels carried equal weight; and response choices to each item lie on a similar interval scale. The models including all individual OP dimensions have a large number of independent variables; however, in terms of prediction ability, those did not outperform the simple additive models. Moreover, some of the coefficients were non-significant or non-monotonic. These findings were in line with previous studies using item response models or adding interaction and other terms [16]. Furthermore, in most published clinical studies, only the OP summary scores were reported. Therefore, we recommend using the simple additive model to map OP data to the SF-6D index scores.

The distributional characteristics of the SF-6D health utility data (UK v1 tariff) posed a challenge for modelling analysis, for example, the values being bounded between 0.301 and 1, skewness, multimodality, and gaps in the values [16, 17, 38]. In our study, we have tested OLS, Tobit, and beta-regression. The performance of OLS and Tobit was quite similar, both were superior to beta-regression. One possible explanation might be that SF-6D index does not suffer from the ceiling effect as much as the EQ-5D index, and in our study, the mean and median of SF-6D were rather close at baseline. In a study which was focused on the application of beta-regression on SF-6D index, the author claimed that the confidence intervals were overlapping across OLS and beta-regressions, suggesting that no model was superior to the others [33]. Although OLS has been criticized for not being appropriate for none-normally distributed data and might underestimate health utility associated with mild health states and overestimated utility for more severe health states [25, 38], there was no obvious



Table 4 Mapping algorithm based on OLS model, untransformed SF-6D index and OP summary score used, baseline and post-surgery data, respectively

	Baceline										Poet-euroe	Post-surgery (1.2.5 years)	are)							
	omizend 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		0.15		26-4-10		2 151 2		7,110		Same sea t	20 (44.1) (1	(em)		0.1-1		7.5		2 15 15 1	
	Model 1	enleV."	Coef.	ouleV.a	Model 3	- Value	Model 4	- Value	Model 3	- Volue	Model 1		Model 2		9		Model 4	- Value	Coef.	aul Value
		p-value		p-value	Coer- ficient	<i>p</i> -value	Coer- ficient	<i>p</i> -value	Coer- ficient	<i>p</i> -value		<i>p</i> -value		p-value	Coet- ficient	<i>p</i> -value	Coer- ficient	p-value	Coer- ficient	p-value
Intercept	0.831	0.000	0.841	0.000	0.847	0.000	0.842	0.000	0.848	0.000	0.852	0.000	0.866	0.000	0.867	0.000	0.872	0.000	0.872	0.000
mary		0000	00.0	0000	60.0		60.0	0000	00.0	0000		0000				0000	60.0	0000	600.0	0000
Patient																				
charac- teristics																				
Age^a																				
36-45 yrs	1	ı	0.001	0.547	0.000	0.818	0.004	0.015	0.003	0.105	ı	ı	-0.013	0.000	-0.013	0.000	-0.009	0.000	-0.009	0.000
46-55 yrs	ı	ı	-0.009	0.000	-0.011	0.000	-0.004	0.028	-0.006	0.001	ı	ı	-0.022	0.000	-0.022	0.000	-0.017	0.000	-0.017	0.000
56-65 yrs	ı	I	-0.017	0.000	-0.019	0.000	-0.010	0.000	-0.012	0.000	ı	1	-0.033	0.000	-0.033	0.000	-0.028	0.000	-0.028	0.000
+ 59	I	ı	-0.018	0.033	-0.020	0.015	-0.010	0.232	-0.013	0.135	I	ı	4	0.000	-0.034	0.000	-0.030	0.000	-0.029	0.000
Man^b	ı	ı	-0.007	0.000	-0.005	0.001	-0.006	0.000	-0.004	0.011	ı	ı	0.010	0.000	0.011	0.000	0.007	0.000	0.007	0.000
BMF																				
40-44	I	ı	ı	ı	-0.007	0.000	,	,	-0.007	0.000	I	1	ı	ı		0.000	,	ı	-0.015	0.001
45-49	ı	ı	1	ı	-0.013	0.000	,	,	-0.012	0.000	I	1	1	ı	-0.023	0.018	,	ı	-0.015	0.111
+05	ı	ı	ı	ı	-0.022	0.000		,	-0.020	0.000	I	ı	ı	ı	-0.014	0.416		ı	-0.017	0.318
Comobidi- ty ^d																				
Sleep	1	1	1	1	1	1	-0.015	0.000	-0.014	0.000	1	1	ı	1	ı	ı	-0.019	0.000	-0.018	0.000
Diabetes	1	1	ı	ı	ı	1	-0.011	0.000	-0.011	0.000	ı	ı	ı	ı	ı	ı	-0.013	0.000	-0.012	0.000
Depres-	1	ı	ı	ı	ı	1	-0.033	0.000	-0.033	0.000	ı	ı	ı	ı	ı	ı	-0.078	0.000	-0.078	0.000
sion																				
Goodness- of fit																				
Adj-Rsq	0.280		0.282		0.285		0.293		0.295		0.290		0.296		0.296		0.333		0.332	
AIC	-46,770		-46,874		-46,966		-47,327		-47,409		-57,683		-58,060		-57,218		-59,492		-59,387	
BIC	-46,746		-46,807		-46,875		-47,236		-47,293		-57,657		-57,991		-57,123		-59,397		-59,267	
Validation																				
MAE																				
Training dataset	0.087		0.087		0.087		980.0		980.0		960:0		960.0		0.095		0.092		0.092	0.087
Cross-val- idation	0.085		0.085		0.085		0.084		0.084		0.097		0.097		960.0		0.094		0.094	0.085
Baseline	0.087		0.087		0.087		980.0		0.086		0.088		0.088		0.090		0.088		0.089	0.087
1-year	0.099		0.098		0.097		960'0		0.095		0.095		0.094		0.094		0.091		0.091	0.099
2-year	0.101		0.101		0.100		0.098		0.097		0.097		0.097		0.097		0.094		0.094	0.101
5-year	0.103		0.103		0.102		0.100		0.100		0.100		0.099		0.099		0.095		0.095	0.103
RMSE																				



Table 4 (continued)

Model 1 Model 2 Model 3 Model 4 Model 5 Model 1 Coef-		Baseline									Post-surge	Post-surgery (1,2,5 years)	ars)							
Coeff- ficient p-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef- ficient D-Value ficient Coef-		Model 1	Model	2	Model 3		Model 4		Model 5		Model 1		Model 2		Model 3		Model 4		Model 5	
0.109 0.109 0.108 0.108 - 0.107 0.106 0.106 0.106 0.109 0.109 0.106 0.106 0.120 0.109 0.108 0.108 0.121 0.123 0.121 0.117 0.124 0.123 0.121 0.121 0.127 0.127 0.124 0.125 0.823 0.821 0.814 0.813 0.823 0.829 0.797 0.797 0.820 0.818 0.838 0.825 0.821 0.824 0.820 0.819 0.801 0.801 0.824 0.820 0.819 0.825 0.821 0.825 0.825 0.825 0.821 0.849 0.793 0.776 0.776 0.775 0.849 0.833 0.835 0.836 0.836 0.849 0.849 0.849 0.836 0.836 0.849 0.849 0.849 0.849 0.836					Coef- ficient	p-Value	Coef- ficient	p-Value	Coef- ficient	p-Value	Coef- ficient	p-Value	Coef- p	p-Value	Coef- ficient	p-Value	Coef- ficient	p-Value	Coef- ficient	p-Value
- 0.107 0.106 0.106 0.106 0.109 0.108 0.108 0.108 0.120 0.123 0.118 0.117 0.124 0.123 0.123 0.121 0.127 0.127 0.124 0.125 0.127 0.127 0.124 0.125 0.823 0.821 0.814 0.813 0.840 0.840 0.845 0.825 0.822 0.844 0.840 0.838 0.825 0.821 0.849 0.793 0.776 0.775 0.849 0.849 0.849 0.841 0.839 0.849 0.833 0.832 0.825 0.839 0.846 0.844 0.844 0.845 0.836 0.846 0.849 0.836 0.836 0.836 0.846 0.849 0.849 0.836 0.836 0.849 0.849 0.849 0.848 0.848 0.849 0.849 0.848	aining dataset	0.109	0.109		0.109		0.108		0.108		0.121		0.121		0.120		0.117		0.117	0.109
0.109 0.108 0.108 0.108 0.120 0.120 0.118 0.117 0.124 0.123 0.121 0.121 0.127 0.127 0.124 0.125 0.127 0.127 0.124 0.125 0.823 0.821 0.814 0.813 0.824 0.840 0.838 0.825 0.820 0.825 0.825 0.825 0.821 0.801 0.796 0.793 0.796 0.776 0.775 0.849 0.849 0.849 0.849 0.832 0.846 0.849 0.849 0.849 0.836 0.849 0.849 0.849 0.848 0.836 0.849 0.849 0.849 0.848 0.836		0.107	0.107		0.106		0.106		0.106		0.122		0.121		0.121		0.118		0.118	0.107
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0.796 0.793 0.793 0.776 0.775 0.849 0.847 0.846 0.841 0.839 - 0.836 0.832 0.826 0.825 0.846 0.844 0.843 0.836 0.836 0.866 0.864 0.862 0.849 0.848 0.849 0.849 0.848 0.832 0.832 0.849 0.849 0.848 0.848 0.848		0.822	0.820		0.819		0.802		0.801		0.798		0.796		0.796		0.770		0.770	0.822
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0.849 0.847 0.846 0.841 0.839 - 0.836 0.833 0.832 0.825 0.846 0.844 0.843 0.838 0.836 0.866 0.864 0.862 0.849 0.848 0.849 0.849 0.848 0.832 0.832	SE																			
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1c 0.846 0.844 0.843 0.836 0.836 0.866 0.864 0.862 0.849 0.848 0.849 0.849 0.848 0.832 0.832		0.836	0.833		0.832		0.826		0.825		0.851		0.848		0.848		0.828		0.828	0.836
0.866 0.864 0.862 0.849 0.848 0.849 0.848 0.832 0.832 0.830 0.832 0.832		0.846	0.844		0.843		0.838		0.836		0.861		0.861		0.865		0.860		0.861	0.846
0.849 0.848 0.832 0.832 0.832		998.0	0.864		0.862		0.849		0.848		0.858		0.855		0.855		0.835		0.835	998.0
2100 2100 0000		0.849	0.849		0.848		0.832		0.832		0.843		0.841		0.841		0.817		0.817	0.849
0.831 0.832 0.815	year	0.832	0.831		0.832		0.815		0.815		0.827		0.822		0.822		0.798		0.797	0.832

Reference group a18-34 years

b Women

 $^{c}BMI < = 39$ $^{d}No disease$

evidence that OLS performed worse than other more complicated statistical models. The easy understanding and application of OLS made it a popular choice for deriving mapping algorithm. The ISPOR guideline for mapping does not advocate any specific statistical methods, with the reasons being "... the performance of different methods will vary according to the characteristics of the target utility measure, the disease and patient population in question, the nature of the explanatory clinical variables, and the form of intended use in the CEA[15]." Like many investigators of mapping studies, we would recommend using the OLS model in this study.

Age and sex were commonly included as a predictor in mapping algorithms, and clinical outcomes such as BMI were also frequently included [16]. In the current study, we observed that in terms of goodness-of-fit and prediction power, mapping algorithms containing more predictors performed better than those with the fewer predictor. However, to satisfy the user with a different need, we presented algorithms with different combinations of predictors.

For estimating mapping algorithms, clinical trials were the most common source of data [17]. However, it is debatable whether it is optimal to use trial data for deriving mapping algorithms. Comparing with registry data, trial data are often derived from smaller, more homogeneous patients samples, thus limiting the generalizability of the resultant mapping algorithms to the real world [17].

Although many mapping studies applied split-sample validation, it is questioned that this approach might reduce the sample size used in the mapping estimation and might have no proven benefit [25]. However, it is quite often the case that there is no external dataset available for external validation. Furthermore, unlike the majority of the mapping studies using data from clinical trials, our study is based on a clinical registry with a rather large sample size, we still consider it appropriate to apply split-sample validation.

The main strength of our study was the use of real-world data from a large national patient register and the provision of multiple mapping algorithms using different combinations of predictors. The main limitation of the study was that some surgical centres had a low response rate HRQoL. Since most centres in Sweden have similar characteristics in patient cohorts, this is unlikely to have a significant impact on the representativeness of our study sample. Moreover, lost to follow-up at 5 year was higher relative to 1-, and 2- year, which might explain the insignificant results in some of the analyses. The implication of missing data needs to be investigated in future studies [39].



This study makes available algorithms enabling crosswalk from the Obesity Problem Scale to the SF-6D for cost-utility analyses of interventions in obesity treatment. Different mapping algorithms are recommended for the mapping of pre-operative and post-operative data.

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Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by the first author. The first draft of the manuscript was written by the first author and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and material Data sharing is not possible according to Swedish law.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no conflicts of interest regarding the publication of this article.

Ethics approval The Ethics Authority in Sweden granted ethical permission for analyses of this study (reference number: 2019–03666).

Consent for publication Not applicable.

Consent to participate All information was retrieved from the existing registers in Sweden. The registers are regulated by the *General Data Protection Regulation (GDPR)* in Sweden since 25 May 2018. The *Central Personal Data Controller (CPDA)* is the health authority who is responsible for the overall data security of the registers in Sweden. Participation of any register is voluntary, and the participants has been informed about the registration of their information. The participant also has the right to get a register extract of their personal data, incorrect information can be corrected, and deletion may take place upon request.

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