Past, present, and future trends of overweight and obesity in Belgium using Bayesian age-period-cohort models

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Abstract

Background

Considering the current overweight and obesity epidemic and its associated increase in non-communicable diseases and healthcare costs, the current study aimed to project the trends in prevalence of overweight and obesity in Belgium using a Bayesian age-period-cohort (APC) model to support policy planning.

Methods

Height and weight of 58,369 adults aged 18+ years, collected in six consecutive cross-sectional health interview surveys between 1997 and 2018, were evaluated. Criteria used for overweight and obesity were defined as body mass index (BMI) ≥ 25 , and BMI ≥ 30 . A Bayesian APC model was applied to evaluate past trends and associated socio-demographic risk factors, and to forecast trends to 2019-2029. All analyses were performed based on integrated nested Laplace approximation (INLA) and took the complex survey design into account.

Results

The prevalence of overweight and obesity has increased between 1997 and 2018. If current trends continue, it is likely that a further increase in the prevalence of overweight and obesity in the population will be seen by 2029 with a probability of growth of 51.2% and 73.3%, respectively. Forecasts indicated a potential prevalence of 50.1% [16.2%; 84.4%] in 2029 for overweight, and 21.4% [9.0%; 43.4%] for obesity. Among survey participants, middle-aged men with no higher education and a middle income showed the highest risk of overweight and obesity.

Conclusions

We projected an alarming increase in the prevalence of overweight and obesity. A decrease in cases seems very unlikely. There is an urgent need to target younger age groups for prevention and implementation of public educational programs to limit the increasing trend in overweight and obesity.

Background

In the European region, the prevalence of overweight increased from 48.0% in 1980 to 59.6% in 2015 and that of obesity from 14.5% in 1980 to 22.9% in 2015 [1]. Obesity is known as an important factor contributing to many negative health outcomes, such as cardiovascular disease, type 2 diabetes, certain types of cancer, and other non-communicable diseases [2–8]. Because of the dramatic increase in cases, overweight and obesity are now considered a global epidemic [9]. Belgium is no exception to this situation: obesity prevalence rose from 9.0% in 1978 to 15.0% in 1993 in a subsample of working, middle-aged men [10], and kept rising since. Consequently, a global obesity target to halt obesity at 2010 levels by 2025 was adopted during the World Health Assembly in 2013.

As obesity has been recognized as a major public health problem in Europe, research on its likely future evolution in European countries is warranted. To this end, a myriad of statistical models has been applied to the European context, such as linear extrapolations and wave functions. The methodologies employed in these previous projections differed substantially, and not all were able to produce realistic obesity estimates for the future [11–20]. Moreover, few of the aforementioned studies took into account the multiple dimensions of the obesity epidemic: namely, age, period, and birth cohort [21]. It is well known that age affects weight status. In addition, overweight and obesity are affected by period-related lifestyle habits, such as sedentary lifestyles and the consumption of high-calorie foods [22, 23]. Lastly, the year of birth could indicate the degree to which individuals are receptive to societal and social changes [21, 24–26]. The limited studies that have applied age-period-cohort (APC) analyses to overweight and obesity prevalence identified that age, period, and cohort effects were all important. However, only limited studies have focused on Europe [9, 22, 27–29].

To tackle the linear dependence between the APC effects, the hierarchical age-period-cohort (HAPC) model has been introduced, which includes a mix of fixed and random effects [30–32]. Applying these HAPC models in a Bayesian framework allows for a direct interpretation of future trends in terms of credibility (e.g., how likely will overweight and obesity increase by at least 10%), whereas in the frequentist setting the projected uncertainty intervals cannot be interpreted as credibility. Hence, Bayesian HAPC models have been applied more frequent to forecast future trends in prevalence and incidence of cancer [33, 34], but to our knowledge, no study has applied the Bayesian APC model to forecast future trends in the prevalence of overweight and obesity.

Therefore, our study aims to (1) assess the past trends of overweight and obesity and identify socio-demographic risk factors, and (2) project the number of cases using a Bayesian APC modelling approach over a period of 15 years. To this end, a flexible Bayesian APC model will be applied to population microdata available through the Belgian Health Interview Survey.

Methods

Data

Statistical analyses were performed using the datasets of the Belgian Health Interview Survey (BHIS), which was organized for the first time in 1997 by Sciensano, the Belgian Institute for Health, and contains a series of repeated cross-sectional sample surveys [35–37]. So far, six national health surveys have been carried out – in 1997, 2001, 2004, 2008, 2013 and 2018. The goal was to collect information on lifestyle and chronic diseases for approximately 10,000 individuals in each survey round. To this end, a stratified multistage, clustered sampling method is applied for each survey year. The combination of the large net sample size and the elaborate sampling methodology ensures that each sample is representative for the Belgian population, and that any trend found using the subsequent health surveys can be generalized to the larger Belgian population. More details on the sampling procedure have been published elsewhere

(Demarest et al., 2013). The survey was carried out in line with the Belgian privacy legislation and approved by the ethical committee of Ghent University.

In the current study, information on self-reported age, gender, education level, migration background, urbanization level, income level, and height and weight of participants was included from the different waves of BHIS [36].

The education level was used as a proxy indicator of the socio-economic status of the household and all its members. This indicator is based on the highest education level of the reference person or his/her partner and allocated to each member of the household. Possible values are “primary or no degree”, “secondary inferior”, “secondary superior”, and “superior education”.

The income level is calculated based on the ‘total available income of the household’, for which an equivalent scale is applied [38]. This allows comparing incomes of different households taking their size and composition into account. The different members of the household receive a specific weight: 1.0 for the first adult member of the household, 0.5 for each additional adult (18+ years) and 0.3 for each child (< 18 years). The total available income of the household is divided by the sum of the weights of all the members of the household to calculate the equivalent income. The income levels (quintiles) include “< 750 euro”, “750-1000 euro”, “1000-1500 euro”, “1500-2500 euro”, and “> 2500 euro”, which are hereafter referred to as quantiles 1 to 5.

The level of urbanization was determined based on morphological and functional characteristics of the municipalities. Two morphological criteria are used to classify the municipalities: the population density and the area of habitation. Three criteria are used to describe the functional characteristics of the municipalities: the commercial function, the educative function and the employment rate. Based on these attributes, municipalities are labelled as “Big cities and dense agglomerations”, “Suburban”, “Urbanized municipalities”, or “Rural”.

The estimate for body mass index (BMI) was based on self-reported height and weight, and categorized as normal weight (< 25 kg/m²), overweight (≥ 25 kg/m²), and obese (≥ 30 kg/m²) [39].

Population data were retrieved from the federal planning bureau, Belgium [40].

Statistical model

Predicted counts were calculated using the population projections from the Belgian Federal Planning Bureau (<https://www.plan.be/publications>) for the Belgian population. All statistical analyses were performed in R 4.1.0 [41]. To model the rates of overweight and obesity using age, period, and cohort effects, an age-period-cohort (APC) analysis was performed. Using the Bayesian framework, APC models [33] were fitted using the INLA package (Version 20.3.17) [42]. INLA stands for Integrated Nested Laplace Approximation, a novel approach that makes Bayesian inference faster compared to the computer-intensive Bayesian Markov chain Monte Carlo methods. More information on the INLA package

can be found elsewhere (<https://www.r-inla.org/>). The number of overweight or obese individuals, y_{ij} , in age group i and period j was modelled as a Binomial process with the mean equal to the product of the population at risk, N_{ij} and the estimated prevalence. The logit of the prevalence, η_{ij} , was estimated as a linear combination of the age, period and cohort effects, respectively α_i , β_j and γ_k where $k = M(l-i)+j$ is the birth cohort, M is the number of periods per age group and l is the number of age groups.

$$y_{ij} \sim \text{Binomial}(N_{ij}, \text{expit}(\eta_{ij}))$$

$$\eta_{ij} = \alpha_i + \beta_j + \gamma_k$$

Second-order random walk priors (RW2) were applied to the age, period and cohort effects. Log-gamma priors were applied to the precision parameters with scale and shape parameters of 1 and 0.00005 for each of the age, period and cohort effects. Modelling priors were based on the methodology from Cameron & Baade (2019) and Riebler & Held (2010). Model selections for factors and priors was based on information criteria: DIC, Deviance information criterion, and WAIC, Watanabe–Akaike information criterion. Projected temporal trends were described as the median and 95% credibility intervals (CrI) around the median were constructed based on the 2.5% and 97.5% quantile of the posterior distribution.

In addition, based on the marginal posterior distribution of the modelled count, we calculated the probability, $P(y_{t+x} > y_t + m \times y_t)$, that a projected rate in year $t + x$ is greater than the modelled value in the final year of observed data ($t=2018$), by some margin m (expressed as percentage increase, %).

Model validation

Model fit and predictive accuracy were assessed by fitting the model to the repeated cross-sectional sample surveys [35]. The explained variance (R^2) and root mean squared error (RMSE) between the observed and projected prevalence counts were calculated for different priors and models. More details on the model validation are provided in **Supplementary material A**.

Results

The raw socio-demographic, and health-related characteristics of each cohort are listed in **Table 1**. The average age across the different cross-sectional cohorts ranged from 44 to 51 years. The majority of participants were females with proportions ranging from 52% to 54%. Over time, the proportion of participants with a higher education has increased from 29% in 1997 to 41% in 2018. The level of urbanization has remained stable over time with the majority of participants living in big cities (47%), and a minority living in a suburban (13%) or rural area (15%) in 2018. The income distribution shows an

increase of incomes in the higher quintiles (Quintile 4 and 5) and a decrease in the lower quintiles (Quintile 1 and 2). The number of non-EU immigrants has doubled from 5.2% in 1997 to 11.0% in 2018.

Table 1

Socio-demographic characteristics of the included periods

Characteristic	1997, N = 8,4711	2001, N = 9,9491	2004, N = 11,2971	2008, N = 9,6371	2013, N = 9,0511	2018, N = 9,9641
Age	44 (32, 61)	46 (33, 62)	51 (35, 69)	51 (33, 70)	48 (34, 63)	50 (35, 64)
Gender						
Man	4,103 (48%)	4,820 (48%)	5,202 (46%)	4,383 (46%)	4,385 (47%)	4,765 (48%)
Woman	4,368 (52%)	5,129 (52%)	6,095 (54%)	5,246 (54%)	4,762 (53%)	5,199 (52%)
Obesity (³ 30 kg/m ²)						
No	7,585 (90%)	8,781 (88%)	10,011 (89%)	8,466 (88%)	7,846 (87%)	8,508 (85%)
Yes	886 (10%)	1,168 (12%)	1,286 (11%)	1,171 (12%)	1,205 (13%)	1,456 (15%)
Overweight (³ 25 kg/m ²)						
No	5,098 (60%)	5,735 (58%)	6,746 (60%)	5,655 (59%)	4,912 (54%)	5,300 (53%)
Yes	3,373 (40%)	4,214 (42%)	4,551 (40%)	3,982 (41%)	4,139 (46%)	4,664 (47%)
Diploma						
No diploma or primary education	1,663 (22%)	1,915 (21%)	2,239 (22%)	1,666 (20%)	1,229 (15%)	905 (10%)
Lower secondary	1,653 (21%)	1,913 (21%)	2,023 (20%)	1,650 (19%)	1,350 (17%)	1,471 (17%)
Higher secondary	2,155 (28%)	2,546 (28%)	2,814 (28%)	2,528 (30%)	2,607 (32%)	2,775 (32%)
Higher	2,248 (29%)	2,590 (29%)	2,975 (30%)	2,684 (31%)	2,919 (36%)	3,526 (41%)
Unknown	752	985	1,246	1,109	946	1,287
Urbanisation						
Big city	4,368 (52%)	4,644 (47%)	5,025 (44%)	4,785 (50%)	4,283 (47%)	4,649 (47%)
Suburban	1,038 (12%)	1,527 (15%)	1,528 (14%)	1,268 (13%)	1,221 (13%)	1,286 (13%)
Urbanized municipality	1,924 (23%)	2,213 (22%)	2,649 (23%)	1,878 (19%)	1,817 (20%)	2,547 (26%)

Rural	1,141 (13%)	1,565 (16%)	2,095 (19%)	1,706 (18%)	1,730 (19%)	1,482 (15%)
Income						
Quintile 1	1,969 (24%)	1,968 (23%)	2,184 (23%)	1,727 (23%)	1,677 (22%)	1,133 (14%)
Quintile 2	1,584 (20%)	1,585 (18%)	1,829 (19%)	1,435 (19%)	1,321 (17%)	1,311 (16%)
Quintile 3	1,623 (20%)	1,600 (19%)	1,858 (20%)	1,537 (20%)	1,542 (20%)	1,606 (19%)
Quintile 4	1,465 (18%)	1,668 (19%)	1,711 (18%)	1,153 (15%)	1,512 (19%)	2,061 (25%)
Quintile 5	1,412 (18%)	1,754 (20%)	1,901 (20%)	1,806 (24%)	1,724 (22%)	2,190 (26%)
Unknown	418	1,374	1,814	1,979	1,275	1,663
Nationality						
Belgian	7,186 (87%)	8,787 (90%)	9,718 (90%)	8,142 (88%)	7,481 (85%)	7,920 (80%)
EU	633 (7.7%)	586 (6.0%)	698 (6.4%)	779 (8.4%)	809 (9.2%)	975 (9.8%)
Non-EU	428 (5.2%)	347 (3.6%)	430 (4.0%)	380 (4.1%)	476 (5.4%)	1,065 (11%)
Unknown	224	229	451	336	284	4

1Median (IQR); n (%)

Past and present trends in overweight and obesity

The rate of overweight in the population adjusted for the survey design increased with 8.9% from 45,348 [45,192; 45,504] per 100,000 in 1997 to 49,412 [49,257; 49,567] per 100,000 in 2018, while the rate of obesity in the population increased by 25.9% from 12,978 [12,892; 13,066] in 1997 to 16,339 [16,238; 16,440] in 2018. Age-specific trends in the observed prevalence for overweight and obesity (**Figure 1**) demonstrated that overweight and obesity were the highest for the middle-aged groups. Generally, the prevalence of overweight and obesity increased with increasing birth year.

Summary measures of model fit in terms of DIC and WAIC for the overweight and obesity model are presented in **Table 2**. DIC and WAIC were the lowest for the model including age, period, and cohort effects together with all fixed effects (gender, urbanisation level, education level, income and nationality). Gender (Woman vs Man) was identified as a risk factor for overweight (OR = 0.55; 95% CrI = [0.55; 0.55]), but was a negligible risk factor for obesity (OR = 0.97; 95% CrI = [0.96; 0.97]). Higher education (OR = 0.67;

95% CrI = [0.66; 0.67]) was associated with decreased odds for overweight compared to no education or primary degree, whereas both higher education (OR = 0.49; 95% CrI = [0.49; 0.49]) and higher secondary education (0.74; 95% CrI = [0.74; 0.75]) were associated with decreased odds for overweight compared to the group with no education or primary degree. Middle incomes (Quantile 3) showed a higher risk of obesity and overweight compared to the lowest incomes (Quantile 1), but the highest incomes (Quantile 5) showed a reduced risk with an estimated OR of 0.92 [0.92; 0.92] for overweight and 0.83 [0.83; 0.84] for obesity. More information on the estimated fixed effects for obesity and overweight can be found in **Table 3**. Estimates of the age, period and cohort effects are also provided in **Table 3**, but interpretation of these terms is limited because of the linear dependence between these effects, i.e. the non-identifiable feature of APC models cannot be completely eliminated [43].

TABLE 2

Model selection for past trends of overweight and obesity

Model	DIC	WAIC
Overweight		
APC	59,870,210	43,824,652
AP	60,028,035	43,825,596
AC	60,490,979	44,267,784
P	63,242,295	47,049,883
APC+F	58,456,210	42,435,966
Obesity		
APC	33,646,425	19,654,269
AP	33,770,297	19,607,961
AC*	NA	NA
P*	34,992,302	19,899,193
APC+F	33,142,627	19,542,554

*Only converted when prior values were fixed; Abbreviations: APC, Age-Period-Cohort; AP, Age-Period; AC, Age-Cohort; P, Period; APC+F, Age-Period-Cohort and covariates; DIC, Deviance information criterion; WAIC, Watanabe–Akaike information criterion.

TABLE 3

Multivariable analysis of risk factors for overweight and obesity based on Bayesian age-period-cohort model.

	Overweight			Obesity		
	Odds ratio	95% Credible interval		Odds ratio	95% Credible interval	
		lower	upper		lower	upper
Fixed effects						
Intercept	0.783	0.747	0.819	0.124	0.119	0.129
Gender						
Man (Ref.)						
Woman	0.545	0.545	0.546	0.966	0.964	0.968
Urbanisation level						
Urban (Ref.)						
Suburban	1.023	1.021	1.025	0.992	0.989	0.994
Urbanized municipality	1.049	1.048	1.051	1.005	1.003	1.007
Rural	1.095	1.092	1.097	1.038	1.035	1.041
Education level						
No diploma /primary education (Ref.)						
Lower secondary	0.997	0.995	0.999	0.934	0.932	0.937
Higher secondary	0.918	0.916	0.920	0.744	0.742	0.746
Higher education	0.665	0.664	0.666	0.491	0.489	0.492
Income level						
Quintile 1 (Ref.)						
Quintile 2	1.166	1.164	1.168	1.123	1.120	1.126
Quintile 3	1.092	1.090	1.094	1.138	1.135	1.141
Quintile 4	1.087	1.085	1.089	0.951	0.948	0.954
Quintile 5	0.922	0.920	0.923	0.834	0.832	0.837
Nationality						
Belgian (Ref.)						
EU	1.064	1.061	1.067	1.023	1.019	1.027
Non-EU	1.142	1.138	1.146	0.969	0.964	0.974

Random effects (with RW2-specification)

Age						
18-25 (ref.)						
26-30	2.175	2.172	2.179	2.270	2.264	2.276
31-35	2.383	2.376	2.390	2.329	2.319	2.339
36-40	2.825	2.814	2.837	3.109	3.090	3.129
41-45	3.387	3.369	3.405	3.851	3.820	3.883
46-50	3.505	3.483	3.528	3.158	3.128	3.188
51-55	3.691	3.664	3.717	3.695	3.655	3.736
56-60	4.055	4.025	4.086	3.769	3.726	3.813
61-65	3.452	3.426	3.478	2.846	2.814	2.879
66-70	3.494	3.470	3.518	2.627	2.599	2.656
71-75	2.868	2.850	2.885	1.996	1.977	2.014
76-80	2.530	2.518	2.543	1.580	1.569	1.593
81-85	1.642	1.636	1.648	0.948	0.943	0.953
86-90	1.246	1.244	1.248	0.585	0.584	0.586
91-95	0.818	0.816	0.820	0.442	0.439	0.444
95+	0.410	0.401	0.419	0.492	0.477	0.506
Period						
1997 (Ref.)						
2001	1.107	1.106	1.108	1.147	1.145	1.148
2004	1.107	1.106	1.109	1.249	1.246	1.252
2008	1.351	1.349	1.354	1.560	1.556	1.564
2013	1.576	1.574	1.577	1.779	1.776	1.781
2018	1.775	1.774	1.775	2.378	2.377	2.379
Cohort (Birth year)						
(1895.1900] (Ref.)						
(1900.1905]	5.390	3.000	18.549	2.822	1.891	5.880
(1905.1910]	29.512	15.812	105.989	8.220	5.126	18.627

(1910.1915]	19.936	10.650	71.827	8.039	4.949	18.475
(1915.1920]	30.645	16.360	110.494	10.393	6.379	23.958
(1920.1925]	28.771	15.353	103.782	10.016	6.140	23.121
(1925.1930]	33.093	17.656	119.400	9.760	5.980	22.543
(1930.1935]	29.198	15.575	105.364	7.680	4.704	17.747
(1935.1940]	28.567	15.237	103.098	7.511	4.599	17.360
(1940.1945]	25.543	13.623	92.190	7.566	4.632	17.493
(1945.1950]	24.069	12.836	86.872	6.350	3.887	14.682
(1950.1955]	20.019	10.677	72.253	5.666	3.469	13.100
(1955.1960]	17.680	9.430	63.807	4.034	2.470	9.325
(1960.1965]	16.753	8.936	60.458	4.187	2.564	9.677
(1965.1970]	17.136	9.142	61.829	4.043	2.477	9.340
(1970.1975]	15.777	8.418	56.915	3.908	2.395	9.022
(1975.1980]	15.049	8.032	54.278	3.510	2.153	8.100
(1980.1985]	14.115	7.535	50.894	3.759	2.306	8.667
(1985.1990]	13.220	7.059	47.652	3.560	2.186	8.202
(1990.1995]	12.013	6.417	43.284	2.592	1.594	5.964
(1995.2000]	13.514	7.222	48.669	3.116	1.918	7.161

Future trends in overweight and obesity

Modelled and projected rates with their 95% credibility interval (CrI) for overweight and obesity are given in **Figure 2**. The explained variance in prevalence expressed as the coefficient of determination (R^2) by the overweight model equalled 87.7%, and the explained variance in prevalence by the obesity model equalled 73.3%. The RMSE based on a comparison of the predicted versus observed prevalence equalled 0.003 and 0.001 for the overweight and obesity model respectively. The estimated age, period and cohort effects on the prevalence of overweight and obesity are shown in **Supplementary material A (Figures 2 and 3)**.

Temporal trends in rates for overweight showed a steady increase from 49,412 [49,257; 49,567] per 100,000 in 2018 towards a projected 50,069 [16,180; 84,441] cases per 100,000 in 2029, and 52,760 [2046; 98,231] cases per 100,000 in 2039. In contrast, a much higher rate of increase in cases from 12,978 [12,892; 13,066] cases per 100,000 in 2018 towards 21,373 [8,968; 43,431] cases per 100,000 in

2029 and 30,433 [3,505; 80,831] cases per 100,000 in 2039 was observed for obesity. Probabilities for exceeding a certain threshold m ($> 0\%$, $> 5\%$, $> 10\%$, $> 25\%$, $> 50\%$, and $> 100\%$) based on the marginal posterior distribution of the modelled counts are listed in **Table 4**. There is a 51.2% and 52.5% probability for an increase in the rate of overweight by the year 2029 and 2039, respectively. Chances for a similar increase for obesity by the year 2029 and 2039 are much higher in comparison, with estimated probabilities of 73.3% and 73.2%, respectively.

When assessing the age-structure of cases, the percentage of all cases occurring in 2018 was the highest in the 36-65 age category for overweight (54.9%) and obesity (57.8%), but was projected to gradually decrease towards 45.1% for overweight, and 44.1% for obesity. An overview of the proportion of all prevalent cases occurring in the age groups 16-35 years, 36-65 years, and 65+ years is presented versus time in **Figure 3**.

TABLE 4

Probability of increase in rate by $>0\%$, $>5\%$, $>10\%$, $>25\%$, $>50\%$ and $>100\%$ based on the marginal posterior distribution of future projections based on the Bayesian APC-model.

	Overweight		Obesity	
	2029	2039	2029	2039
Increase $> 0\%$	51.2%	52.5%	73.3%	73.2%
Increase $> 5\%$	46.6%	50.6%	69.5%	71.7%
Increase $> 10\%$	42.0%	48.7%	65.7%	70.2%
Increase $> 25\%$	28.9%	42.9%	54.2%	65.8%
Increase $> 50\%$	11.0%	32.2%	37.0%	59.0%
Increase $> 100\%$	1.5%	$< 0.1\%$	13.9%	46.7%

Discussion

Our analyses of nationally representative data collected over six large scale health interview surveys, covering a period spanning over 20 years from 1997 to 2018, showed a disturbing picture of the future overweight and obesity epidemic in Belgium, assuming similar future increase rates as observed in the past. If current trends continue, at least a 10% increase in cases by 2039 in overweight and obesity would be reached with a respective probability of 48.7% and 70.2%, making an increase by at least 10% likely.

The age, period and cohort effects are similar to those reported in previous literature [1, 29]. Among inhabitants of Belgium, a middle-age man, born before 1970 with no higher education and a middle income shows the highest risk for overweight and obesity. In the current study, the socio-demographic factors for overweight and obesity associated with the highest risk were gender and education, which

emphasizes the complex interactive operation at multiple levels that underlies the obesity epidemic [11, 26]. To halt the current increase, a multilevel policy intervention will be necessary.

Worryingly, our projections already indicate that Belgium is unlikely to meet the global obesity target to halt obesity “at 2010 levels” by 2025, which was adopted during the World Health Assembly in 2013. The current projected rates are estimated to reach most likely 52.8% for overweight and 30.4% for obesity. In another study, it was estimated that the global rate of overweight in established economic markets would rise to 36.3% by 2030 following population projections and a steady prevalence rate of 2005. The same study shows an increase to 30.0% when modelling the prevalence based on past data. Likewise, the obesity prevalence was estimated at 22.1% and 36.2% [19]. These estimates are lower compared to our result, however, the observed prevalence in 2018 already exceeded the projection for overweight by 10.6%. The faster growth in cases with obesity compared to cases with overweight is similar to previous findings [11–20]. These findings emphasize that a perpetuating growth in obesity and overweight will result in an increased proportion of people that suffer from obesity among overweight cases with resulting detrimental health effects. The importance of early prevention of childhood obesity is emphasized by our estimates, since the projected increase in obesity is expected to be proportionally higher in the age group between 18 and 35 years.

Moreover, if the trajectory continues as projected, the rates of disease burden and associated healthcare cost of non-communicable diseases are also predicted to rise [44, 45]. The results of this projection exercise demonstrate the importance of implementing policies on prevention and management strategies. Clinical practice guidelines for the prevention and treatment of obesity in children and adults, and multidisciplinary approaches to obesity treatment in a chronic disease management framework have been published [46, 47]. Increasing proportions of the population who are obese may result in changes in attitudes about what constitutes a healthy body weight. The environmental and behavioural forces fuelling the obesity epidemic are unlikely to be modified overnight, and even effective prevention programs may take years to show a significant impact [11].

Lastly, the current forecasted rate of increase might have been exacerbated by the COVID-19 pandemic, as government introduced a myriad of measures such as cancellation of small gatherings, quarantine, lockdowns, and individual movement restrictions to combat the spread of the coronavirus [48]. Consequently, decreases in physical activity and increases in sedentary behaviours during lockdowns have been reported by different studies [49, 50], resulting in a potential increase of overweight and obesity in the current generations [51].

Strengths and limitations

APC models account for trends in risk factors, without requiring measurements of exposures. Projected counts are hence susceptible to unforeseeable changes, which might result in an over- or underestimate the actual future prevalence. The key assumption in the APC models is, as with any projection model, a

continuation of the observed historical trends. However, evaluating the validity of that assumption is impossible.

Despite the wide uncertainty in projections beyond 5 or 10 years, governments require longer term projections for effective planning and policy development. The increased uncertainty provides a more realistic picture of the accuracy of projections, particularly when unforeseen interventions and changing circumstances (e.g. COVID-19) that could take place are considered. Since the cohort is a linear combination of age and period, the effects are not identifiable and cannot provide statistical evidence of change in prevalence [52]. Nevertheless, the models provide information on the prevalence and distribution across the population. The current study includes a large population of individual data over a time-span of 20 years. These data were modelled using a well-described modelling strategy including the incorporation of weights according to the sampling procedure, which results in realistic projections of future scenarios.

BMI has been defined according to the WHO definition, and based on self-reported estimates for weight and height. Consequently, the actual number of participants with obesity and overweight might have been higher as BMI is on average underestimated by 0.97 kg/m² [53].

In a next step, future research could focus on integrating policy-decisions based on a scenario-based modelling approach. For example, including information on the level of physical activity or nutritional habits, and associated policy interventions could be expressed in terms of the changes in projected rate.

Conclusions

In conclusion, an alarming increase in the prevalence of overweight and obesity is predicted with a very likely increase of at least 10% in the prevalence obesity and overweight among Belgian adults within the next 20 years. There is an urgent need to target younger age groups for prevention and implementation of public educational programs to limit the increasing trend in overweight and obesity.

Declarations

Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

The survey was carried out in line with the Belgian privacy legislation and approved by the ethical committee of Ghent University. Participants gave informed consent prior to study participation.

Consent for publication

There are no details on individual participants within the manuscript.

Availability of data and materials

The data that support the findings of this study are available from the Health Interview at Sciensano but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Health Interview team at Sciensano.

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Authors' contributions

R.D.P. and B.D. wrote the main manuscript text. V.G. and M.C. performed the data management and descriptive statistics. R.D.P. and C.F. performed the APC-analysis and future projections based on the Bayesian APC model. S.D. coordinated and performed the survey in which data was gathered used in this manuscript. All authors contributed to the manuscript text and reviewed the manuscript.

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Figures

Figure 1

Observed prevalence rates for overweight and obesity. plotted versus birth year by age group.

Figure 2

Predicted prevalence rates for overweight and obesity. plotted by year.

The modelled observed data is depicted in black. Projections are depicted from the vertical line onwards for the period 2019-2039 in white, with quantiles from the estimated marginal posterior distribution of the projected prevalence. The colours reflect the credibility intervals expressed as quantile, coloured consecutively from dark blue to yellow.

Figure 3

Predicted prevalence rates for overweight and obesity plotted by age group and year.

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