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The neighbourhood obesogenic built environment characteristics (OBCT) index: Practice versus theory

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ABSTRACT

Background: Obesity is a key risk factor for major chronic diseases such as type 2 diabetes and cardiovascular diseases. To extensively characterise the obesogenic built environment, we recently developed a novel Obesogenic Built environment CharacterisTics (OBCT) index, consisting of 17 components that capture both food and physical activity (PA) environments.
Objectives: We aimed to assess the association between the OBCT index and body mass index (BMI) in a nationwide health monitor. Furthermore, we explored possible ways to improve the index using unsupervised and supervised methods.
Methods: The OBCT index was constructed for 12,821 Dutch administrative neighbourhoods and linked to residential addresses of eligible adult participants in the 2016 Public Health Monitor. We split the data randomly into a training (two-thirds; n = 255,187) and a testing subset (one-third; n = 127,428). In the training set, we used non-parametric restricted cubic regression spline to assess index's association with BMI, adjusted for individual demographic characteristics. Effect modification by age, sex, socioeconomic status (SES) and urbanicity was examined. As improvement, we (1) adjusted the food environment for address density, (2) added housing price to the index and (3) adopted three weighting strategies, two methods were supervised by BMI (variable selection and random forest) in the training set. We compared these methods in the testing set by examining their model fit with BMI as outcome.
Results: The OBCT index had a significant non-linear association with BMI in a fully-adjusted model ($p<0.05$), which was modified by age, sex, SES and urbanicity. However, variance in BMI explained by the index was low (<0.05%). Supervised methods increased this explained variance more than non-supervised methods, though overall improvements were limited as highest explained variance remained <0.5%.
Discussion: The index, despite its potential to highlight disparity in obesogenic environments, had limited association with BMI. Complex improvements are not necessarily beneficial, and the components should be re-operationalised.

1. Introduction

Obesity is a chronic relapsing disease (Bray et al., 2017) and a key risk factor for major chronic diseases, such as type 2 diabetes, cardiovascular diseases, musculoskeletal disorders and some cancers (World Health Organization, 2018). Obesity prevention continues to be a public health priority in developed countries; increasingly so in developing countries due to both high health and economic burdens (Organization for Economic Co-operation and Development, 2019). Early-stage evidence suggests that some built environmental characteristics such as urban sprawl, fast food outlets and land use mix drive adult overweight and obesity (Lam et al., 2021; Mackenbach et al., 2014). However, despite our best effort, evidence remains inconclusive for many other environmental factors, especially those in the food environment such as supermarkets, convenience stores and restaurants (Lam et al., 2021). One explanation is the multi-dimensionality of obesity where not one, but several environmental factors could potentially play a role in obesogenesis. Therefore, the standard single-exposure approach might not suffice and even be counter-productive since it disregards co-occurrence of environmental factors and often results in inconsistencies of associations (Lam et al., 2021). A comprehensive characterisation of the built environment relevant for overweight and obesity is therefore both

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necessary and desirable (Lam et al., 2021; Wilkins et al., 2019).

A composite indicator combines relevant environmental features (components) into a single index that quantifies a multidimensional concept (Organization for Economic Co-operation and Development, 2008). Composite indicators have been widely used by economists to rank areas in terms of economic, health, and happiness inequality; or benchmark these areas against a gold standard (Saib et al., 2015). Their application in environmental epidemiology is on the rise, with spatial indices being developed to measure neighbourhood walkability (Frank et al., 2010; Lam et al., 2022), driveability (den Braver et al., 2022) and obesogenic environments for both children (Kaczynski et al., 2020), adolescents (Prados et al., 2023) and adults (Marek et al., 2021). We recently developed a novel, evidence-based, expert-informed theoretical framework and composed a comprehensive, high-resolution index that quantified the obesogenicity of neighbourhoods in the Netherlands (Lam et al., 2023). This so-called Obesogenic Built environment CharacterisTics (OBCT) index incorporated 17 built environmental components across the food and physical activity environments corresponding with dietary behaviours and physical activity. The components were organised into different constructs commonly studied such as fast food outlet density, walkability (Lam et al., 2022), drivability (den Braver et al., 2022) bikeability (Pereira Marghidan, 2020) and sports facility density (Hoekman et al., 2016) (Fig. 1). Effectively, the index ranks all neighbourhoods in the Netherlands in terms of their obesogenicity, based on the totality of physical urban design and the density and healthiness of food options.

In theory, composite indicators enable ranking and clear communication, especially to non-technical stakeholders. However, in practice, the process of index development is complex and subject to numerous methodological decisions and assumptions. This poses considerable challenges related to index development in general and our OBCT index in particular (Greco et al., 2019; Becker et al., 2017). Firstly, the OBCT index's association with actual overweight and obesity has not been extensively studied, which limits its usefulness for downstream outcomes (Marek et al., 2021). Furthermore, Garfinkel-Castro et al. (2015) postulated that the effects of the environment on health might vary among sociodemographic groups, as some groups have more autonomy and choices than others; resulting in differential interactions with the environment. Therefore, when examining the association of an index with health outcomes, it is also important to account for this heterogeneity, particularly among age groups, urbanicity and along the socioeconomic divide (Black and Macinko, 2008).

Secondly, by combining components, we expect that the overall index will explain more variance in obesity than the individual components in single exposure models; assuming that, in our case, each of the 17 built environment components individually influences obesity. However, this latter might not necessarily be the case, especially when univariate associations are not tested before combining. This approach contrasts with data-driven methods such as variable selection techniques where components could be mutually adjusted, and irrelevant components removed. However, variable selection techniques become complicated with high intercorrelations, which are typically observed among variables capturing (urban) built environment. Combining variables into an index is then arguably a simple and elegant method to deal with multicollinearity. Nevertheless, some issues remain, such as the potential interaction between components that cannot easily be accounted for using either an index or dimension-reduction techniques.

Thirdly, most indices apply equal weighting between components for two reasons: either (Bray et al., 2017) due to a lack of evidence suggesting differential weights or (World Health Organization, 2018) to ensure transparency and easy interpretation for readers (Brousmiche et al., 2020). However, Becker et al. (2017) mathematically proved that the weights assigned to components might not always directly translate to their relative importance and thus, equal weights do not necessarily imply equal importance. This could be attributed to the individual variance of each component and their correlations with one another (Becker et al., 2017). For example, the OBCT index's correlation with the food environment (Spearman's $\rho = 0.55$) is much higher than that of the

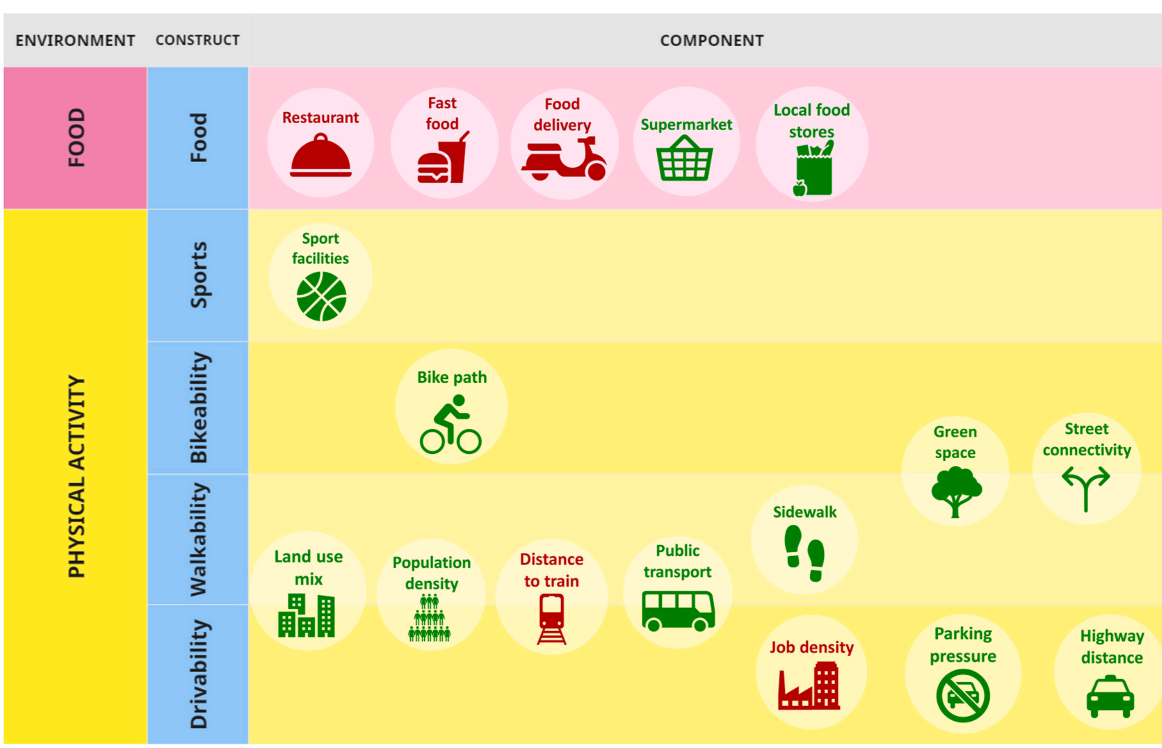

Fig. 1. Conceptual framework for composing the Obesogenic Built environment CharacterisTics (OBCT) index. The environmental domains are food (pink) and physical activity (yellow), the respective constructs in blue and components are either in red (obesogenic/unhealthy) or green (leptogenic/healthy). Components overlapping borderlines are shared between bordering constructs (e.g., green space is relevant for both bikeability and walkability).

PA environment (ρ = 0.39) despite having equal weighting (Lam et al., 2023). Therefore, when assessing the internal consistency of an index, it is crucial to also consider the correlations between components and the index rather than looking at the weights alone.

We designed this study with both practical and exploratory aims in mind: firstly, to examine the association between the current theory-based OBCT index and body mass index (BMI) data from a large, representative health monitor; and to assess whether this association differs for subgroups defined by age, sex, urbanisation degree, neighbourhood SES level, and household incomes. Secondly, we also examined the association between BMI and the food and PA environmental domain scores separately to test our assumption about combining. Thirdly, we explored several unsupervised and supervised learning methods to improve the current OBCT index and its association with BMI, with particular focus on weighting between the components.

2. Methods

2.1. Data and study setting

2.1.1. Study setting

Individual data from the cross-sectional Dutch Public Health Monitor (PHM) 2016 were used to estimate BMI for a representative sample of the Dutch population (Statistics Netherlands, 2018). The main objective of this monitor is to collect national, regional, and local information about the health (including overweight and obesity (National Institute for Public Health & the Environment)), social situation and lifestyle of the Dutch individuals aged 19 years and older every four years. The PHM is a collaboration between the Dutch National Institute for Public Health and the Environment (RIVM), Statistics Netherlands (CBS) and all 25 Community Health Services (GGD). Briefly, the CBS employed complex sample method, stratified by location and demographics and share them with participating GGD who are in charge of recruitment and data collection. This was to ensure that residents were well represented centrally (Hiemstra and Dinnissen, 2020).

The survey data, combining the health monitors for Dutch adults and the elderly, were thus skewed towards the elderly by design, with 51.5% sample above 65 years of age compared to 18.2% in the general population. In terms of gender, there were more females (54.1% versus 50.4%), native Dutch (87.0% versus 77.9%) and high-income earners (25.4% versus 20% in the highest income quintile) than in the general population, which was probably attributed by differential response rates (Supplementary Table S4). General population statistics for 2016 were obtained from StatLine, the official statistics site from Statistics Netherlands (Statistics Netherlands, 2024).

Relevant personal data collected in the survey include age, sex, education, work situation, household composition, socioeconomic status, chronic conditions, height, and weight. This specific survey was chosen due to its large sample size (close to half a million individuals) and geographical coverage across the country. Participants were invited to complete an online survey, and in case of non-response, they could be invited for a home interview instead. Participating municipal health services could also opt to distribute paper-and-pencil surveys or conduct phone calls. The response rate was approximately 40% nationwide, varying across regions and age groups (Statistics Netherlands, 2018). The current index, as well as the Winsorised z-scores of individual components, were linked to participants' residential addresses based on administrative neighbourhood codes (n = 12,821), which represent high-resolution conterminous areas with median population of 675 (Inter Quartile Range = 1635) (Statistics Netherlands, 2016).

2.1.2. Exposures

The OBCT index comprises 17 components related to the food environment (density measures of five types of food outlets including fast food) and PA environment (including twelve components under four constructs: walkability, drivability, bikeability and sport facilities) (Fig. 1). Details regarding the construction of this index were provided elsewhere (Lam et al., 2023). The geographic information system (GIS) data for the components came from different commercial as well as public sources (Supplementary Table S1) and were collected and coordinated by the Geoscience and hEalth Cohort COnsortium (GECCO (Lakerveld et al., 2020),). In terms of data processing, briefly, the components were standardised based on the median and median absolute deviance (MAD), a modified form of z-score which was more robust against outliers. Subsequently, all components were Winsorised at 5th and 95th percentiles (e.g. values below the 5th and above the 95th percentile were capped at the 5th and 95th percentiles respectively) to reduce the influence of outliers on the final scores (Leys et al., 2019). The food environment score was calculated as an average between its five components (in pink, Fig. 1), and the PA environment score was the average between its twelve components (in yellow, Fig. 1). The index was then calculated by averaging between the food and the PA and scaled between 0 and 100 where a higher score denoted a higher level of obesogenicity. When using either food or PA environmental domain scores as exposures, they were also scaled between 0 and 100 where a higher score denoted a higher level of obesogenicity.

2.1.3. Outcome

Self-reported height and weight were used to calculate BMI with the following formula: $(\textit{weight in kilogram})/(\textit{height in meter})^2$. Overweight was defined as having a BMI of more than 25 kg/m^2 and obesity as 30 kg/m^2 or higher. Prior to this calculation, unrealistic or erroneous self-reported heights or weights were corrected by Statistics Netherlands (Statistics Netherlands, 2018).

2.1.4. Analytic sample

Out of 457,153 respondents, we excluded respondents whose categorisation of covariates differed, preventing them from being harmonised with the rest of the data (1.5%, n = 7007). Subsequently, cases with missing data for any outcome, exposure (residential addresses) or covariates were also removed (15.0%, n = 67,531) (Fig. 2). We then divided the analytical sample (n = 382,615) into two datasets: a training set consisting of two-thirds of the data (n = 255,187) for assessing association of the current index and training improvements, and a testing set (n = 127,428) to compare the performance of the improvement methods.

2.1.5. Confounders

The following individual-level characteristics were considered *a priori* as potential confounders to be included in all models: age group (19–34, 35–50, 51–65, 66–85 and > 85 years old), sex (male/female), ethnicity (categorised as native Dutch, Western non-Dutch and non-Western non-Dutch), household composition (2-person household single household and others), highest obtained education categorised into low (up to primary education), middle-low (lower secondary vocational education), middle-high (senior secondary vocational education to pre-university) and high (university degrees); social participation (working fulltime, part-time, study, not working or retired), income quartiles and survey format (written, online, phone interview or home interview). The neighbourhood SES score, constructed by the Netherlands Institute for Social Research, was a composite score consisting of income, the percentage of residents with low income (defined as minimum wage of that year), the percentage of residents with low education (defined as having obtained up to lower secondary level of education) and the percentage of unemployed residents (Knol et al., 2012). Neighbourhood SES was dichotomised into low and high based on nationwide median values. It is worth noting that most variables were pre-categorised by Statistics Netherlands without the possibility for further sub-categorisation.

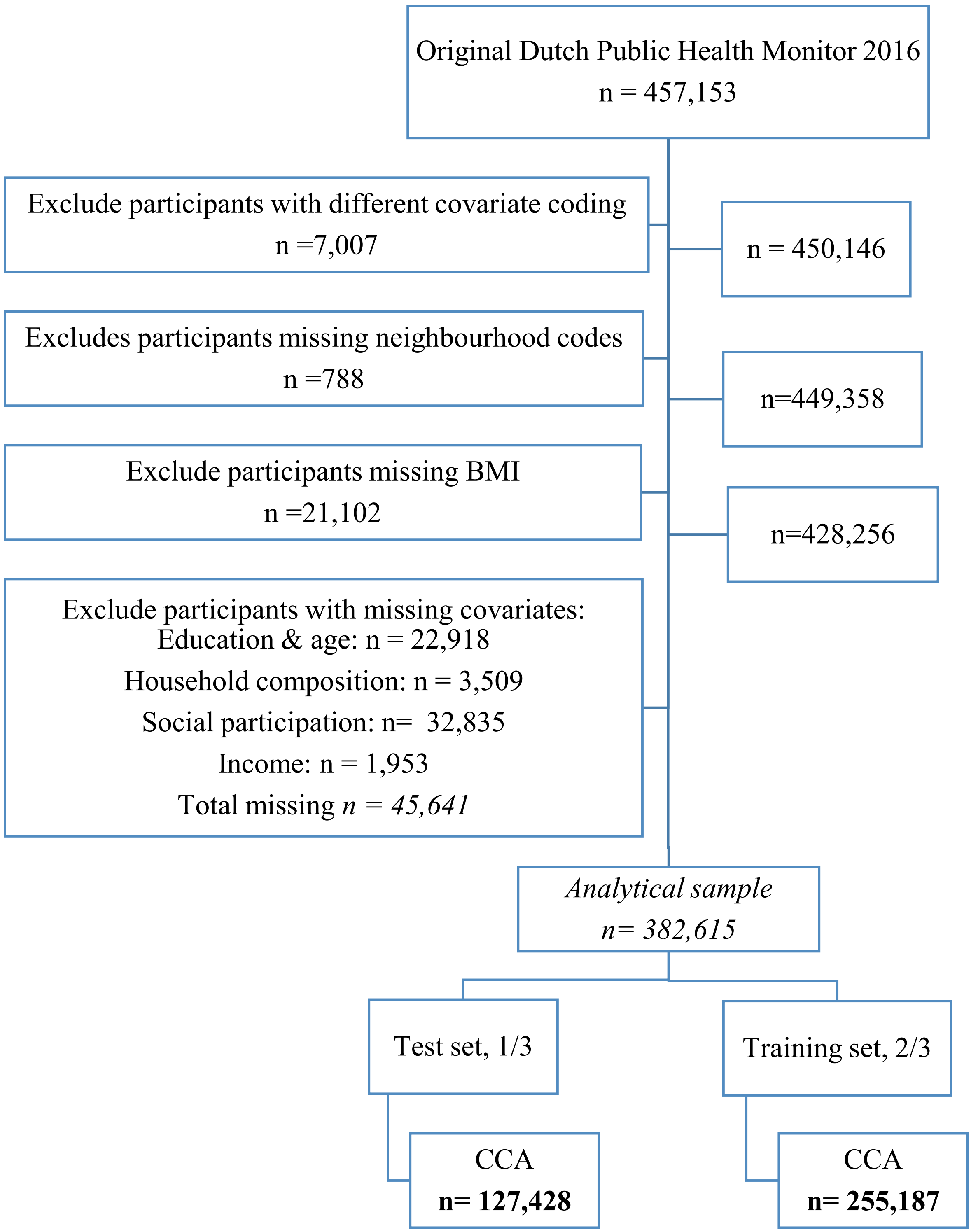

Fig. 2. Inclusion/exclusion of participants from analysis in the Dutch Public Health Monitor 2016. CCA = complete case analysis.

2.2. *Statistical analyses*

2.2.1. *Descriptive analysis*

Descriptive statistics regarding individual and neighbourhood characteristics of participants were summarised as percentages for categorical variables, mean (standard deviation) or median [interquartile range] for continuous variables. Descriptive statistics about the OBCT index and its components at neighbourhood level were reported elsewhere (Lam et al., 2023).

2.2.2. *Index association with BMI*

We examined the non-linear association between the continuous OBCT index and BMI using restricted cubic spline (RCS) following violation of linearity assumptions (Schuster et al., 2022). We adjusted *a priori* for categorical confounders (age, sex, ethnicity, household composition, highest obtained education, social participation, income quartiles and survey format). The RCS was fitted using a generalised additive model (*gam)* and specified as y ~ s (x, bs = "cr") with automatic smoothing parameter estimation by specifying (method = "GCV.Cp") using the *mgcv* package. Model Akaike Information's Criterion (AIC) and R^2 value were reported as measures of fit. Similarly, we fitted a spline for either the food or PA environmental domain score against BMI adjusting for the aforementioned confounders. The percentage of variance in BMI explained by an index was calculated as the increase in model fit resulting from including the index term compared to a confounder-only model.

2.2.3. Effect modification

The following five variables were considered for potential effect modification between OBCT indices and BMI: age, sex, urbanisation degrees, neighbourhood and personal socioeconomic status. Age group was categorised as 19–35, 35–65, >65 years of age; neighbourhood urbanisation degrees as >2500, 1000–2500, <1000 addresses/km^2. Neighbourhood SES score was dichotomised (higher or lower than the national median). Household income was categorised into three categories: low (lowest and second lowest quintiles), middle (middle and second highest) and high (highest quintile). All effect modifiers were derived from the PHM survey except for NSES, which was constructed by the Netherlands Institute for Social Research and linked to residential addresses of participants. An interaction term with the OBCT index was added to the fully adjusted model for each of these potential modifiers; the significance of the interaction terms (p-value <0.05) was used as a basis to stratify the models.

2.3. Index improvement methods

We proposed five improvement methods for our index: two focusing on the index components and three on component weighting (Table 1). To improve the index at component level, we incorporated neighbourhood address density into the food environment measures as suggested by recent Dutch literature (van Erpecum et al., 2022a, 2022b). Using the residual method commonly applied in nutrition epidemiology (Willett et al., 1997), we removed any variance in each of the five food environment components that might be explained by address density, and extracted the residuals as the "improved" food environment measures. We also explored the added value of neighbourhood housing price as an extra component to the index, given that a recent Dutch study found it to be the most predictive and consistent variable related to BMI outcomes among 85 environmental characteristics (Ohanyan et al., 2022a). We assigned neighbourhood housing prices the same weight as the food or the PA environmental domain, so that each domain weighs a third towards the index.

When outcome variables (such as BMI) are available, they could be used to supervise variable selection procedures to filter out statistically relevant components. Although ordinary least square (OLS) regression is commonly used as a variable selection method, spline-based regression or machine learning (ML) method are better suited to accommodate non-linearity in associations between components and outcomes. For the splines-based variable selection, we chose the RCS due to its flexibility in modelling non-linearity and its demonstrated competitive predictive power compared to other splines (Schuster et al., 2022). For ML methods, we opted for random forest due to its effectiveness in capturing non-linear associations and interactions between predictor variables, and its pragmatic automatic calibration features (Ohanyan et al., 2022b). However, it is important to note that neither method provides directly interpretable effect estimates similar to linear regression; instead, predicted values are more useful in this case (Shepherd and Rebeiro, 2017). Additionally, we examined the performance of the hierarchical version of the OBCT index and BMI. Details of the hierarchical index were reported elsewhere (Lam et al., 2023), the major difference with the current index is that instead of equal weights between the food and PA environments, the hierarchical index assigns equal weights to the five constructs (Fig. 1, in blue: obesogenic food, sports, walkability, driveability and bikeability), effectively increasing the weight of the PA environment compared to the food environment. All improvement methods were outlined with numbers in Table 1 for reference, and elaborated below.

1. Density-adjusted food environment measurements

To account for the density-dependency of food retailers, we incorporated urbanicity adjustments using residual method (Willett et al., 1997). Specifically, we regressed each specific food environment measure against address density as independent variable using spline regression similar to the main analysis. The residual of each regression was then extracted as the "improved" food environment measure since they are independent of urbanicity measured by address density.

2. Adding housing price to the index

We explored the role of neighbourhood-level housing price, either as an independent predictor of BMI or as part of the index. The housing price information for 2016 was available for each neighbourhood through Statistics Netherlands. In the latter scenario, housing price was treated as a separate "environmental score", equally weighted alongside the food and the PA environments.

3. Hierarchical index

To modify the component weights, we applied equal weights within components under the same construct and equal weights between the distinct constructs (obesogenic food, sports-facility density, walkability, drivability, and bikeability). This resulted in the hierarchical index, representing an average score between the various constructs (shown in blue, Fig. 1) where each component within a construct contributed equally. For more comprehensive information about the hierarchical index, please refer to Lam et al. (2023).

4. Backward selection with restricted cubic spline (RCS)

All 17 components of the index were included as RCS in a multivariate spline regression, and backward selection was performed on the training set. Variables with effective degrees of freedom of 1 were transformed to linear terms. Then, variables with the highest p-value were progressively eliminated, and the regression was updated after the removal of each term. This elimination was iterated until only variables with p-values <0.05 remained in the model, forming the "selected model". The selected model was then used to predict neighbourhood-level BMI for all neighbourhoods in the Netherlands. Given spline

Table 1
Overview of improvement methods.

No changes	1. Current index	
Adjusting components	1. Residual adjustment of food environment scores	2. Adding housing price as a separate exposure to index
Adjusting weights:	3. Hierarchical index	
- Without outcome		
- With outcome	4. Backward selection of components	5. Random forest

regression does not yield effect estimates in the same manner as linear regression, the predicted BMI was used to derive the obesogenic score, which was scaled between 0 and 100 with higher value indicating higher level of obesogenicity.

5. Random forest

Random forest (RF) is a nonparametric ensemble machine learning (ML) method. During each iteration, a random subset of predictors is selected to build a decision tree supervised by the outcome BMI; the predictions from which are aggregated to form the forest (Breiman and Schapire, 2001). Parameters such as the number of observations to sample for each decision tree (*"sample.fraction" = 0.2366941*), the minimum size of terminal nodes to control for the depth of decision trees (*"min.node.size" = 428*), and the number of variables considered for potential splits at each node (*"mtry" = 6*) were calibrated automatically and reported between brackets. Similar to the backward selection method, the selected model from the training set was used to predict neighbourhood-level BMI, which was scaled from 0 to 100 with higher value indicating a higher level of obesogenicity.

2.3.1. Comparing performances between methods

The performance of each improvement method was primarily evaluated based on the strength of association with BMI in the testing set. In particular, performance metrics such as the model Akaike Information Criterion (AIC), model R^2 and the direction of association based on the splines were reported. Additionally, we also assessed the internal consistency of resulting indices by how effectively each construct and environment were represented in the index. This was achieved by examining Pearson's correlation coefficients between constructs, environments and the different versions of the indices, which were reported in the Supplementary Materials.

All data were analysed using RStudio (R Core Team, Boston, MA). Splines were modelled using *mgcv* package and illustrated graphically with *gratia* package. Random forest parameters were calibrated using the *tuneRanger* package and the model was built using the *ranger* package (Ohanyan et al., 2022b).

3. Results

3.1. Descriptive statistics

Among the 382,615 participants included in the analyses, more than half of the sample had overweight and 15% of sample had obesity-which closely aligned with national averages (Table 2). The participants resided in 11,891 distinct neighbourhoods (out of a total of 12,821 in the Netherlands) across all 390 municipalities. There were participants in the most (OBCT score = 100) as well as least obesogenic neighbourhoods (OBCT score = 0), indicating that our sample was evenly spread across the Netherlands. The mean residential OBCT score was 40.1 (SD = 10.1). In terms of sociodemographic characteristics, the analytic sample was slightly more selective than the full sample (n = 453,157) with more % in the higher income quintiles and education categories (Supplementary Table S4), however, these differences were negligible and were not expected to bias our findings. Furthermore, OBCT scores and BMI did not differ between the analytical and full sample (Table S4). The training and testing sets were similar in terms of socio-demographic characteristics, exposure and outcome (Table 2).

3.2. Association with BMI

There was a significant, non-linear association between the current index and BMI in fully-adjusted models. When OBCT index increases from 25 to 60, BMI drops from +0.18 above average to −0.40 below average, indicating an inverse association where uncertainties were smallest (or where most people live). For OBCT values between 0-25 and

Table 2
Socio-demographic characteristics of the Dutch Public Health Monitor sample included in analysis.

	Overall n = 382,615	**Training set** n = 255,187	**Testing set** n = 127,428
Sex			
% female	204,446 (53.4%)	136,112 (53.3%)	68,334 (53.6%)
Age group (age in years)			
19 - 34	43,001 (11.2%)	28,741 (11.3%)	14,260 (11.2%)
35 - 50	57,263 (15.0%)	38,011 (14.9%)	19,252 (15.1%)
51 - 65	91,382 (23.9%)	60,945 (23.9%)	30,437 (23.9%)
66 - 85	158,259 (41.4%)	105,661 (41.4%)	52,598 (41.3%)
>85	32,710 (8.5%)	21,829 (8.6%)	10,881 (8.5%)
Education attainment			
Low	25,049 (6.5%)	16,612 (6.5%)	8437 (6.6%)
Middle-low	124,349 (32.5%)	82,995 (32.5%)	41,354 (32.5%)
Middle-high	118,959 (31.1%)	79,188 (31.0%)	39,771 (31.2%)
High	114,258 (29.9%)	76,392 (29.9%)	37,866 (29.7%)
Ethnicity			
Native Dutch	335,391 (87.7%)	223,817 (87.7%)	111,574 (87.6%)
Western non-Dutch	32,931 (8.6%)	21,880 (8.6%)	11,051 (8.7%)
Non-Western non-Dutch	14,293 (3.7%)	9490 (3.7%)	4803 (3.8%)
Household composition			
2-person household	276,726 (72.3%)	184,431 (72.3%)	92,295 (72.4%)
Single household	39,929 (10.4%)	26,705 (10.5%)	13,224 (10.4%)
Others	65,960 (17.2%)	44,051 (17.3%)	21,909 (17.2%)
Social participation			
Full-time work	97,339 (25.4%)	65,052 (25.5%)	32,287 (25.3%)
Part-time work	65,018 (17.0%)	43,321 (17.0%)	21,697 (17.0%)
Study	6380 (1.7%)	4222 (1.7%)	2158 (1.7%)
Not working	80,039 (20.9%)	53,266 (20.9%)	26,773 (21.0%)
Retired	133,839 (35.0%)	89,326 (35.0%)	44,513 (34.9%)
Disposable household income			
Lowest (max €16,000)	29,536 (7.7%)	19,586 (7.7%)	9950 (7.8%)
Second lowest (max €21,300)	71,126 (18.6%)	47,530 (18.6%)	23,596 (18.5%)
Middle quintile (max €27,200)	84,393 (22.1%)	56,243 (22.0%)	28,150 (22.1%)
Second highest (max €35,100)	95,105 (24.9%)	63,410 (24.8%)	31,695 (24.9%)
Highest (>€35,100)	102,455 (26.8%)	68,418 (26.8%)	34,037 (26.7%)
Survey methods			
Written on paper	183,457 (47.9%)	122,338 (47.9%)	6,1119 (48.0%)
Written, internet	198,598 (51.9%)	132,469 (51.9%)	66,129 (51.9%)
Face-to-face & via phone	560 (0.1%)	380 (0.1%)	180 (0.1%)
Urbanisation degrees			
>2500 addresses/km^2	54,660 (14.3%)	36,559 (14.3%)	18,101 (14.2%)
1500 - 2500 addresses/km^2	85,116 (22.2%)	56,810 (22.3%)	28,306 (22.2%)
1000-1500 addresses/km^2	72,798 (19.0%)	48,568 (19.0%)	24,230 (19.0%)
500- 1000 addresses/km^2	80,206 (21.0%)	53,362 (20.9%)	26,844 (21.1%)

(*continued on next page*)

Table 2 (*continued*)

	Overall n = 382,615	**Training set** n = 255,187	**Testing set** n = 127,428
<500 addresses/km^2	89,835 (23.5%)	59,888 (23.5%)	29,947 (23.5%)
Overweight, %	204,322 (53.4%)	136,134 (53.3%)	68,188 (53.5%)
Obesity, %	57,293 (15.0%)	38,151 (15.0%)	19,142 (15.0%)
Body mass index, kg/m^2			
Mean (SD)	25.9 (4.25)	25.9 (4.24)	25.9 (4.25)
OBCT index, Mean (SD)	40.1 (10.1)	40.1 (10.1)	40.1 (10.0)

*Education categories were defined as: low (primary/LO in Dutch), middle low (general secondary education/MAVO, lower vocational training/LBO), middle high (higher general secondary education/HAVO, pre-university/VWO, secondary vocational education/MBO) & high (university of applied sciences/HBO & research university/WO).

75–100, associations seemed intuitive, but variance was large (due to low number of observations) (Fig. 3a). The variance in BMI explained (%VE) by the index was minimal (0.05%, Table 4). In terms of the environmental domains, while the PA domain scores generally had an intuitive association with BMI (Fig. 3d), %VE was the smallest (0.01%, Table 4). The food environment domain was more similar to that of the overall OBCT score in terms of association direction (Fig. 3b) and %VE (0.04%, Table 4).

3.3. Effect modification

There was significant effect modification by age, sex, socioeconomic status both at neighbourhood and personal level; and urbanisation degrees (all *p-value* for interaction ≪0.05, Table 3). The variance explained (%VE) by the OBCT index was slightly higher for women (%VE = 0.09%), residents of high-income neighbourhoods (%VE = 0.09%), middle-aged individuals (36–50 years old, %VE = 0.10%), those in the highest quintile of household income (%VE = 0.14%). The highest percentage of variance explained was observed in younger adults (19–35 years old, %VE = 0.20%) and in the most urban residential neighbourhoods (>2500 addresses/km^2, %VE = 0.20%) (Table 3). Nonetheless, the direction of association in these specific strata remained similar to the main analysis (Supplementary Fig. S1 versus Fig. 3a).

3.4. Index improvement results

Adjusting the food environment for address density did not significantly change the association between the food environment and BMI (Fig. 3b versus 2f, %VE changed from 0.05 to 0.03% in the testing set); nor the overall association between the resulting index and BMI (Fig. 3a versus 2e) and the model fit (%VE = 0.01%, Table 4). Adding housing price reversed the index association with BMI (Fig. 3g) and slightly increased model fit (%VE = 0.09%, Table 4). The hierarchical index, where more weight was assigned to the PA environment compared to the food environment (Supplementary Fig. S2), did not significantly change the association shape (Fig. 3c) with worse model fit (%VE = 0.01%, Table 3).

Variable selection and random forest were two supervised methods in which BMI was used to improve the index association with outcome. These two methods, by default, generated indices that corresponded positively and linearly with BMI (Supplementary Fig. S1). Through the backward selection process, distance to highway, distance to train station and density of sports facilities were removed, the backward-selected index performed better than most non-supervised method (%VE = 0.26, Table 4). In this index version, the direction of association within the food environment was reversed, as indicated in an overall negative correlation between the original food environment score and the backward-selected index (Supplementary Fig. S2). The overall best-performing index was created by random forest with the lowest AIC and the highest R^2. However, explained variance only increased by less than 1% (%VE = 0.44%, Table 4). Similar to variable selection process, the variables contributing the least to the random forest index are land use mix, distance to highway, green space and distance to train station (variable importance scores <0.4, Supplementary Table S3). In general, these two methods produce relatively similar indices (Spearman's correlation coefficient 0.7, Supplementary Fig. S2). Further results on internal consistency of each index and the correlations between different indices were presented in Supplementary Materials (Fig. S2).

Finally, associations between all index versions and BMI; stratified by sex, age, personal and neighbourhood-level SES and urbanisation degrees; are presented in Table 3 (for the current OBCT index) and Supplementary Table S2 (all other index versions).

4. Discussion

4.1. Main findings and interpretations

We assessed the association between the recently developed OBCT index, its environmental domain scores and BMI in a large cross-sectional population survey in the Netherlands. The current index highlighted the exposure disparity to obesogenic environment among the general population, although the association with BMI was not straightforward. Restricted cubic spline regression showed that the current index was largely inversely and non-linearly associated with BMI, which was mostly driven by the food environment measures. The PA measure, on the other hand, demonstrated an association in the expected direction even though its contribution to BMI variance was minimal. Overall, the current index explained 0.05% variance in BMI, which was higher in some strata: in females (0.20%), most urban neighbourhoods (0.20%) and neighbourhoods with high household incomes (0.14%). Several methods of improvement were applied, including improvement at component level for the food environment and reweighting index components, either with or without using BMI as outcome. We found that outcome-supervised methods performed better in terms of predicting BMI, however, the overall improvement was limited across all methods (<1% increase in variance explained).

Our findings on the association of the OBCT index with BMI contributed to a growing evidence base on built environment indices and health outcomes, particularly the United States Flint-based Geospatial Healthfulness index (FGHI), the national Childhood Obesogenic Environment Index (COEI) and the New Zealand Healthy Location Index (HLI). In the first, Sadler developed a GIS-based index to quantify healthiness of the local environment for Flint, Michigan including 22 variables across the food, PA as well as the social environments (Sadler et al., 2019). A later validation study found that the index was not consistently nor significantly associated with physical health outcomes (including diabetes, high blood pressure and cholesterol) at individual level (Sadler et al., 2022). However, on top of sociodemographic characteristics, the FGHI did explain some variance in studied health outcomes (0.004% in diabetes, 0.006% in high cholesterol, 0.014% in heart diseases and 0.018% in high blood pressure), which was in line with our results (0.06% in BMI). We further showed that this percentage was higher in some subpopulations: younger adults, females, high income and neighbourhood SES, and those who live in highly urbanized areas;

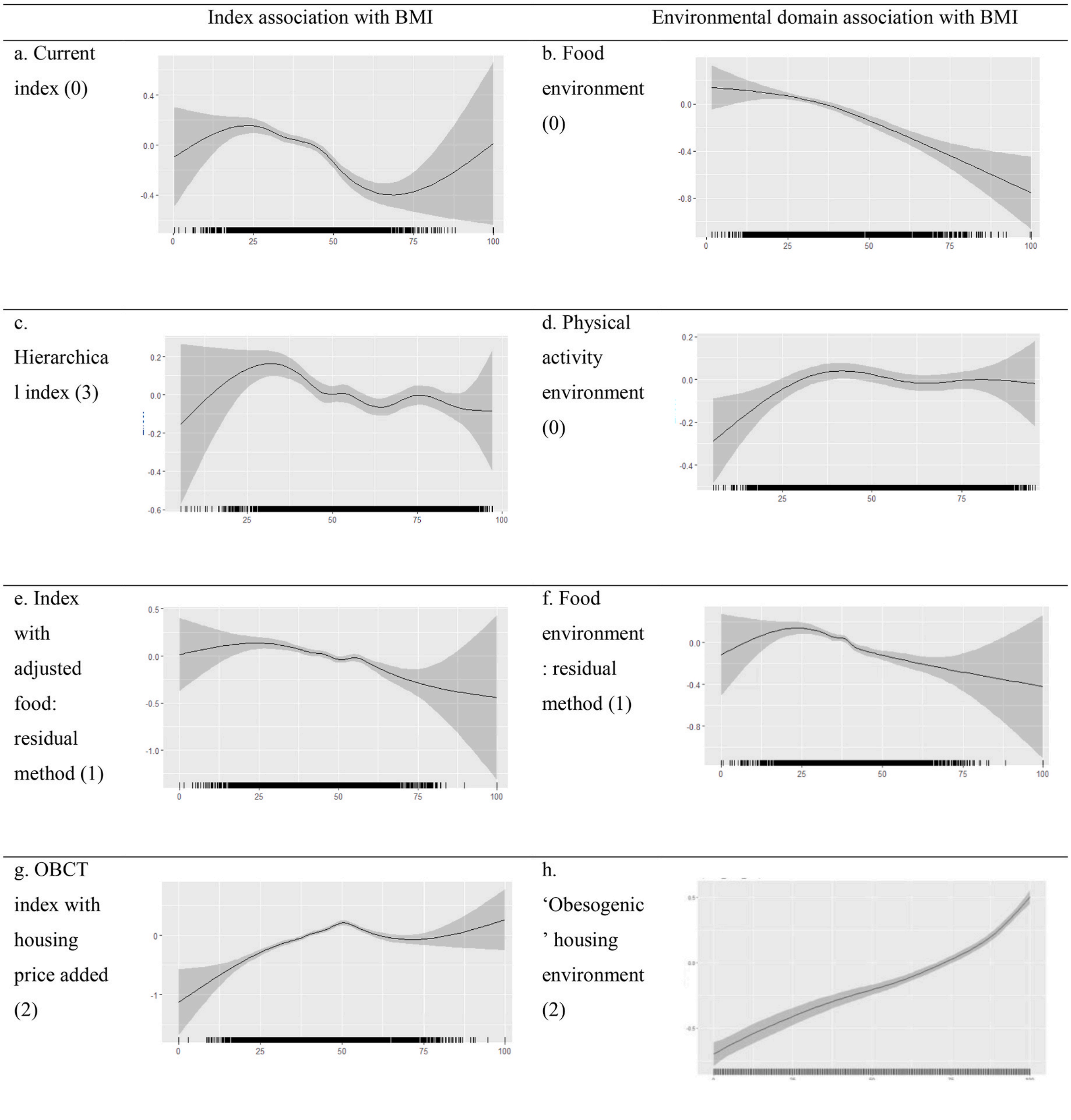

Fig. 3. Spline regression between versions of OBCT indices (left column) and respective environmental domain scores (right column) as numbered in Table 1; and continuous body mass index (BMI) in the training dataset from the Dutch Public Health Monitor (n = 255,187). All models were adjusted for age, sex, ethnicity, household composition, highest obtained education, social participation, income quartiles and survey format. The plots show the partial effect of each version of OBCT indices (left) or domain scores (right) on BMI, with shaded areas showing 95%CI and the tick marks on x-axis showing the observations in the training set. The y-axis showing outcome BMI centred around mean 0.

indicating areas for future targeted studies.

Two other studies however found somewhat more intuitive results. Guo et al. (2022) adapted the US-based COEI (Kaczynski et al., 2020) to measure obesogenic built environment relevant for adults using nine objectively measured indicators across the food, PA, socio-structural and economic environments. They found that people living in the highest tertile of obesogenicity was associated with higher odds of developing CVD. This was in congruence with recent results from HLI index by Hobbs et al. (2022) which included components from the food environment (fast food outlets, takeaways, supermarkets, fruits and vegetable stores, and dairy shops) and five other components (gaming locations, alcohol sales points, PA facilities, green space and blue space) (Marek et al., 2021). In their study, healthier environmental score categories were associated with lower continuous BMI, whereas less healthy categories were associated with having high BMI, with an overall area under the ROC curve (AUC) value of 0.67 (Hobbs et al., 2022).

While the OBCT index used density measures, HLI utilised distance metrics and the COEI access measures. In terms of operationalisation, the OBCT and FGHI were used as continuous variables, while both HLI and COEI were both categorised in respective health association studies. HLI results also suggest that other built environment factors related to health behaviours such as alcohol intake and gaming could also be obesogenic.

Interestingly, Hobbs et al. noted that associations between the HLI and different health outcomes were much less consistent than those of partial indices of only health-promoting or only health-constraining features (Hobbs et al., 2022). In other words, the sub-indices perform

Table 3
Stratified analysis for associations between the current OBCT index and Body Mass Index of the included Dutch Public Health Monitor participants. All interaction terms were statistically significant ($p < 0.05$). All models were adjusted for age, sex, ethnicity, household composition, highest obtained education, social participation, income quartiles and survey format. Analysis was done in the training set, n = 255,187.

Variable & Stratum values		n	Confounder-only model		Current index (0)		
			AIC	R^2	AIC	R^2	%VE
Age	19–35 years old	28,741	160,845	0.043	160,789	0.045	**0.20**
	36–65 years old	98,956	565,802	0.047	565,710	0.0478	**0.10**
	>65 years old	127,490	716,575	0.031	716,539	0.031	0.04
Sex	Male	119,075	643,136	0.070	643,116	0.070	0.01
	Female	136,112	793,407	0.070	793,280	0.071	**0.09**
NSES	Low	125,766	719,922	0.066	719,891	0.066	0.02
	High	129,421	722,177	0.071	722,055	0.072	**0.09**
pSES	Lowest + second lowest quintiles	67,116	393,580	0.060	393,557	0.060	0.04
	Middle + second highest quintiles	119,653	674,218	0.054	674,181	0.055	0.03
	Highest quintile	68,418	372,991	0.055	372,894	0.056	**0.14**
Urbanicity	>2500 addresses/km^2	36,559	209,570	0.103	209,498	0.105	**0.20**
	1000–2500 addresses/km^2	105,378	597,974	0.064	597,947	0.065	0.03
	<1000 addresses/km^2	113,250	635,131	0.064	635,123	0.064	<0.01
Overall		**255,187**	**1,443,134**	**0.070**	**1,442,991**	**0.070**	**0.05**

NSES = neighbourhood SES, low NSES was defined as NSES median and below, high NSES above median; pSES = personal SES/income quintiles, %VE = percentage variance in BMI explained, AIC = Akaike information criterion.

Table 4
Performance of all indices (top) and respective environmental domain scores (bottom) across improvement methods (as numbered in Table 1) in terms of association with BMI; outcome data from the Dutch Public Health Monitor and split into training and testing sets. All models were adjusted for age, sex, ethnicity, household composition, highest obtained education, social participation, income quartiles and survey format.

Models		Training set, n=255,187			Testing set, n=127,428		
		AIC	R^2	%VE	AIC	R^2	%VE
Confounder only		1,443,134	0.070	6.99*	21,483	0.070	6.97*
All index versions							
0	**Original index**	**1,442,991**	**0.070**	**0.05**	**721,403**	**0.070**	**0.06**
1	Index with adjusted food domain scores	1,443,083	0.070	0.02	721,466	0.070	0.01
2	Index including housing price	1,442,817	0.071	0.12	721,359	0.071	0.09
3	Hierarchical index	1,443,080	0.070	0.02	721,470	0.070	0.01
4	Index created by variable selection	1,442,403	0.073	0.27	721,125	0.072	0.26
5	Index created by random forest	1,437,797	0.089	1.93	720,871	0.074	0.44
Environmental domain scores							
Food	Original food environment score (0)	1,443,019	0.070	0.04	721,410	0.070	0.05
	Residual-adjusted food environment score (1)	1,443,044	0.070	0.03	721,439	0.070	0.03
Physical activity environment score (0)		1,443,121	0.070	0.01	721,477	0.070	< 0.01
Housing price (2)		1,442,171	0.073	0.35	721,056	0.073	0.31

AIC: Akaike information criterion, %VE: % variance in BMI explained by respective indices or environmental domain scores, *: variance in BMI explained by all confounders in the model. Numbers in grey should not be interpreted because these indices were generated based on the training set.

better than the overall HLI index in terms of explaining health outcomes, a finding that was partly in line with our results. The original food environment has approximately the same explained variance with the overall original index, while housing price on its own has much higher explained variance compared with the index included housing price. This result implies a potential "benefit cap" for the aggregation of index components. In other words, a larger index with more components might not always explain more variance than a smaller index with fewer components. For example, a recent study by Dalmat et al. (2021) demonstrated that simple walkability proxies such as population density could reasonably predict walking compared to composite indicators such as WalkScore, whose operationalisation was much more complex and black-box (Dalmat et al., 2021).

A plausible explanation for our counterintuitive findings is that we were unable to account for non-residential exposures to obesogenic environments, which could substantially contribute to dietary behaviours, physical activity and subsequently to BMI. Recent studies found that walkability averaged across the activity space was most predictive of transport-related PA, followed by non-residential and residential walkability (Howell et al., 2017). Similarly, Mackenbach et al. (2023) suggested that for the Dutch context, fast food exposures at residential and workplace differed significantly, highlighting that combining residential and work exposures offered a more comprehensive perspective than relying solely on residential exposures (Mackenbach et al., 2023). An earlier study by Chum and O'Campo suggested that including non-residential exposures could enhance model fit, increase explained variance and association strength between built environment and CVD (Chum and O'Campo, 2013). Another study by Moore et al. (2013) suggested a synergistic effect between residential and work food environment that is relevant for BMI.

Furthermore, our study also confirmed the complexity of the food environment's role in overweight and obesity, both as independent factors and in combination with other built environment factors. Contrary to evidence suggested by earlier studies, adjusting food environment scores for address density did not improve its association with BMI, neither in terms of explained variance nor direction of association. It is worth nothing that so far, food environment studies in the Netherlands have inconsistent results, especially in terms of health outcome associations. van Erpecum et al. found a positive association between proximity of fast food and person-level BMI (van Erpecum et al., 2022b), Aretz et al. also found a positive association between access to fast food and area-level obesity (Aretz et al., 2023) while Mackenbach et al. found a negative association between fast food and person-level BMI (Mackenbach et al., 2023). Another study in older adults found no association between fast food and person-level obesity (Harbers et al., 2021); while Hoenink et al. found no association between a composite measure of retail food environment and person-level obesity (Hoenink et al., 2019). Our study added to this literature by confirming that combining healthy and unhealthy food environment measures does not necessarily result in more intuitive association with person-level obesity.

In general, Mahendra et al. (2017) argued that absolute density (of food outlets) is only one of the three indicators of the retail food environments. Relative density between unhealthy and healthy outlets, and proximity to food outlets play conceptually distinct roles in defining the food environment (Pinho et al., 2019). The US Department of Agriculture also suggested incorporating income, food prices and food (in)security; all traditionally socioeconomic determinants, into food environment index measures (Economic Research Service and US Department of Agriculture, 2020). Given the complexity and fast-changing foodscape in the Netherlands (Pinho et al., 2020), it is valuable to gain better understanding into the individual components and their optimal operationalisation (Pinho et al., 2018) before aggregating them into indices.

Nevertheless, it is important to keep in mind that obesogenic environments as defined by built environment characteristics in our studies, are rather upstream determinants of health. The pathway between the built environment exposure and downstream BMI is complex and involves multiple mediators and modifiers, only a few of which we were able to consider in this study. For example, dietary behaviours are central to a complex adaptive system with feedback loops and paradigms, where the built environment is just one among other sociodemographic determinants (Sawyer et al., 2021). Therefore, small estimates as observed in our study (and also in other indices, particularly the FGHI as reported above) are not complete unexpected. Guo et al. (2022) found that health-compromising behaviours (such as dietary behaviours, smoking or alcohol consumption) only mediated about 3% of the total effect of obesogenic environment (measured by the COEI) and CVD incidence.

Adding housing price as an extra environmental exposure in the index seemed to improve the direction of association and model fit. This perceptible improvement aligns with our previous discussion regarding the complementary nature between socioeconomic status and the food environment. Moreover, housing price reflects other (socioeconomic) characteristics of the neighbourhood independent of the food environment such as general desirability of location, education and income of residents (Knol et al., 2012; Coffee et al., 2013; Rehm et al., 2012). On its own, housing price could also be considered as an indicator of physical built environment, as it reflects age, average sizes, aesthetic quality of the house and the neighbourhood that might be relevant for quality of life of the residents (McDonald, 2011). We therefore advise built environment researchers to proceed with caution: if the goal is prediction, then housing price should be considered for inclusion in analysis. In our case, housing price explained 0.35% variance in BMI, which was higher than the OBCT index with 17 components. However, if policy or intervention is concerned, then housing price might be an indicator of area socioeconomic status, necessitating interventions that extend beyond urban design improvements.

We attempted to improve the index by modifying the weights of individual components by several methods. With the hierarchical index, we assigned more weight to the PA environment, whose association with BMI was more intuitive. However, this did not directly translate to an overall improvement in explained variance. Furthermore, in both backward selection and maching learning methods, we expected the model fit to increase from the combination of modelling components as non-linear terms and assigning them differential weights by regression with BMI, as compared to the original index where components were linearly modelled and equally combined. Using these two methods, we observed substantial increase in model fit, albeit in relative, not in absolute terms. RF performed slightly better than RCS since optimal transformations of components as well as interactions between components were considered. However, black-box operation meant that neither specific transformation nor interactions could be explicitly specified, as opposed to a more transparent RCS. Moreover, due to the data-driven nature of both methods, the association of each component with BMI might deviate from intuitive expectations, and the interpretability of the index as a whole is potentially compromised. This has led us to conclude that the weighting itself might not necessarily have been the issue, but rather, the operationalisation of the components was not optimal to effectively explain BMI.

4.2. Strengths and limitations

Our study has some notable merits. First, we applied a high-resolution, extensive 17-component index that highlighted spatial disparity of environmental obesogenicity in the Netherlands. The outcome data were drawn from a large population survey which captured extensive demographic and geographic distributions across the Netherlands. Several methods from both literature and statistics were used to improve the performance of the index. Notably, we included two methods (variable selection and random forest) that allow for non-linear modelling of associations between index components and BMI, which is typical in dose-response relationship with BMI (Aune et al., 2016).

However, there were also some limitations to consider. Firstly, accounting for non-linearity in the association between the index and BMI introduced challenges in interpreting analysis outcomes, particularly in associations strength and effect modification. Secondly, we were not able to consider spatial clustering of participants, since the number of participants per neighbourhood fluctuated considerably. Spatial autocorrelation could have potentially biased our model R^2 value. Moreover, neighbourhoods with more participants might eventually have larger influence on the indices generated from variable selection and random forest. Thirdly, it is important to acknowledge that height and weight were self-reported, even though previous investigations in other Dutch cohorts have shown generally good agreement between self-reported and measured weight (Intra-class correlations >0.90 across all demographic subgroups) (Dekkers et al., 2008). Finally, the cross-sectional nature of our outcome data precluded any causal inference.

4.3. Suggestions for future research

For research with composite indicators, several key lessons emerge. First and foremost, critical care should be given to the operationalisation and selection of index components. Second, when outcome data are present and could be used to supervise variable selection, both association strength and direction (with health outcomes) should be considered as criteria for inclusion. Third, where outcomes could not be measured directly, correlations between components should be considered to create a balanced and representative index.

We propose some ideas for future epidemiological studies. For the OBCT index specifically, studying the congruency and clustering of the food and PA environments as conducted earlier on the COEI by Wende et al., 2021a, 2021b could offer relevant insights for policymaking. Similarly, such geographically-weighted regression model, as performed by Aretz et al. (2023) could potentially help identify local hotspots where associations between obesogenic environment and health outcomes were strongest. For the working adult population, incorporation of workplace obesogenicity could provide a more complete picture of personal exposures. Moreover, it might help strengthen the evidence base to examine the index in relation to relevant health and behavioural intermediaries such as physical activity, sedentary behaviours, dietary behaviours and physiological dysfunction (Guo et al., 2022). This necessitates routine collection of reliable and validated large-scale health behaviour data in public health monitors such as the Dutch PHM used in this study. For future studies on obesity, it is desirable to incorporate other measures such as waist circumference, waist-to-height or waist-to-hip ratios in addition to BMI to better estimate central obesity. Lastly, applying the index in longitudinal settings might allow for more robust causal inference, given that environmental data are available for multiple years.

4.4. Implications for practice

Although the association with BMI was not straightforward, the OBCT index still serves as a useful tool for policymakers. It offers a heatmap that illuminates disparity in exposure to obesogenic environment among the general population. However, it is important to note that indices have inherent limitations in indicating which specific changes to the built environment are desirable. To address this, a different study design such as quasi-experimental or natural experiments with clearly defined interventions is necessary. This requires policy makers to make bold decisions with regard to acting upon societal problems around obesity. For instance, a fast-food ban around schools or lowering speed limits in urban areas would very likely be beneficial and would provide a strong case for evaluation in a natural experiment, enabling the generation of scientific evidence for such policy interventions.

For practical applications with non-technical stakeholders, adding complexity through data-driven techniques for composite indicators might not necessarily yield benefits. In fact, it could hinder interpretability of neighbourhood obesogenicity. In benchmarking and ranking neighbourhoods, simpler methods could be more valuable, especially in communication with policymakers. These methods include the categorisation of index components, similar to what has been done with the HLI and COEI. Additionally, providing interactive tools to visualise target neighbourhoods with high obesogenicity could be of interest to policy makers, such as the ArcGIS Online dashboard for the HLI.[1] Finally, the lack of epidemiological associations observed in our studies should not be a cause for inaction, since reducing environmental barriers to healthy food and active lifestyles should still be prioritised in our efforts against the obesity epidemic.

5. Conclusion

Our theory-driven OBCT index serves as tool to underscore disparity in exposure to obesogenic environment among the general population. However, its association with self-reported BMI was limited, and data-driven methods did not significantly improve these associations. Future improvements should instead focus on refining the operationalisation of the individual components in the index.

[1] http://tinyurl.com/HLI-NZ.

CRediT authorship contribution statement

Thao Minh Lam: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Nicolette R. den Braver:** Writing – review & editing, Supervision, Methodology, Investigation. **Haykanush Ohanyan:** Writing – review & editing, Resources, Methodology. **Alfred J. Wagtendonk:** Writing – review & editing, Methodology, Data curation. **Ilonca Vaartjes:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Joline WJ. Beulens:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Jeroen Lakerveld:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.118625.

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