## 1. Introduction

Globally, few public health conditions parallel the rapid and sustained increase in obesity prevalence (1). Within the UK, from 1993 to 2013, adult obesity increased from 14.9% to 24.9% (2). This is concerning as obesity is associated with a plethora of adverse medical conditions (3) and economic costs (4). Increased BMI for instance, is often strongly associated with clinical outcomes such as diabetes, and all-cause and selected cause-specific mortality rates (5-7). Systematic reviews and meta-analyses have demonstrated that few individual-level interventions have been effective in lowering BMI in the long-term apart from surgery in adults with a body mass index (BMI) >30kg/m2 (8-10).

Researchers have proposed that trends in obesity are driven by contextual changes such as inequities in food environments rather than biological or genetic shifts (11). One factor that has received increasing interest is the food environment, defined here as exposure to food outlets within a residential neighbourhood, and the role its distinctive combinations might play in promoting obesity (11-15). The proliferation of food outlets is suggested to influence food choice via easy and convenient access. Food choices may not just be intentional though, but may be automatic where a flood of sensory cues such as a lot of unhealthy food adverts may encourage individuals to eat unhealthy diets even when they may not require food (16, 17). Food availability may also be restrictive depending on what items are stocked in local neighbourhoods, leading to individuals consuming unhealthier diets due to a lack of healthier alternatives. Studies that have investigated this association tend to be dominated by cross-sectional research designs, rarely considering how food outlets cluster, and sometimes overlook how groups for instance males and female adults, may be distinctively responsive to certain types of food environments.

Modifying the food environment, to ensure the availability of healthy foods may supplement existing preventive approaches (18). Several studies internationally, and within the UK, have demonstrated relationships between different aspects of the food environment, such as fast-food outlets and BMI (19-21). However, while these associations are intuitively appealing, evidence linking different food outlets and BMI is equivocal (19, 22-25). A recent study (n=1.7 million, 382 metropolitan areas) (26), which controlled for self-selection bias and extensively cleaned and validated environmental data (27, 28) showed no association between supermarkets, fast-food restaurants, or mass merchandisers and change in BMI (five year follow-up). Other issues also affect evidential consistency, including variations in how food outlets are defined, geographical scale, and differences in confounder adjustment. Moreover, most studies included within reviews rarely assess change in BMI over time. This means any on-going inconclusiveness may reflect reverse causality (19).

Food outlets have been shown to cluster in similar locations; for instance Hawkesworth, Silverwood (29) noted a reasonably high correlation (r=0.64) between the count/area of fast-food outlets and stores selling fruits and vegetables. Furthermore, incorporating multiple food outlet types, e.g. the ratio of fast-food and convenience stores to supermarkets and greengrocers, has led to stronger and more consistent associations with obesity-related outcomes than simple measures of access to specific store types (18, 30-32). Overall this suggests that the composition, rather than absolute count of food outlet types may be a more important predictor of obesity. However, the use of ratio measures is not without its own problems. For instance, two fast-food outlets and one supermarket would be treated the same as 10 fast-food outlets and 5 supermarkets. It is questionable whether these two combinations should indeed be considered similar for health behaviours and outcomes. In this understanding, measuring the clustering between neighbourhood food outlets - to develop ‘typologies’ of food environments - may offer a new way to more accurately demonstrate how the wider food environment influences human behaviour, leading to obesity. However, despite its intuitive appeal, recent reviews suggest this approach has rarely been used (33). Few studies consider if food outlets cluster differentially by population density (34). It is plausible that population density could be a competing factor affecting the relation between food outlets and BMI, possibly due to increased walkability (35, 36).

Even though contextual exposures (in our case the food environment) may not affect all individuals to the same extent, differential effects between population groups are rarely considered (37). Evidence has shown that increased availability of fast-food outlets was most harmful for increased BMI in lower socioeconomic status population sub-groups (14, 21). Research has also explored differences by age (38) and gender (39, 40). A recent study suggested for instance, that an individual's mobility varies with age, and although effects were small, it showed that the availability of physical activity facilities and parks were associated with obesity but only in younger adult age (38). Despite this, these sociodemographic factors are rarely combined with repeated measures of BMI that also considers how food outlets cluster. Failing to address how the relationship between food outlets and change in BMI differs by population groups represents an important gap in our understanding of the nuances of obesity-related disparities.

Gender differences may be a particularly important area to explore as some research suggests that a myriad of sociocultural dynamics may exacerbate gender disparities in excess weight gain (41). While there are often no simple explanations for these findings (42), these differences may relate to traditional gender roles that result in women spending more time than men in their local neighbourhood and therefore more exposed to the local food environment (43). Emerging qualitative research from highly accessible urban food environments in Seoul supports this tentative evidence, demonstrating that females were generally tasked with preparing meals for their family (44). This in turn made it a struggle for them to prepare meals for the family on time, and they found it time consuming and inconvenient and therefore preferred dining out (44). Extensive evidence also demonstrates that males have poorer diets and consumer higher quantities of fast food (45). Greater accessibility to outlets selling such foods may result in sex differences in the importance of the local food environment (42, 43). Few studies have explored whether any sex-specific differences exist between the local food environment and BMI and greater investigation is warranted particularly as sex differences exist for other health outcomes (43).

Our study uses a large cohort specifically recruited to inform local-level decision making on weight and weight management. It aims to extend the evidence by developing a typology of neighbourhood food environments by considering the clustering of food outlets by population density at baseline. Second, it considers if food environment typologies are associated with BMI. Finally, it addresses how the relationship between BMI and food environments types varies by gender by including a three-way interaction with change in BMI and food environment type. We hypothesise that (i) individuals who lived in areas with poorer food environment typologies saw larger increases in BMI over time, and (ii) that there are significant differences by gender.

## 2. Methods

### 2.1 Individual-level data: participants and settings

Data were collected by questionnaire from the Yorkshire Health Study (YHS) over two waves of data collection (wave one 2010-12; wave two 2013-15) which included residential postcode. Data were obtained for n=8,864 individuals at both time points. In the UK, postcodes contain on average around 15 addresses (46). Described in detail previously (47), the YHS is an observational cohort study collecting information on adult residents from the Yorkshire and Humberside region (supplementary material: Figure S1) of England (99.1% cohort were based in South Yorkshire region). Yorkshire is a county in northern England housing several major cities like Leeds and Sheffield. The target population for wave one (2010-2012) of the YHS was all patients registered within General Practitioner (GP) (Medical Practice) surgeries in South Yorkshire aged 16 to 85 years. A two-stage approach was used for the initial data collection. Firstly, GP surgeries were invited to participate in the study (43 agreed: 50% acceptance). Consenting GP surgeries then mailed letters of invitation out to all patients between 16 and 85 years of age. Included with the letter of invitation was an eight-page questionnaire for data collection. Of the 156,866 questionnaires sent out, 27,806 were returned (response rate; 15.9%). The follow up wave two data was collected on the three-year anniversary of wave one data collection. Compared to the 2011 census for the total South Yorkshire population, participants over-represented people who were older, of white ethnicity, and female (47).

Age group (18-35, 36-45, 46-55, 56-65, 66-75, 76+ years), gender (male/female), and education-level (low=no formal qualifications/education, moderate=secondary school qualifications/education, college or trade qualifications/education or equivalent and high=university qualifications/education or equivalent) were obtained from the YHS and included in all models as individual-level covariates. Descriptive statistics for those who completed all waves of data and those who only completed wave one are provided in supplementary materials (Table S1 and Table S2). The key outcome of BMI and all covariates were largely similar. Ethical clearance for secondary data analysis was granted by the ethics committee of the Carnegie Faculty, Leeds Beckett University.

### 2.2 Area-level covariates

Environmental data were provided by Ordnance Survey (OS), a national mapping agency for the UK. The dataset (Points of Interest (PoI), 2013) included information on the locations of all commercial facilities in the UK. It provided food outlet locations for 2010 and easting and northings which are geographic coordinates for a point. Easting refers to the x-coordinate, while northing refers to the y-coordinate. PoI has recently been shown to be a valid source of secondary data for food outlets across four local authorities, and comparable to administrative local authority data within the UK (48). Unlike local authority data, PoI data has a standard classification across different local authorities. Food outlets were categorised by the researcher into six types (see supplementary materials Table S3 for a detailed breakdown of classifications): restaurants (n=6,750) (including but not limited to the PoI classification “pubs, bars and inns”), cafés (n=2,075) (i.e. PoI classification: “cafes, snack bars and tea rooms”), fast-food (n=6,259) (i.e. PoI classification: “fast food and takeaway outlets”), speciality (n=2,266) (i.e. PoI classification: “delicatessens”), convenience (n=3,612) (i.e. PoI classification: “convenience stores and independent supermarkets”, e.g. Tesco Express, Nisa Express, Sainsbury’s Local) and large supermarkets (n=888) (i.e. PoI classification: “supermarket chains”).

We used the Index of Multiple Deprivation (IMD) 2010 as a measure of area-level deprivation as it provides a multidimensional measure of deprivation and is commonly used by Local Governments (49). IMD is based on 37 separate indicators, organised across seven distinct domains of; income deprivation; employment deprivation; health deprivation and disability; education, skills and training deprivation; crime; barriers to housing and services; and living environment deprivation. IMD scores were assigned to the lower super-output area (LSOA) of each individual, as determined by their geocoded postcode. A higher IMD score equates to a higher level of deprivation. To allow comparison of relative effects IMD was considered in all models by quartile. A LSOA is a geographical area defined for statistical purposes containing a minimum population of 1000 and a mean of 1500. UK population density data were produced by the Office for National Statistics in 2011 at the LSOA level.

### 2.3 Outcome variable

Height (cm) and weight (kg) of participants were self-reported at both time points (three-year follow-up). BMI was then calculated for each participant as weight (kg) / height2 (m2). While it is not a direct measure of body fat, previous research has shown that BMI is useful for understanding obesity in epidemiological studies (50).

### 2.4 Neighbourhood

To define exposure, YHS participant home addresses were geocoded to postcode centroids in ArcGIS V10.5.1 (51). Neighbourhood was then defined as a 1600m Euclidean radial buffer centred on the home postcode. This gives an approximate measure of exposure by walking and previous analyses on the same sample have shown little difference in associations when using different radial buffers (52). Food outlets within each 1600m buffer were counted using a point in polygon analysis using ArcGIS V10.2.2 (ESRI Inc., Redlands, CA) and summed using a spatial join between food outlet layers and each individual’s 1600m radial buffer.

### 2.5 Statistical analyses and confounders

To examine the co-occurrence of exposure variables, we first used spearman’s rank correlation to examine the correlation between the counts of all seven types of food outlets. We then used a cluster analysis approach to develop typologies of food environments. Variables included in the cluster analysis included counts of restaurants, cafés, fast-food, speciality, convenience and large supermarkets. These were included together with population density (per square hectare (ha2)). Population density was also included as it was hypothesised that the number of food outlets may be correlated with population density. Population density may present a competing exposure for the relation between food outlets and BMI due to increased walkability for instance.

We used a k-means cluster analysis, a partitional classification method, to develop a food environment typologies. Our approach was exploratory to identify clusters of food environment characteristics, since there are few alternative approaches to guide how these might be defined. No assumption was made on the number of clusters *a priori*. The change in total within-cluster sum of squares score was assessed iteratively moving from 1 to 10 cluster solutions. The number of clusters was selected through comparing different model solutions using the change in total within-cluster sum of squares score. In addition to this, model fit was also assessed based on the real-world interpretability of cluster solutions. Figure S1 (supplementary materials) presents the results of the change in total within-cluster sum of squares score from a one to ten cluster solution. A three-class solution was deemed interpretable and the point at which the change in within-cluster sum of squared ceased to improve further (elbow method). We also explored k-means cluster analysis using standardised food outlet count and population density however, this again resulted in three clusters with counts of food outlets and population density which were substantively the same.

Participants included in this analysis and those lost to follow up were compared using descriptive statistics to investigate the extent to which attrition may have produced biased results, as well as contextualise our findings. Participants lost to follow-up included those who moved to a new house between waves, died or refused to take part in wave two. As shown in supplementary Table S2, 18,886 individuals consented to be contacted again and 11,164 (40.15%) returned the follow-up at wave two (2013-15). A three-level multilevel model (random intercept) in Stata SE V.15 was used to account for the clustering of observations (measurement occasions, nested within individuals which were nested within lower super output areas). Models included interaction terms between food cluster and time which investigate the association between food cluster and change in BMI. Finally this was extended to a three-way interaction term to account for differences in the association between food environment typologies and change in BMI over time by gender. Food environment data were only modelled at baseline. To aid the interpretation of the three-way interaction, we also calculated the marginal effect (i.e. predicted probability) of the change in the outcome for each cluster over time. To explore whether the association between food cluster and change over time is differential between the genders we included gender stratified margins. All regression parameters (unstandardised coefficients) were reported with 95% confidence intervals. Age, gender, education-level, and area-level deprivation were included in models as covariates.

## 3. Results

### 3.1 Exploring the colocation and clustering of food outlets

Correlation between food outlet counts is shown at Table 1. The weakest correlations are highlighted in white, and the strongest in darker grey. It is worth noting that all seven types of food outlets were positively correlated together to varying extents. For instance, fast-food outlets were strongly correlated with convenience (rho=0.713, p<0.001), cafés (rho=0.661, p<0.001), speciality food outlets (rho=0.642, p<0.001), restaurants (rho=0.548, p<0.001) and large supermarkets (rho=0.528, p<0.001).

*INSERT TABLE 1 HERE*

Comparisons between the clusters in our data are shown within Figure 1. The optimal number of clusters was defined as three, due to clear knee point where increasing numbers of clusters produced smaller improvements in model fit. Four and five class solutions were explored; however, clusters became less distinguishable from one another and the food environment descriptive statistic were similar. Moreover, rerunning our analyses without population density included in the cluster analysis did not alter our findings.

*INSERT FIGURE 1 HERE*

Table 2 presents descriptive statistics for the study population and compositional differences by food environment cluster. Cluster 1 (n=2,973) contained a moderate amount of neighbourhood food outlets; a median of three restaurants, one café, four fast-food outlets, one speciality store, three convenience stores and one large supermarket. It was also slightly above the study average in terms of population density (33.85/ha2). Cluster 2 (n=1,224) had the highest population density (50.55/ha2). Accordingly, it had the most food outlets; a median of eight restaurants, two cafés, ten fast-food outlets, three speciality stores, six convenience outlets and one large supermarket. Finally, cluster 3 (n=4,667) had the lowest population density (23.36/ha2) and the lowest number of food outlets; a median of two restaurants, two fast-food outlets, and two convenience outlets but no cafés, speciality outlets or large supermarkets.

*INSERT TABLE 2 HERE*

Table 2 also highlights that demographic characteristics differed by neighbourhood food type. When considering differences by age, cluster 2 had the highest proportion of individuals aged 18-35 years and lowest proportion of adults within the older age groups compared to the other clusters. The proportion of males and females was relatively consistent across neighbourhood food environment types. There were, however, differences by education-level. While food environment types within cluster 1 and 3 were broadly similar in terms of education-level, a greater proportion of those within cluster 3 were highly educated (33.4% high education). There were also slight differences in change in BMI between clusters but all remained relatively stable over time. Finally, in terms of area-level deprivation, cluster 3 had the highest proportion of participants in the two least deprived clusters (55.1%) while cluster 2 had the lowest proportion (41.5%).

### 3.2 The relationship between residential food environment type and change in BMI

As outlined in Table 2, mean BMI did not substantively change over the waves from baseline at 26.42 kg/m2 (SD=4.71) to follow up at 26.41 kg/m2 (SD=4.72). However, the number of obese individuals decreased slightly from n=1646 (18.6%) at baseline to 1622 (18.3%) at three-year follow up. Results from the fully adjusted multi-level regression model (b [95% CI]) investigating the relationship between food environment type and change in BMI are shown in Table 3. The interaction terms between food cluster and time examined the association between food cluster and change in BMI. Compared to cluster 1, the mean change in BMI for those in cluster 2 was 0.146 [-0.274, 0.566]) while mean change in cluster 3 was 0.065 [-0.224, 0.356] however, both changes were not statistically significant. These initial multilevel models were supplemented by including a three-way interaction between gender, time and neighbourhood food environment type adjusting for education-level, area-level deprivation and age (characteristics which were hypothesised to influence differentials in BMI by gender, time and neighbourhood environment type) (Figure 2). Full effects are shown within supplementary material (Table S4) however, there was little evidence of any change in mean BMI in the association by gender.

*INSERT TABLE 3 HERE*

*INSERT FIGURE 2 HERE*

## 4. Discussion

### 4.1 Key findings

This study contributes to our understanding of how residential food environments may contribute to change in BMI, by providing an alternative means of conceptualising types of food environments. By abandoning the contemporary focus on food outlets in isolation, the current study first highlights the multidimensional nature of a food environment as large supermarkets, restaurants, cafés, fast-food, speciality and convenience food outlets clustered together within the same residential neighbourhoods. Despite this, and in contrast to our initial hypothesis, the interaction terms between food cluster and time, demonstrated no association between neighbourhood food environment types and change in BMI. Moreover, the interaction terms between food cluster, gender and time showed this relationship did not differ by gender. While the evidence within this study is predominantly null, it provides new evidence of the multidimensional nature of food environments. Our typologies of food environments may encourage future criticality when considering the multidimensional nature of neighbourhood and place.

### 4.2 Interpretation

Our study demonstrates the broader context of food environments. The evidence responds to recent evidence showing that single-attribute measures of residential food environments are insufficient to characterise the environment where people make their food-related decisions; all food outlets cluster together to some extent (see Table 1) (18). Indeed, recent evidence from New Zealand which focused on a more holistic picture of the food environment by using an enhanced two‐step floating catchment area model of spatial accessibility, found an increased exposure to all types of food retailers in deprived areas (53). In our study, the number of food outlets that clustered together closely aligned with population density. It is plausible that components of the food environment operate in concert and therefore should be modelled in this way.

Internationally, research has demonstrated that an unfavourable exposure to food outlets - for instance, a high exposure of fast-food outlets - may result in adverse weight-related outcomes (12, 54). Policy has begun to act upon this evidence, for instance in the UK, 50.5% of 325 local government areas had a policy specifically regulating proliferation of takeaways through urban planning. (55). However, it is important to note that a greater number of studies have shown null associations (26, 39, 40, 56). Our food typologies provide an initial attempt to better understand the interaction of multiple risk factors in food environments. We add to the mixed evidence base because our food environment types were not associated with change in BMI over three years. Findings in our study mirror the null or very small associations found in other longitudinal studies using longer time series to understand the role of the food environment on changes in BMI (46,47). Our study extends current evidence by examining differences in this association by gender. However, in contrast to previous evidence which has suggested gender differences may exist in the importance of the local food environment (41-44), there was again, no evidence of any association. These results may reflect recent evidence which suggested that the residential food environment was not a major driver of the socioeconomic differentials in BMI when accounting for how they vary by gender and age (18). Equally, while we extend evidence by considering food environment types, these inconsistencies may be due to the overly simplistic measure of the food environment employed which did not account for factors such as price or actual use.

While our study provides an important addition to evidence (57), contemporary research, including this study rarely explicitly consider the pathways by which factors such as population density and exposure to food outlets may impact on changes to BMI. For example, reviews and meta-analyses have shown that high population density is associated with increased walkability and favourable weight-related outcomes (35, 36, 58). While controlling for the effects of population density is often the approach taken, as shown here and in other evidence (53, 59, 60), fast-food outlets and other types of food outlets are likely to cluster together in highly populated areas potentially due to customer demand. A better consideration of the pathways by which these potential competing influences may impact on change in BMI may help uncover meaningful associations. While the causes of obesity may well extend beyond these factors, for instance to price of foods or quality of foods available (61), it remains important to consider multiple environment factors and the pathways by which they are interlinked which may provide a means to uncover influential factors in future research.

Finally, definitions of food outlet exposure measures, geographical scale, and differences in covariate adjustment may limit the consistency of evidence. Most, if not all studies are limited by not capturing other sources of food exposure such as mobile street vendors or online delivery services (62). Street vendors are often excluded from food-environment research as they have a variable and fluid presence in urban environments. For instance, a rare study of mobile food vendors found nearly a third (30%) changed selling locations (e.g. streets, neighbourhoods or boroughs) day-to-day or within a given day (63). Furthermore, home delivery services, offered by most fast-food franchises within the UK, have increased access to food without necessarily changing the physical environment (64). Moreover, supermarket delivery is also widely available. Nonetheless, this is rarely if ever captured in existing studies. It is plausible that food exposures not captured by secondary data sources may also explain additional variation in BMI.

### 4.3 Implications for policy

For policymakers in public health and planning, this study highlights the multi-dimensional nature of food environments, which local authorities and policymakers may need to account for when making health-related decisions. Policy has often focused on the regulation of fast-food outlets only. However, our study confirms previous research in the US (59, 65, 66), New Zealand (67) and to some degree within the UK (60, 68) which shows that food outlets cluster together, most likely due to the need for a customer demand to prosper as a business (69). While the proportion of different food outlets making up each cluster did not differ considerably, mean count varied substantially and outlets clustered together. This highlights the multidimensional nature of place as large supermarkets, restaurants, cafés, fast-food, speciality and convenience food outlets clustered in the same neighbourhoods. A consideration of all food outlet types, not just specific types in isolation, may therefore be warranted in both policy and research. This is supported by previous evidence which suggests that automatic food choices occur when a flood of sensory cues such as lots of food outlets encourage individuals to eat unhealthy diets even when they may not require food (17). When relating food outlet exposure to change in BMI, local authorities have previously had to rely on anecdotal evidence to fill gaps in the current evidence base, while being driven by the political imperative to ‘do something’ (70). Policy cannot wait until the perfect evidence base emerges to support action (70-72). However, this study showed no association with change in BMI over time which suggests that efforts to tackle increases in BMI based on restricting the location of food outlets in particular geographical areas may be of limited value as a standalone intervention. Food outlet typologies that incorporate more information about the geographic clusters including factors such as resident composition, street connectivity, building/housing density or pricing may be a valuable area of future research.

### 4.4 Limitations

Scientific study is conducted with a certain degree of uncertainty; the results within this study should be interpreted with these limitations in mind. First, BMI was calculated using self-reported height and weight. While BMI remains a useful and feasible measure at the population-level for research, this measure may have biased the study. However, even when using self-reported measures, which tend to be lower than objectively measured BMI, associations are often strong between clinical outcomes such as diabetes, and all-cause and selected cause-specific mortality rates (5-7). Second, this study was limited by the short three-year follow-up period that may have limited the ability to detect changes in body weight over time and we had no data on length of residence in neighbourhood. Changes in weight across this period were small. However, it is also important to note that it was still plausible that subgroups of individuals within certain clusters may have changed in BMI over time. Third, food outlet location was only collected at baseline and time-varying food outlet and socio-demographic characteristics at both the area- and individual-level would have supplemented the analyses. However, given the short follow-up period it is debatable whether these factors would have changed substantively. Fourth, our definition of neighbourhood assumed that participants used food outlets within 1600m of their home data on workplace location would have benefitted analyses. Fifth, although UK postcodes offer relatively precise geocoding, each postcode area averages 15 addresses which may lead to some inaccuracies. Sixth, participants in the YHS were over-representative of older adults, females, and white ethnicity relative to the actual population limiting the generalisability of our findings. As described previously, most individuals (approx. 90%) within this study reside within urban areas (73). One of the most serious drawbacks to our study is that individuals are lost to follow-up. It is also worth considering that associations between food outlet exposures and BMI may be confounded by self-selection into neighbourhoods. We also acknowledge that while considering typologies can be useful, this approach also has limitations in assuming homogeneity within clusters and ignoring relative densities of outlets. Further thought is required into the best ways for research and policy to characterise the food environment. The addition of longer-ranging historical longitudinal data on food outlets may help characterise the food environment – as it may be that the exposure to the food environment over an extended period of time influences weight.

### 4.5 Unanswered questions and future research

Several key directions for future research are offered, to progress understanding of how food environments relate to change in BMI. First, there is a need for longitudinal research with longer follow-up periods that allow for significant change to be captured in both food environments and change in weight status. Tracking over longer periods will also better account for self-selection bias of individuals into neighbourhoods. Furthermore, using natural experimental opportunities – due, for example, to relocation such as student assignment to dormitories at university - may help tease out how food environments are related to change in weight. Second, more work is needed to investigate appropriate measurement of food environments, for instance, by tracking with GPS to gain a better understanding of estimated and actual exposure. Third, complexity may be addressed by accounting for divergent effects across population groups, particularly where mobility differences may be important (74). This study hypothesised that susceptibility to food environments differed by population group (gender); while no modification effects were observed, further research is required to confirm our findings. Finally, routinely collected data, such as store loyalty card data, would provide valuable information on where people do their food shopping and what they are likely to consume.

## 5. Conclusion

Existing research investigating links between the food environment and BMI is largely cross-sectional and focused on food outlets in isolation. This study investigates the association between the food environment and change in BMI. Large supermarkets, restaurants, cafés, fast-food, speciality and convenience food outlets clustered together. However, accounting for clustering of food outlets alongside population density did not reveal relationships with change in BMI over a three-year period. Given the clustering of food outlet types, policymakers in planning and public health may need to move beyond relatively simplistic policy initiatives that focus on the geographic exposure of specific food outlet types. While any food environment intervention should form only one aspect of any obesity prevention strategy, considering other food environment influences on body weight may be important for future research. While the evidence within this study questions any over-reliance on food environment interventions, it provides an important addition to the current evidence base and highlights the multidimensional nature of food environments.

## 6. References

1. Kushner RF. Clinical assessment and management of adult obesity. Circulation. 2012;126(24):2870.

2. HSCIC. Statistics on Obesity, Physical Activity and Diet: England 2016. London: The Health and Social Care Information Centre (HSCIC),; 2016.

3. Mechanick JI, Youdim A, Jones DB, Garvey WT, Hurley DL, McMahon MM, et al. Clinical practice guidelines for the perioperative nutritional, metabolic, and nonsurgical support of the bariatric surgery patient--2013 update: cosponsored by American Association of Clinical Endocrinologists, the Obesity Society, and American Society for Metabolic & Bariatric Surgery. Endocrine Practice. 2013;19(2):337.

4. Dee A, Kearns K, O’Neill C, Sharp L, Staines A, O’Dwyer V, et al. The direct and indirect costs of both overweight and obesity: a systematic review. BMC Research Notes. 2014;7:242-.

5. Gorber SC, Tremblay M, Moher D, Gorber B. A comparison of direct vs. self-report measures for assessing height, weight and body mass index: a systematic review. Obesity reviews : an official journal of the International Association for the Study of Obesity. 2007;8(4):307.

6. Merrill R, Richardson J. Validity of Self-Reported Height, Weight, and Body Mass Index: Findings From the National Health and Nutrition Examination Survey, 2001-2006. Preventing Chronic Disease. 2009;6(4):121.

7. Stommel M, Schoenborn CA. Accuracy and usefulness of BMI measures based on self-reported weight and height: findings from the NHANES & NHIS 2001-2006. BMC Public Health. 2009;9(1):421.

8. Shaw K, Gennat H, O'Rourke P, Del Mar C. Exercise for overweight and obesity. The Cochrane Database Of Systematic Reviews. 2006;18(4):CD003817.

9. Colquitt J, Loveman E, Clegg A. Surgery for obesity. The Cochrane Database of Systematic Reviews. 2009;15(2):CD003641.

10. Padwal R. Long term pharmacotherapy for obesity and overweight: updated meta-analysis. BMJ. 2007;335:1194.

11. Brandkvist M, Bjørngaard JH, Ødegård RA, Åsvold BO, Sund ER, Vie GÅ. Quantifying the impact of genes on body mass index during the obesity epidemic: longitudinal findings from the HUNT Study. BMJ. 2019;366:l4067.

12. Cobb LK, Appel LJ, Franco M, Jones-Smith JC, Nur A, Anderson CA. The relationship of the local food environment with obesity: A systematic review of methods, study quality, and results. Obesity. 2015;23(7):1331.

13. Burgoine T, Mackenbach J, Lakerveld J, Forouhi N, Griffin S, Brage S, et al. Interplay of Socioeconomic Status and Supermarket Distance Is Associated with Excess Obesity Risk: A UK Cross-Sectional Study. International journal of environmental research and public health. 2017;14(11):1290.

14. Burgoine T, Sarkar C, Webster CJ, Monsivais P. Examining the interaction of fast-food outlet exposure and income on diet and obesity: evidence from 51,361 UK Biobank participants. International Journal of Behavioral Nutrition and Physical Activity. 2018;15(1):71.

15. Lakerveld J, Mackenbach J. The Upstream Determinants of Adult Obesity. Obesity facts. 2017;10(3):216.

16. Ziauddeen N, Page P, Penney TL, Nicholson S, Kirk SF, Almiron-Roig E. Eating at food outlets and leisure places and "on the go" is associated with less-healthy food choices than eating at home and in school in children: cross-sectional data from the UK National Diet and Nutrition Survey Rolling Program (2008-2014). The American journal of clinical nutrition. 2018;107(6):992-1003.

17. Penney TL, Burgoine T, Monsivais P. Relative Density of Away from Home Food Establishments and Food Spend for 24,047 Households in England: A Cross-Sectional Study. International journal of environmental research and public health. 2018;15(12).

18. Feng X, Astell-Burt T, Badland H, Mavoa S, Giles-Corti B. Modest ratios of fast food outlets to supermarkets and green grocers are associated with higher body mass index: Longitudinal analysis of a sample of 15,229 Australians aged 45 years and older in the Australian National Liveability Study. Health & place. 2018;49:101-10.

19. Cobb LK, Appel LJ, Franco M, Jones-Smith JC, Nur A, Anderson CAM. The relationship of the local food environment with obesity: a systematic review of methods, study quality, and results. Obesity. 2015;23(7):1331-44.

20. Burgoine T, Forouhi N, Griffin S, Wareham N, Monsivais P. Associations between exposure to takeaway food outlets, takeaway food consumption and body weight in Cambridgeshire, UK: population based, cross sectional study. British Medical Journal. 2014;348:1464.

21. Burgoine T, Forouhi NG, Griffin SJ, Brage S, Wareham NJ, Monsivais P. Does neighborhood fast-food outlet exposure amplify inequalities in diet and obesity? A cross-sectional study. The American Journal of Clinical Nutrition. 2016;103(6):1540.

22. Jiao J, Moudon AV, Kim SY, Hurvitz PM, Drewnowski A. Health Implications of Adults' Eating at and Living near Fast Food or Quick Service Restaurants. Nutrition & Diabetes. 2015;5(7):e171.

23. Ghosh-Dastidar M, Hunter G, Collins RL, Zenk SN, Cummins S, Beckman R, et al. Does opening a supermarket in a food desert change the food environment? Health and Place. 2017;46(Supplement C):249.

24. Maleki-Yazdi KA, Peñalvo JL, Marsden D, Rompay MV, Micha R, Mozaffarian D. Abstract P289: The Neighborhood Food Environment and Change in Body Mass Index: A Systematic Review and Meta-Analysis of Longitudinal Studies. Circulation. 2017;135(Suppl 1):AP289.

25. Gamba RJ, Schuchter J, Rutt C, Seto EYW. Measuring the Food Environment and its Effects on Obesity in the United States: A Systematic Review of Methods and Results. Journal of Community Health. 2015;40(3):464.

26. Zenk SN, Tarlov E, Wing C, Matthews SA, Jones K, Tong H, et al. Geographic Accessibility Of Food Outlets Not Associated With Body Mass Index Change Among Veterans, 2009–14. Health Affairs. 2017;36(8):1433.

27. Jones KK, Zenk SN, Tarlov E, Powell LM, Matthews SA, Horoi I. A step-by-step approach to improve data quality when using commercial business lists to characterize retail food environments. BMC Research Notes. 2017;10:35.

28. Boone-Heinonen J, Gordon-Larsen P, Guilkey DK, Jacobs DR, Popkin BM. Environment and physical activity dynamics: The role of residential self-selection. Psychology of Sport and Exercise. 2011;12:19.

29. Hawkesworth S, Silverwood RJ, Armstrong B, Pliakas T, Nanchahal K, Sartini C, et al. Investigating the importance of the local food environment for fruit and vegetable intake in older men and women in 20 UK towns: a cross-sectional analysis of two national cohorts using novel methods. The international journal of behavioral nutrition and physical activity. 2017;14:128.

30. Polsky JY, Moineddin R, Dunn JR, Glazier RH, Booth GL. Absolute and relative densities of fast-food versus other restaurants in relation to weight status: Does restaurant mix matter? Prev Med. 2016;82:28-34.

31. Clary C, Lewis DJ, Flint E, Smith NR, Kestens Y, Cummins S. The Local Food Environment and Fruit and Vegetable Intake: A Geographically Weighted Regression Approach in the ORiEL Study. American Journal of Epidemiology. 2016;184(11):837.

32. Clary CM, Ramos Y, Shareck M, Kestens Y. Should we use absolute or relative measures when assessing foodscape exposure in relation to fruit and vegetable intake? Evidence from a wide-scale Canadian study. Prev Med. 2015;71:83-7.

33. Lytle LA, Sokol RL. Measures of the food environment: A systematic review of the field, 2007–2015. Health and Place. 2017;44:18.

34. Sarkar C, Webster C, Gallacher J. Association between adiposity outcomes and residential density: a full-data, cross-sectional analysis of 419 562 UK Biobank adult participants. The Lancet Planetary Health. 2017;1(7):e277.

35. Saelens BE, Handy SL. Built environment correlates of walking: a review. Med Sci Sports Exerc. 2008;40(7 Suppl):S550-66.

36. Den Braver NR, Lakerveld J, Rutters F, Schoonmade LJ, Brug J, Beulens JWJ. Built environmental characteristics and diabetes: a systematic review and meta-analysis. BMC Med. 2018;16(1):12.

37. Egger G, Swinburn B. Ecological model and obesity. British Medical Journal. 1997;515(7106):477–80.

38. Hobbs M, Griffiths C, Green M, Christensen A, McKenna J. Examining longitudinal associations between the recreational physical activity environment, change in body mass index, and obesity by age in 8864 Yorkshire Health Study participants. Social Science and Medicine. 2018.

39. Block JP, Christakis NA, O’Malley AJ, Subramanian SV. Proximity to food establishments and body mass index in the Framingham heart study offspring cohort over 30 years. American journal of preventive medicine. 2011;27(3):211-7.

40. Boone-Heinonen J, Gordon-Larsen P, Kiefe CI, Shikany JM, Lewis CE, Popkin BM. Fast food restaurants and food stores: longitudinal associations with diet in young to middle-aged adults: the CARDIA study. Archives of internal medicine. 2011;171(13):1162-70.

41. Kanter R, Caballero B. Global Gender Disparities in Obesity: A Review. Advances in Nutrition: An International Review Journal. 2012;3(4):491.

42. Van Dyck D, Cerin E, De Bourdeaudhuij I, Salvo D, Christiansen LB, Macfarlane D, et al. Moderating effects of age, gender and education on the associations of perceived neighborhood environment attributes with accelerometer-based physical activity: The IPEN adult study. Health & place. 2015;36:65-73.

43. Stafford M, Cummins S, Macintyre S, Ellaway A, Marmot M. Gender differences in the associations between health and neighbourhood environment. Social science & medicine. 2005;60(8):1681-92.

44. Yoon N-H, Yoo S, Kwon S. Influence of Highly Accessible Urban Food Environment on Weight Management: A Qualitative Study in Seoul. International journal of environmental research and public health. 2018;15(4):755.

45. Imamura F, Micha R, Khatibzadeh S, Fahimi S, Shi P, Powles J, et al. Dietary quality among men and women in 187 countries in 1990 and 2010: a systematic assessment. The Lancet Global Health. 2015;3(3):e132-e42.

46. Smith D, Cummins S, Clark C, Stansfeld S. Does the local food environment around schools affect diet? Longitudinal associations in adolescents attending secondary schools in East London. BMC Public Health. 2013;13:70.

47. Green M, Li J, Relton C, Strong M, Kearns B, Wu M, et al. Cohort Profile: The Yorkshire Health Study. International Journal of Epidemiology. 2014:doi: 10.1093/ije/dyu121.

48. Wilkins E, Morris M, Radley D, Griffiths C. Validation of two secondary sources of food environment data against street audits in England. The Society For Social Medicine; Manchester, UK: Journal of Epidemiology and Community Health 2017.

49. Department for Communities and Local Government. Neighbourhood statistics: The English Indices of Deprivation 2015. London: Department for Communities and Local Government,; 2015.

50. Green MA. Do we need to think beyond BMI for estimating population-level health risks? Journal of Public Health. 2015.

51. ESRI. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute; 2011.

52. Smith G, Gidlow C, Davey R, Foster C. What is my walking neighbourhood? A pilot study of English adults' definitions of their local walking neighbourhoods. International Journal of Behavioral Nutrition and Physical Activity. 2010;7(1):34.

53. Wiki J, Kingham S, Campbell M. Accessibility to food retailers and socio-economic deprivation in urban New Zealand. New Zealand Geographer. 2018;0(0).

54. Gateshead Council. Hot food takeaway: supplementary planning document. Gateshead, UK2015.

55. Keeble M, Burgoine T, White M, Summerbell C, Cummins S, Adams J. How does local government use the planning system to regulate hot food takeaway outlets? A census of current practice in England using document review. Health & place. 2019;57:171-8.

56. Zenk SN, Mentz G, Schulz AJ, Johnson-Lawrence V, Gaines CR. Longitudinal Associations Between Observed and Perceived Neighborhood Food Availability and Body Mass Index in a Multiethnic Urban Sample. Health Education & Behavior. 2016;44(1):41.

57. Green MA, Radley D, Lomax N, Morris MA, Griffiths C. Is adolescent body mass index and waist circumference associated with the food environments surrounding schools and homes? A longitudinal analysis. BMC Public Health. 2018;18(1):482.

58. Hajna S, Ross NA, Brazeau A-S, Bélisle P, Joseph L, Dasgupta K. Associations between neighbourhood walkability and daily steps in adults: a systematic review and meta-analysis. BMC Public Health. 2015;15(1):768.

59. Myers CA, Denstel KD, Broyles ST. The context of context: Examining the associations between healthy and unhealthy measures of neighborhood food, physical activity, and social environments. Preventive Medicine. 2016;93:21.

60. Hobbs M, Griffiths C, M G, Jordan H, Saunders J, McKenna J. Neighbourhood typologies and associations with body mass index and obesity: a cross-sectional study Preventive Medicine. 2017.

61. Glanz K, Sallis J, Saelens B, Frank L. Healthy nutrition environments: concepts and measures. American Journal of Health Promotion. 2005;19(5):330.

62. Penney T, Almiron-Roig E, Shearer C, McIsaac J, Kirk S, editors. Modifying the food environment for childhood obesity prevention: challenges and opportunities. Nutrition Society Meeting: Conference on 'Childhood nutrition and obesity: current status and future challenges'; 2014; Dublin.

63. Lucan SC, Varona M, Maroko AR, Bumol J, Torrens L, Wylie-Rosett J. Assessing mobile food vendors (a.k.a. street food vendors)-methods, challenges, and lessons learned for future food-environment research. Public Health. 2013;127(8):766.

64. Abdullah NN, Mokhtar MM, Bakar MHA, Al-Kubaisy W. Trend on Fast Food Consumption in Relation to Obesity among Selangor Urban Community. Procedia - Social and Behavioral Sciences. 2015;202(Supplement C):505.

65. Lamichhane AP, Warren J, Puett R, Porter DE, Bottai M, Mayer-Davis EJ, et al. Spatial patterning of supermarkets and fast food outlets with respect to neighborhood characteristics. Health and Place. 2013;23:157.

66. Meyer K. Combined measure of neighborhood food and physical activity environments and weight-related outcomes: the CARDIA study. Health and Place. 2015;33.

67. Pearce J, Blakely T, Witten K, Bartie P. Neighborhood deprivation and access to fast-food retailing: a national study. American journal of preventive medicine. 2007;32(5):375.

68. Maguire ER, Burgoine T, Monsivais P. Area deprivation and the food environment over time: A repeated cross-sectional study on takeaway outlet density and supermarket presence in Norfolk, UK, 1990-2008. Health and Place. 2015;33:142.

69. Demrican M, editor Site selection in fast food industry. Proceedings of the International Symposium of GIS; 2002 9-23-2002.

70. May Goodwin D, Mapp F, Sautkina E, Jones A, Ogilvie D, White M, et al. How can planning add value to obesity prevention programmes? A qualitative study of planning and planners in the Healthy Towns programme in England. Health and Place. 2014;30:120.

71. Petticrew M, Whitehead M, Macintyre SJ, Graham H, Egan M. Evidence for public health policy on inequalities: 1: The reality according to policymakers. Journal of Epidemiology and Community Health. 2004;58(10):811.

72. McQueen DV. Strengthening the evidence base for health promotion. Health promotion international. 2001;16(3):261.

73. Hobbs M, Green M, Griffiths C, Jordan H, Saunders J, McKenna J. How different data sources and definitions of neighbourhood influence the association between food outlet availability and body mass index: a cross-sectional study. Perspectives in Public Health. 2016.

74. Falkingham J, Sage J, Stone J, Vlachantoni A. Residential mobility across the life course: Continuity and change across three cohorts in Britain. Advances in Life Course Research. 2016;30(Supplement C):111.

## Tables

**Table 1** - The correlation of different food outlets within residential neighbourhoods (n=8,864)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Large Supermarkets** | **Speciality** | **Restaurants** | **Fast-food** | **Convenience** | **Café** |
| **Large supermarkets** |  | 0.391 | 0.489 | 0.528 | 0.358 | 0.386 |
| **Speciality** |  |   | 0.465 | 0.642 | 0.431 | 0.514 |
| **Restaurants** |  |   |   | 0.548 | 0.455 | 0.498 |
| **Fast-food** |  |   |   |   | 0.713 | 0.661 |
| **Convenience** |  |   |   |   |   | 0.470 |
| **Café** |  |  |  |  |  |  |
| All food outlet correlations (rho) were statistically significant (p<0.001). Correlations are calculated between the count of food outlets within 1600m of participant postcode. |

**Table 2** – Cluster and sample characteristics by food environment type (n=8,864)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Overall**(n=8,864) | **Cluster 1**(n=2,973) | **Cluster 2**(n=1,224) | **Cluster 3**(n=4,667) |
| **Cluster characteristics** **Food outlets1** Restaurant Café Fast-food Speciality Convenience  Large supermarket **Population density2** (/ha2)**Sample characteristics**  **Age (years)** 18-35 36-45 46-55 56-65 66-75 76+ | 3.0 (4.0)1.0 (2.0)4.0 (7.0)1.0 (2.0)3.0 (4.0)1.0 (1.0)30.64 (26.21)799 (9.0)1,028 (11.6)1,678 (18.9)2,552 (28.8)2,108 (23.8)699 (7.9) | 3.0 (4.0)1.0 (2.0)4.0 (5.0)1.0 (3.0)3.0 (2.0)1.0 (1.0)33.85 (15.59)241 (8.1)345 (11.6)570 (19.2)847 (28.5)724 (24.4)246 (8.3) | 8.0 (10.0)2.0 (3.0)10.0 (8.0)3.0 (5.0)6.0 (4.0)1.0 (1.0)50.55 (21.25)170 (13.9)150 (12.3)219 (17.9)340 (27.9)269 (22.0)76 (6.2)  | 2.0 (3.0)0.0 (1.0)2.0 (5.0)0.0 (1.0)2.0 (2.0)0.0 (1.0)23.36 (29.46)388 (8.3)533 (11.4)889 (19.0)1,365 (29.2)1,115 (23.9)377 (8.1) |
|  **Gender** Male Female | 3,818 (43.1)5,046 (56.9) | 1,275 (42.9)1,698 (57.1) | 524 (42.8)700 (57.2) | 2,019 (43.3)2,648 (56.7) |
|  **Education**  Low Moderate  High  | 1,793 (20.2)4,608 (52.0)2,463 (27.8) | 653 (22.0)1,569 (52.8)751 (25.3) | 233 (19.0)582 (47.5)409 (33.4) | 907 (19.4)2,457 (52.6)1,303 (27.9) |
|  **BMI2 (kg/m2)** W1 W2  **Mean change in BMI** W2-W1 (kg/m2) **Area-level deprivation** Q1 (least deprived)  Q2 Q3 Q4 (most deprived) | 26.42 (4.71)26.41 (4.72)-0.012,337 (26.4)2,172 (24.5)2,221 (24.1)2,134 (24.1) | 26.56 (4.69)26.50 (4.61)-0.06 882 (29.7)548 (18.4)713 (24.0)830 (27.9) | 26.13 (4.68)26.21 (4.79)0.08280 (22.9)228 (18.6)415 (33.9)301 (24.6) | 26.40 (4.71)26.40 (4.76)0.001,175 (25.2)1,396 (29.9)1,093 (23.4)1,003 (21.5) |
| Data are n (%) unless stated as: 1Median (Interquartile range) or 2Mean (Standard Deviation). W1= wave I of data collection (2010-2013); W2= wave II of data collection (2013-15). |

**Table 3** – Longitudinal findings (n=8,864) from multilevel linear regression investigating the association between food environment type and change in BMI (b [95% CI])

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Model 1:**  | **Model 2:**  | **Model 3:**  |
| Intercept Food environment type \* time Cluster 1 \* Time 2 Cluster 2 \* Time 2 Cluster 3 \* Time 2 TimeFood environment type Cluster 1 Cluster 2 Cluster 3Age 18-35 36-45 46-55 56-65 66-75 76+Gender      Male     FemaleEducation      Low     Moderate      High Area-level deprivation  Q1 Q2 Q3 Q4Level-3 variance Level-2 variance Level-1 variance  | 26.733 [26.481, 26.985]REF0.145 [-0.279, 0.570]0.066 [-0.227, 0.359]-0.064 [-0.294, 0.164]REF-0.347 [-0.725, 0.030]-0.047 [-0.337, 0.243]REF-----REF-REF--REF---2.583 [2.119, 3.151]6.51e-17 [6.44e-18, 6.58e-16]20.404 [19.975, 20.841] | 26.180 [25.796, 25.565]REF0.145 [-0.274, 0.565]0.066 [-0.224, 0.356]-0.065 [-0.291, 0.161]REF-0.245 [-0.614, 0.123]-0.029 [-0.310, 0.251]REF**0.971 [0.671, 1.271] \*****1.523 [1.246, 1.801] \*****1.792 [1.525, 2.059] \*****1.539 [1.258, 1.821] \***0.808 [0.461, 1.156] REF**-0.471 [-0.607, -0.247] \***REF**-0.435 [-0.624, -0.247] \*****-1.288 [-1.516, 1.061] \***REF---2.036 [1.636, 2.534]1.29e-16 [8.11e-18, 2.04e-15]19.912 [19.493, 20.339] | 24.939 [24.450, 25.429]REF 0.146 [-0.274, 0.566]0.065 [-0.224, 0.356]-0.064 [-0.291, 0.162]REF-0.227 [-0.587, 0.131]0.037 [-0.232, 0.307]REF**0.993 [0.693, 1.293] \*****1.543 [1.267, 1.820] \*****1.827 [1.561, 2.094] \*****1.583 [1.302, 1.864] \*****0.841 [0.495, 1.188] \***REF**-0.466 [-0.602, -0.330] \*** REF**-0.374 [-0.563, -0.186] \*****-1.165 [-1.393, -0.936] \***REF**0.599 [0.157, 1.041] \*****1.003 [0.590, 1.416] \*****1.977 [1.579, 2.376] \***1.339 [1.035, 1.734]8.73e-17 [6.50e-18, 1.17e-15]19.949 [19.530, 20.377] |
| Values are b [95% CI]. \*p<0.05.  |