



Impact of subjective and objective neighbourhood characteristics and individual socioeconomic position on allostatic load: A cross-sectional analysis of an all-age UK household panel study

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ARTICLE INFO

Keywords:

Inequalities
Allostatic load
Neighbourhood
Socioeconomic status

ABSTRACT

Research suggests that individuals living in more disadvantaged neighbourhoods experience higher levels of stress but this has generally been based on self-reported stress. We used survey-based neighbourhood quality indicators and biomarker data from *Understanding Society*, linked to census and crime statistics to explore associations of allostatic load (AL), an objective biomarker-based measure of cumulative stress, with subjective and objective neighbourhood characteristics. Analyses of 6887 respondents living in England show greater AL among those living in more disadvantaged areas, with objective measure associations stronger than subjective. Neighbourhood inequalities in AL were lower among respondents with higher individual SEP. These results suggest that individual-level SEP mitigates against the impact of negative, particularly objective, neighbourhood characteristics. Policies to reduce health inequalities should consider both individual and neighbourhood circumstances.

1 Introduction

Place and area-based effects on health have been well-researched by geographers, social scientists and public health researchers (Arcaya et al., 2016; Diez Roux, 2001; Macintyre and Ellaway, 2003); it is an important and well-established framework for understanding environmental influences on behaviours and health outcomes (Kwan, 2018). For example, area-based environmental and deprivation measures have been associated with higher BMI, being overweight or obese, worse self-reported health and coronary artery calcification (Schüle and Bolte, 2015) and their related risk factors (Riva et al., 2007), and with lung function, blood pressure and inflammatory markers (Chaparro et al., 2018). Neighbourhood environment and its design is associated with health and wellbeing outcomes across all age groups, for example, systematic reviews have presented associations of neighbourhood condition with functional loss and neighbourhood deprivation with poor mental health (Ige-Elegbede et al., 2020).

Neighbourhood effects on health are multidimensional, including both social and environmental influences (Diez Roux, 2001; Kwan, 2018), and it is important to explore both subjective and objective

characteristics of these. Both subjective and objective neighbourhood characteristics influence health outcomes, for example individuals who reported a higher level of perceived street-level incivilities have been reported as being twice as likely to report feelings of anxiety and depression compared to those who perceived the lowest levels of street-level incivilities (Ellaway et al., 2009). Worsening neighbourhood factors, including crime and disorder, social environment, and physical environmental factors, have also been associated with increased anxiety and depression scores (Olsen et al., 2017). Subjective neighbourhood environment measures are based on residents' perceptions and assessment of neighbourhood features (Zhang et al., 2019) and include, for example, individual assessments of neighbourhood quality, neighbourhood stress, safety, and social cohesion (Yakubovich et al., 2020). Objective neighbourhood environment measures may be derived from secondary or spatial datasets to provide neighbourhood context (Zhang et al., 2019), and typically include deprivation and crime statistics. However, area-based measures can also encompass aspects of the social environment (Oberndorfer et al., 2022). For example Durkheim's theory of social fragmentation recognises the negative impact of living in areas characterised by unstable social bonds and lack of permanency in local

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<https://doi.org/10.1016/j.healthplace.2022.102930>

Received 27 April 2022; Received in revised form 14 October 2022; Accepted 21 October 2022

Available online 5 November 2022

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social relations (Durkheim, 1952). A census-derived measure of social fragmentation has been derived (Congdon, 1996), which refers to a lack of social integration into society and is based on measuring individuals with less stable social institutions and social bonds, including the family and religion (Stafford et al., 2008). It has been widely employed in the mental health literature (Stafford et al., 2008). For example, it has been found to be associated with loneliness and social isolation independent of other factors (Lai et al., 2021) as well as negative health outcomes such as suicide (Whitley et al., 1999), and mental health functioning (Stafford et al., 2008). Objective and subjective neighbourhood characteristics have been shown to have diverse effects on health outcomes, both positive and negative (Zhang et al., 2019) and with varying effect sizes (Godhwani et al., 2019). For example, objective neighbourhood deprivation measures have been shown to have stronger and more consistent associations with health outcomes than those with subjective measures (Godhwani et al., 2019; Gong et al., 2016), which accumulate over the life course (Jivraj et al., 2020; Yakubovich et al., 2020). It is therefore important to explore the differential effects of objective and subjective neighbourhood measures to better understand their health impacts whilst controlling for factors such as age, gender and individual socioeconomic position, which may modify these relationships (Schüle and Bolte, 2015).

Socioeconomic health inequalities are present globally, with higher socioeconomic position associated with better health (Beckfield et al., 2013) and longer life expectancy (Lago et al., 2018). Socioeconomic health inequalities are shown to be present when applying individual-level indicators of socioeconomic position, including income (Jutz, 2015) and education, an important determinant of occupational level (Klokgetiers et al., 2021). Area-based deprivation, as well as individual income, also yields health inequalities (Siegel et al., 2015) and the relationship between individual-level measures, ecological measures and health is complex (Ingleby et al., 2020). This is largely because the relationship between individuals' socioeconomic position and their health outcomes vary according to their socioeconomic context (Ingleby et al., 2020). Differences have been found in the magnitude of neighbourhood characteristics and health outcomes across different levels of neighbourhood disadvantage, when using cross-level interactions. For example, individuals with the lowest household income or education-levels were most likely to report worse self-reported health across each quintile of neighbourhood disadvantage (Badland et al., 2013). Sex, ethnicity and individual socioeconomic position have also been shown to modify the relationship between the built environment and health (Schüle and Bolte, 2015). It is important to further explore the multiple contexts that can influence socioeconomic health inequalities, ranging from individual-level to ecological measures using multilevel modelling techniques to examine cross-level effects (Moran et al., 2016).

Conventionally, individual stress measures, to investigate with neighbourhood environments, have been quantified using validated survey instruments (Badland et al., 2013; Gibbons, 2019; Olsen et al., 2017), such as the perceived stress scale (Cohen et al., 1994). However, developments in the collection of biomarker data for large population studies have provided the opportunity to collect objective measures of stress that could shed light on how features of the environment may impact health (Gidlow et al., 2016; Thompson et al., 2012). Biomarkers are an important tool for understanding exposure and risk from the environment as well as providing early warnings or evidence of biological effect (Travis, 2013). Allostatic load (AL) is a biomarker-based measure of cumulative stress (McEwen, 2015) and has been used to explore associations between stress and processes leading to disease (Hansen et al., 2014). Evidence shows that biological measures of stress, based on AL, are associated with a number of individual factors such as age, gender, income and race. There is also strong evidence of individual socioeconomic inequalities in AL (Prior et al., 2018; Robertson and Watts, 2015), particularly in terms of education, income and occupational social class (Seeman et al., 2014), as well as reported associations

with individuals' social relations (Rouxel et al., 2022). In addition, AL has been found to mediate the relationship between neighbourhood deprivation and both physical and mental health outcomes in the UK, providing strong evidence of a stress pathway acting between neighbourhoods and health (Prior et al., 2018).

There is a growing body of research from different countries investigating the association between neighbourhood characteristics and AL (controlling for individual socioeconomic status), which suggests that neighbourhood socioeconomic status affects health outcomes through its simultaneous and cumulative impact on a number of interrelated biological systems (Bird et al., 2010; Merkin et al., 2009). For example, lower objective census-based neighbourhood socioeconomic status has been shown to be associated with increased AL in the NHANES III study (Bird et al., 2010) and in MIDUS (Robinette et al., 2016) in the USA, although not in Puerto Rico (Jiménez et al., 2015). In addition, an analysis of the Chinese Health and Nutrition Survey has reported associations of high urbanicity with high AL (Xu, 2018). The biological strain of living in more socioeconomic deprived areas has been shown to vary according to individual characteristics, such as race (Merkin et al., 2009) and sex (Kezios et al., 2022), and also according to perceptions of the living environment. However, studies that explore perceptions of neighbourhoods have not always controlled for actual neighbourhood characteristics. For example, an analysis of the US Health and Retirement Survey found perceived neighbourhood cohesion but not disorder was associated with cardiometabolic risk (a subset of systems in AL) (Robinette et al., 2018), while an analysis of a Danish cohort study found neighbourhood perceptions to be associated with AL but was only able to control for the neighbourhood and not its characteristics (van Deurzen et al., 2016). We have only found three studies that combine objective and subjective measures of neighbourhoods with AL. In a study in a Texas city Buschmann et al. (2018), found AL to be associated with perceived measures of neighbourhood (crime, overall satisfaction, and cohesion) after controlling for individual variables, but not with an objective measure of neighbourhood socioeconomic status based on economic census variables. In a small study in Detroit, Schulz et al. (2013) found that both objective and subjective measures of the environment helped to explain the association between neighbourhood poverty and AL while controlling for individual socioeconomic circumstances. In the only (to our knowledge) representative survey to look at this (MIDUS), Carbone (2020) found a latent variable of perceptions of the neighbourhood covering trust, safety and cohesion measures; the subjective measure of neighbourhood was significant, but not the objective measure based on economic census indicators.

There is also a growing body of evidence suggesting that certain neighbourhood factors, such as greater neighbourhood trust and safety, may mediate the relationship between neighbourhood socioeconomic status and health outcomes (Jakobsen et al., 2022). Evidence has shown that both objective and subjective neighbourhood factors may mediate the association between neighbourhood socioeconomic status and cumulative biological wear and tear (AL) (Schulz et al., 2013). However, protective factors that mediate this relationship are not always the same for individuals with low and high (individual) socioeconomic position (Chen and Miller, 2013). As AL has been shown to be an important marker of neighbourhood socioeconomic status, it is important to explore whether certain neighbourhood qualities could be equigenic (disrupting the relationship between neighbourhood socioeconomic status and poor health) and if these differ between subjective and objective neighbourhood qualities, and individual-level socioeconomic position.

In this study, therefore, we investigate the association between AL and both subjective and objective neighbourhood measures and individual-level socioeconomic position in a nationally representative sample of the UK population. Drawing on the existing literature we have identified three domains of the environment that may be important for AL: general circumstances, social relations, and crime and safety, and have identified both objective and subjective measures for them. This

research will shed light on whether these associations exist outside of the USA and consider what domains of neighbourhood are important. In addition, it will explore whether objective or subjective measures are more influential and examine the role of individual socioeconomic status.

We have used self-reported neighbourhood quality indicators and biomarker data from a large representative survey of UK adults linked to census data and UK Home Office crime statistics to explore associations of AL with subjective and area-based objective neighbourhood characteristics, and individual socioeconomic position. In particular, we aim to understand: (i) if there is a difference in the strength of associations between AL and objective versus subjective neighbourhood characteristics and (ii) if these associations vary according to individual socioeconomic position. Improvements in life expectancy in the United Kingdom (UK) have stalled since 2011 and evidence suggests that health inequalities are widening (Marmot, 2020), highlighting the need for a wide range of interventions that improve health and reduce health inequalities. Here, by using AL as a robust measure of cumulative stress we are able to assess both subjective and objective neighbourhood measures and cross-level interactions of individual socioeconomic position. The results may provide important evidence to support interventions that improve health and reduce inequalities.

2 Methods

Analyses are based on data from *Understanding Society*, the UK Household Longitudinal Study (UKHLS) (Buck and McFall 2011; University of Essex, 2021) details of which have been reported previously (Lynn, 2009). Briefly, the UKHLS, which began in 2009, is a longitudinal survey of initially ~40,000 households in England, Scotland, Wales and Northern Ireland with data currently available from eleven collection waves. At Waves 2 and 3 (collected between 2010 and 2012) separate nurse health assessments were carried out and blood samples collected from the General Population Sample and the former British Household Panel Survey (Benzeval et al., 2014; McFall et al., 2014). The current analyses are based on respondents who took part in the nurse health assessments, from which at least one blood biomarker was obtained, and who completed the mainstage interview at waves 2 and 3. In order to link survey data to relevant objective area characteristics attention was restricted to respondents living in England who lived at the same address in both waves 2 and 3, to ensure that neighbourhood characteristics were relevant to the period in which AL was measured and to avoid associations being impacted by the short-term impact of moving.

2.1 Allostatic load

AL (McEwen, 1998) was derived from biomarker data following the approach developed by Seeman et al. (2004) and is based on the number of “worst” quartiles (derived separately for gender and 10 year age group) across 11 measures. The biomarkers covered physiological systems involved in allostatic load available in *Understanding Society* (Chandola and Zhang, 2018): the neuroendocrine system (DHEA-S, insulin growth factor 1); the metabolic system (ratio of total to HDL cholesterol, triglycerides, HbA1c, creatinine clearance rate); the immune and inflammatory systems (C-reactive protein, C-reactive protein); the cardiovascular system (systolic and diastolic blood pressure); and the anthropometric system (waist-to-height ratio). Adjustments were made to the biomarkers to account for the effect of medications, so that the score represents underlying health rather than the outcome of treatment (Chandola et al., 2019; Robertson and Watts, 2015). Worst quintiles were as follows: Creatinine clearance rate (lowest quartile); Dehydroepiandrosterone Sulfate (lowest quartile); Insulin-like growth factor (lowest quartile); C-reactive protein (accounting for statins, hormone replacement, contraception, and anti-inflammatories) (highest quartile); Total-HDL cholesterol ratio (accounting for statins) (highest quartile); Triglycerides (highest quartile); Haemoglobin A1c

(accounting for anti-inflammatory and aspirin use) (highest quartile); Systolic blood pressure (accounting for anti-hypertensives) (highest quartile); Diastolic blood pressure (accounting for anti-hypertensives) (highest quartile); Waist-height ratio (highest quartile); Fibrinogen (accounting for hormone replacement, contraception, anti-fibrinolytic and haemostatics) (highest quartile). AL is then represented by a score from 0 to 11 with higher scores indicating greater cumulative stress.

2.2 Neighbourhood characteristics

Three subjective neighbourhood characteristics were identified from respondents' questionnaire data. The first was based on responses to a summary question “Overall, do you like living in this neighbourhood – yes or no?”. The second social capital measure, based on the Project on Human Development in Chicago Neighborhoods scale (Project on Human Development in Chicago Neighbourhoods), is the sum of positive responses (agree or strongly agree) to three statements: “This is a close-knit neighbourhood”, “People in this neighbourhood are willing to help their neighbours”, “People in this neighbourhood can be trusted”; and negative responses (disagree or strongly disagree) to one: “People in this neighbourhood don't get along”. Finally a crime and safety measure was based on the number of positive responses to two statements regarding crime and safety: “Do you ever worry about the possibility that you, or anyone else who lives with you, might be the victim of crime” (no/just an occasional doubt); “How safe do you feel walking alone in this area after dark?” (very or fairly safe). In all of these questions the definition of neighbourhood is left to the respondent to interpret as appropriate for themselves.

Three objective neighbourhood measures were derived at the Lower Layer Super Output Area (LSOA) level using linked external data. Firstly, Townsend score (Townsend et al., 1988) was calculated from 2011 census data as a measure of material deprivation using: % individuals in the area who were unemployed (out of all those aged 16–74); % households with no access to car or van (out of all households); % households not owned (out of all households); and % household overcrowding based on negative occupancy (out of all households). For each variable the % of interest was calculated, log transformed (as all distributions were skewed), and standardised (to z-score) before summing to create a continuous variable, which was then grouped into quintiles based on all LSOAs in England. A census-based social fragmentation score (Congdon, 1996) was also derived based on: % single person households (out of all households); % people not married/civil partnership (out of all people); % people living in privately rented accommodation (out of all people); % people who didn't live at same address a year ago. This index has been widely used elsewhere (Davey Smith et al., 2001; Stafford et al., 2008; Whitley et al., 1999) and reflects potential lack of close/intimate relationships and transient residence in the area. Again, percentages were log-transformed and standardised before calculating score quintiles. Finally, objective neighbourhood area crime rates were derived from 2011 Home Office data (Home Office, 2018). The total number of reported crimes of any type was calculated for each LSOA; there was no restriction to any particular subtype of crime for consistency with the subjective question, which did not specify any crimes of particular interest. LSOAs were again subdivided into quintiles according to crime rates.

2.3 Socioeconomic position

Individual socioeconomic position was assessed in three ways. The first focussed on highest educational qualification, with respondents classed as: Degree, Other higher level qualification, A-level or equivalent, GCSE or equivalent, Other, or No qualification. Secondly total net household income from all sources was derived and grouped in quintiles (Fisher et al., 2019). Finally occupational social class was determined from respondents' current or, if not working, most recent occupation and grouped according to the Five Class National Statistics

Socioeconomic classification (NS-SEC): Management and professional, Intermediate, Small employers and own account, Lower supervisory and technical, and Semi-routine, routine and never worked.

2.4 Dataset

Analyses are based on respondents with complete data for AL, socioeconomic position, and all subjective and objective neighbourhood variables. A total of 11,955 respondents took part in the main and nurse surveys and gave a blood sample that was used to produce biomarkers and, when weighted, are representative of the UK population net of those who were ineligible. In all, 9915 of these respondents lived at the same address in England in waves 2 and 3 and, of these, 6887 (69.5%), 6847 (69.1%), and 6396 (64.5%) had complete data for AL, all neighbourhood variables and education, income and occupational socioeconomic position respectively. The weighted characteristics of the representative, non-moving respondents living in England, and analytical samples for analyses of educational qualification are presented in Table 1. Based on available data, restriction to non-movers living at addresses in England had no impact on the representativeness of the sample while those included in the analytical sample were only marginally more likely to be older, have higher socioeconomic position, and live in a more advantaged neighbourhood.

2.5 Statistical methods

There was variation in the number and magnitude of categories in the socioeconomic position and neighbourhood variables, making direct comparison between their respective associations with AL difficult. We therefore derived an Index of Inequality (Kunst et al., 1998; Mackenbach and Kunst, 1997; Regidor, 2004) for each measure, which puts them all on the same scale and reduces the influence of extremes in the distribution of respondents in each category. The Index of Inequality is based

Table 1

Weighted characteristics of representative, non-moving respondents in addresses in England, and analytical samples for analysis of neighbourhood and educational qualification.

	Representative baseline sample (N = 11,955)	Non-moving, living in England, non-proxy sample (N = 9915)	Analytical sample (N = 6887)
% male	45.2	45.2	45.4
% aged <45	46.4	46.3	43.6
% A level qualification or higher	54.5	54.1	54.8
% manager/professional/intermediate occupation	47.0	47.2	49.4
% highest income quintile	18.8	18.3	19.4
% like living in neighbourhood	93.4	93.2	94.0
% lowest (least deprived) Townsend score quintile	19.7	19.5	17.5
% 3+ positive social capital responses	57.6	57.0	58.6
% lowest social fragmentation score quintile	20.7	20.8	22.0
% 2 positive crime & safety responses	46.3	44.9	46.2
% lowest area crime quintile	19.3	19.4	20.6

on the cumulative proportion ranking of the study population and produces a score between 0 and 1 (the lowest and highest possible respectively) based on the midpoint of the proportion of the population in each category. For example, if the proportion of respondents in a four-category measure is 0.1 (lowest), 0.3, 0.4, and 0.2 (highest) then respondents in the lowest category are assigned its midpoint value of 0.05 (0.1 ÷ 2), and those in subsequent categories are given values of 0.25 (0.1 + 0.3 ÷ 2), 0.6 (0.1 + 0.3 + 0.4 ÷ 2) and 0.9 (0.1 + 0.3 + 0.4 + 0.2 ÷ 2) respectively. Using this method, the different socioeconomic position and neighbourhood variables were all scaled from most to least advantaged, on a scale between 0 and 1. The Slope Index of Inequality (SII) for each measure was obtained by regressing AL on the corresponding Index of Inequality and compares those with the least versus most advantaged socioeconomic position or neighbourhood characteristic. Associations calculated in this way for different socioeconomic position and neighbourhood variables are then comparable.

Age and gender-adjusted multilevel models were used throughout to account for the non-independence of individuals clustered within households and LSOAs. For each socioeconomic position and neighbourhood characteristics we fitted a 3-level random intercept model with individual *i* nested in household *j*, which in turn is nested in area *k* as follows:

$$y_{ijk} = \beta_0 + \beta_1 x_{1ijk} + \beta_2 x_{2ijk} + \beta_3 x_{3ijk} + v_{0k} + u_{0jk} + e_{0ijk}$$

where:

$$y_{ijk} = \text{Allostatic load}; x_{1ijk} = \text{Socioeconomic position/neighbourhood variable};$$

$$x_{2ijk} = \text{Age}; x_{3ijk} = \text{Gender}$$

and *v*, *u* and *e* are error terms at the different levels:

$$v_{0k} \sim N(0, \sigma_{v_0}^2)$$

$$u_{0jk} \sim N(0, \sigma_{u_0}^2)$$

$$e_{0ijk} \sim N(0, \sigma_{e_0}^2)$$

Just under 60% of respondents lived in single-person households or were the only occupant included in the analyses with 3% of respondents coming from a household where there were three or more residents included in the analytical dataset. In terms of the LSOAs 40%, 36% and 14% had one, two or three respondents respectively; 10% of LSOAs had four or more respondents with the nine the maximum number.

In these regression models SII coefficients represent the difference in AL comparing the lowest versus the highest socioeconomic position and least versus most advantaged neighbourhood characteristics. Preliminary analyses considered individual associations of socioeconomic position and neighbourhood characteristics with AL, with separate age and gender-adjusted models fitted for each socioeconomic position or neighbourhood variable. Subsequent analyses explored neighbourhood inequalities in AL according to respondents' socioeconomic position. Socioeconomic position variables for these analyses were collapsed into three groups to allow for smaller numbers of respondents, e.g. separate age and gender-adjusted multilevel models were fitted to explore associations of AL with each neighbourhood characteristic for respondents with (a) post-school, (b) school level, and (c) no/other qualifications. All models included inverse probability weights to take account of unequal selection probabilities into the study and differential drop-out at each stage in the process of obtaining blood measures, viz. non-response to the wave, consent to give blood, successfully taking blood, and successfully extracting analytes from the blood sample (Benzeval et al., 2014). These weights ensure the results are reliable estimates representative of the adult population living in private households in England (Kaminska and Lynn, 2019). Results from analyses excluding London were almost identical to those presented here.

3 Results

Associations of AL according to socioeconomic position are presented in Table 2. Mean AL, calculated using inverse probability weights to ensure representativeness, was greater in those with lower socioeconomic position across all three measures, e.g. mean (SD) AL in respondents with degree level versus no qualifications was 2.5 (1.9) versus 4.0 (2.1). SII obtained from (separate) age and gender-adjusted multilevel models regressing AL on the Index of Inequality for each socioeconomic position variable compare AL in respondents with the least versus most advantaged position. These demonstrate a pattern of increasing AL with lower socioeconomic position across all measures and indicate that the strongest association was observed for highest educational qualification (SII (95% confidence interval (CI)) comparing those in the lowest versus highest category: 1.13 (0.93, 1.33)), i.e. respondents with the lowest educational qualification had, on average, 1.1 additional biomarker in the worst quartile compared with those with the highest qualifications. Associations with income and occupational socioeconomic position were weaker but still consistent with more biomarkers in the worst quartile among respondents with lower socioeconomic position (0.65 (0.45, 0.86) and 0.83 (0.63, 1.04) for income and occupation respectively).

AL associations with subjective and objective neighbourhood characteristics are presented in Table 3. Weighted means and SII were consistent with higher cumulative stress among respondents living in areas that were regarded less favourably by respondents and with greater objective measures of deprivation, social fragmentation and crime. The strongest associations were those with Townsend score (SII (95% CI) comparing highest versus lowest quintile of Townsend score (most versus least deprived area): 0.94 (0.76, 1.13), i.e. an additional biomarker in the worst quartile) and enjoying living in the neighbourhood (SII (95% CI) comparing respondents who did not versus did enjoy living in their neighbourhood: 0.74 (0.19, 1.29). Results for (subjective) social capital versus (objective) social fragmentation were broadly similar with just a suggestion of a stronger association with AL for the objective measure (0.42 (0.23, 0.62) versus 0.56 (0.37, 0.74) for social

Table 2

Weighted mean (SD) allostatic load and SII (95% CI) for difference in allostatic load comparing lowest versus highest education, income and occupational groups.

	Mean (SD)
Education	
Degree	2.5 (1.9)
Other higher	2.9 (2.0)
A-level	2.9 (2.0)
GCSE	3.1 (2.0)
Other	3.4 (2.0)
No qual	4.0 (2.1)
SII (95% CI)	1.13 (0.93, 1.33)
Income	
Highest quintile	2.6 (2.0)
4	2.9 (2.0)
3	3.1 (2.1)
2	3.4 (2.1)
Lowest quintile	3.2 (2.0)
SII (95% CI)	0.65 (0.45, 0.86)
Occupation	
Management/professional	2.7 (2.0)
Intermediate	2.9 (2.0)
Small employers/own account	3.0 (2.1)
Lower supervisory/technical	3.1 (1.9)
Semi-routine/routine/never worked	3.4 (2.1)
SII (95% CI)	0.83 (0.63, 1.04)

Table 3

Weighted mean (SD) allostatic load and SII (95% CI) for difference in allostatic load comparing least versus most advantaged subjective and objective neighbourhood characteristics.

	Mean (SD)		Mean (SD)
Enjoy living in neighbourhood		Townsend quintiles	
Yes	2.0 (2.0)	1 (Low)	2.7 (2.0)
No	3.4 (2.3)	2	3.0 (2.1)
		3	3.1 (1.9)
		4	3.2 (2.1)
		5 (High)	3.4 (2.2)
SII (95% CI)	0.74 (0.19, 1.29)	SII (95% CI)	0.94 (0.76, 1.13)
N good social capital variables (out of 4)		Social fragmentation quintiles	
4	3.0 (2.0)	1 (Low)	2.8 (2.0)
3	3.0 (2.0)	2	3.0 (2.0)
2	3.0 (2.1)	3	3.2 (2.1)
1	3.1 (2.2)	4	3.2 (2.0)
0	3.3 (2.1)	5 (High)	3.1 (2.1)
SII (95% CI)	0.42 (0.23, 0.62)	SII (95% CI)	0.56 (0.37, 0.74)
N good crime/safety variables (out of 2)		Area crime quintiles	
2	3.0 (2.0)	1 (Low)	2.8 (2.0)
1	3.1 (2.1)	2	3.0 (2.1)
0	3.4 (2.0)	3	3.0 (2.0)
		4	3.3 (2.0)
		5 (High)	3.3 (2.1)
SII (95% CI)	0.45 (0.25, 0.66)	SII (95% CI)	0.75 (0.57, 0.94)

capital versus social fragmentation). SII for respondent perceptions of crime/safety versus Home Office derived area crime suggested that AL associations with the objective measure (area crime) were stronger than those with the subjective measure (0.45 (0.25, 0.66) versus 0.75 (0.57, 0.94) for respondent perceptions versus area crime). Across the models, 1–3% of the total variance was attributed to the clustering effect at the LSOA level, 31–33% at a household level and, as is common in these kinds of models, 65–68% at an individual level, supporting the notion that individual characteristics are important predictors of AL.

Associations of AL with neighbourhood characteristics among respondents with post-school, school level and no/other qualifications are presented in Fig. 1. Results stratified by income and occupational socioeconomic position, based on smaller numbers of respondents, were somewhat weaker but broadly similar to those presented here. Bars represent weighted mean AL according to neighbourhood characteristics, with lighter bars corresponding to more advantaged areas, and are grouped according to highest educational qualification (none/other, school level, post-school level). SII from individual age and gender-adjusted multilevel models comparing the least versus most advantaged neighbourhood characteristics separately for respondents in each educational qualification group are represented by diamonds. As would be expected from results in Table 2, mean AL was greater in respondents with fewer qualifications across all neighbourhood characteristics. However, in addition, inequalities across most neighbourhood characteristics, represented by SII, were greater in respondent groups characterised by fewer educational qualifications. For example, SII (95% CI) for Townsend score among respondents with post-school, school level and no/other qualifications were: 0.37 (0.07, 0.67), 0.95 (0.67, 1.23), and 1.13 (0.75, 1.51) respectively (p for interaction = 0.004). So respondents with post-school qualifications living in the most versus least deprived areas had an additional 0.4 biomarkers in the worst quartile while respondents with no qualifications living in the most versus least

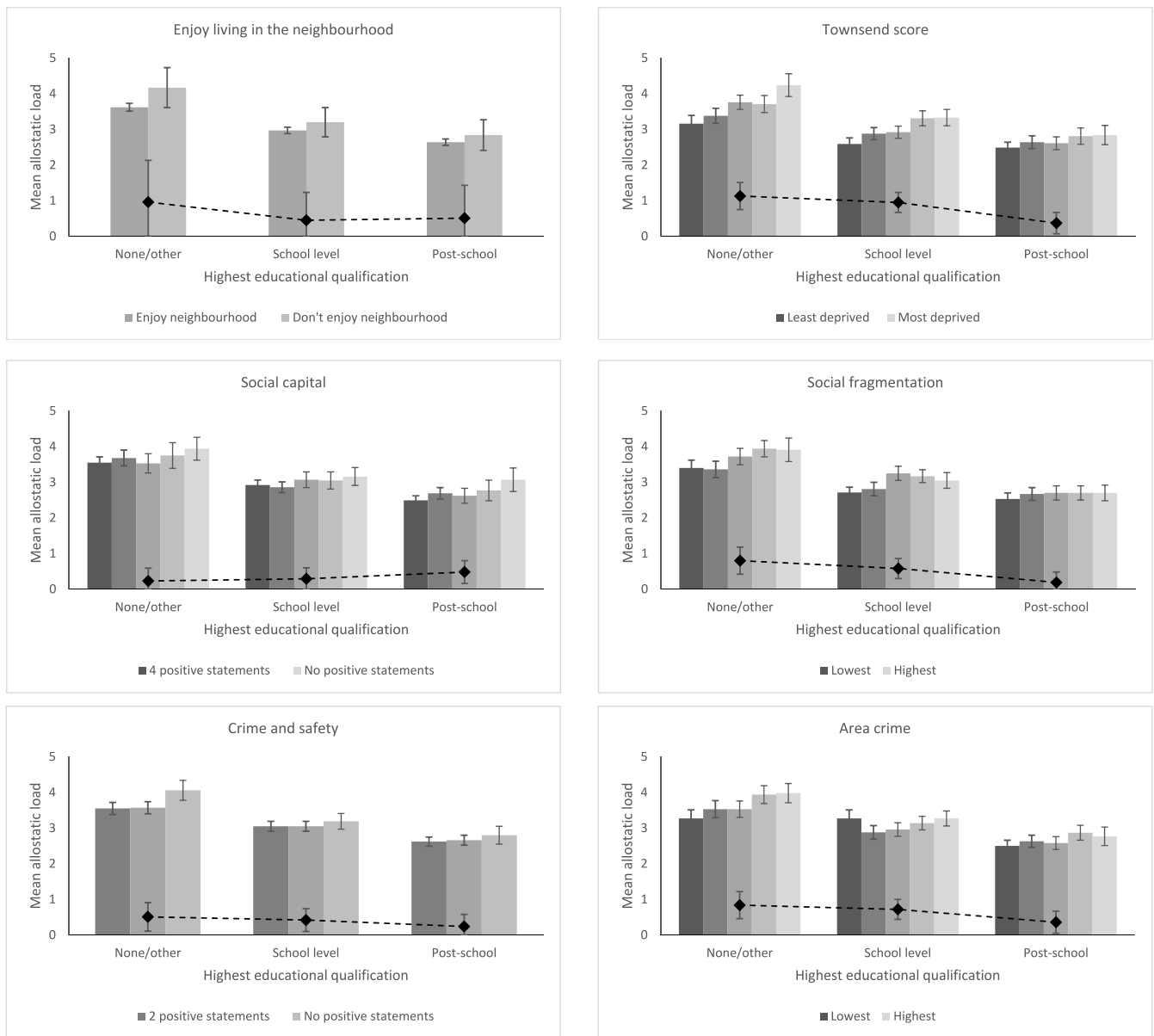


Fig. 1. Bars represent weighted mean (95% confidence interval) allostatic load by subjective and objective neighbourhood characteristics (adjusted for age and sex) stratified by highest educational qualification. Diamonds represent SII (95% confidence intervals) for weighted difference in allostatic load comparing least versus most advantaged neighbourhood characteristic.

deprived areas had 1.1 additional biomarkers in the worst quartile. Similar patterns were observed for social fragmentation (0.19 (−0.10, 0.48), 0.58 (0.30, 0.76), and 0.80 (0.42, 1.22); p for interaction = 0.03), perceived crime and safety (0.24 (−0.10, 0.58), 0.42 (0.10, 0.674), and 0.51 (0.011, 0.91); $p = 0.87$), and area crime (0.36 (0.05, 0.67), 0.72 (0.44, 1.00), and 0.84 (0.46, 1.22); $p = 0.13$). SIIs comparing those who did and did not enjoy living in their neighbourhood showed less marked differences across respondents with increasing educational qualification (0.51 (−0.41, 1.43), 0.45 (−0.33, 1.23), and 0.96 (−0.21, 2.13); $p = 0.82$), although comparisons were underpowered due to small numbers of respondents responding negatively. There was no evidence of a decline in SIIs according to social capital across the different respondent educational qualification groups (0.48 (−0.13, 0.59), 0.29 (−0.02, 0.60), and 0.23 (−0.13, 0.59); $p = 0.27$). It is also of note that, in general, AL was lower among higher qualified respondents living in more disadvantaged areas than for less qualified individuals living in more advantaged areas.

4Discussion

Results from the present study confirm previous findings of higher AL among individuals with lower socioeconomic position (Prior et al., 2018; Seeman et al., 2014). In addition, AL was greater among those who regarded their neighbourhood less favourably in general and in terms of social cohesion and crime/safety, or who lived in an area characterised objectively by higher levels of deprivation, social fragmentation and crime. These findings add to prior studies suggesting that living in areas with more crime (Olsen et al., 2017), weaker social cohesion (Elliott et al., 2014) and higher area-level deprivation (Ribeiro et al., 2019; Robertson and Watts, 2015) are associated with higher objective measures of stress. Similarly to previous studies (Zhang et al., 2019), we found that objective measures of neighbourhoods were somewhat more strongly associated with higher levels of stress than subjective measures.

Yakubovich et al. (2020) highlight that ecological measures should not be inferred as a definitive marker that neighbourhood characteristics

will affect health at an individual-level, and results from the current analyses further strengthen this argument. We found that overall, negative neighbourhood characteristics were associated with higher AL but individual-level socioeconomic status mitigated against this. Indeed, individuals with higher educational qualifications who resided in more disadvantaged areas often had similar levels of AL as those living in the most advantaged places but with fewer qualifications, suggesting that individual socioeconomic status can act as a protective factor against residing within areas characterised as less advantaged, more deprived, or with higher crime rates or poorer social cohesion.

Perceptions of place and perceived local problems have long been shown to be associated with a number of negative mental health outcomes (Ellaway et al., 2001; Macintyre et al., 2002); we show they are also associated with objective measures of physiological stress. We provide evidence that perceptions of place remain important and can act as a barrier to narrowing socioeconomic health inequalities. Our results suggest that the effect of individual-level socioeconomic status in narrowing inequalities across neighbourhood was weaker where individuals reported not enjoying living in an area. However, the majority of the unexplained variance in our model was at an individual level (65–68%) compared to area level (1–3%), highlighting that although “place” matters, individual-level factors are the most important determinants of physiological stress.

Our study contributes to the understanding of neighbourhood factors and inequalities in levels of stress by highlighting that individual level SEP can mitigate against living in areas with worse reported crime, that are less socially cohesive, and more disadvantaged. SEP gradients were more pronounced when applying education as a measure of SEP compared to income or occupation, although all three measures were statistically significant. This may reflect the more stable nature of education as a measure of disadvantage across the whole life course (Badland et al., 2013). Further, recent evidence has shown persistent exposure to disadvantage over the life course to be associated with worse AL (Prior, 2021). This provides two important messages; firstly, AL provides a robust temporal measure of stress and, secondly, policies to improve health must focus not only on strategies at an area-level but also at an individual-level.

The study has a number of strengths and limitations. Analyses are based on data from a large population-based survey of adults in England, with analytical weights used in all analyses to increase representativeness of the sample with the adult population living in England. The restriction to respondents living in England potentially limits the generalisability of our results to rest of UK because of the uniqueness of London. However, we conducted a sensitivity analysis including/excluding London, which did not influence the main results, and it is likely the results will be relevant to similar populations across the UK, Europe and Western developed countries. Analyses were based on respondents with complete data for AL and neighbourhood variables, introducing potential bias. Respondents included in the analyses were slightly older, had higher socioeconomic position, and tended to live in more advantaged neighbourhoods than the population from which they were drawn. Potentially, therefore, individuals with low socioeconomic status who were living in more disadvantaged areas, and who might be expected to have particularly high AL, were under-represented, meaning that associations presented here may be underestimates. The outcome measure, AL, was derived from biomarker data, offering an unbiased estimate of cumulative stress. However, this was only available at one time-point for each respondent, and it was therefore not possible to assess longitudinal changes with neighbourhood characteristics. Longitudinal life-course approach could also explore associations between neighbourhood characteristics and health that may operate in the other direction due to factors such as selection effects. Analyses were restricted to longer-term residents to ensure that associations were not impacted by short-term influences of moving in terms of stress and perceptions of a new neighbourhood. Associations with neighbourhood characteristics were based on both subjective (respondent self-report)

and objective (linked census and crime data) measures, allowing a direct comparison of the relative importance of perceived versus objective neighbourhood quality. However, the neighbourhood characteristics that were considered were determined by available data and do not cover all aspects of neighbourhood likely to be of importance for determining AL. In addition, although the census-based neighbourhood measures have been widely used in the literature, their success in capturing deprivation and social fragmentation may vary in different areas, and over time. For example, not having access to a car may not reflect deprivation to the same extent in very rural or urban areas and may be less of a concern today than when the index was first conceived. Likewise, being legally married may not reflect the ways in which complex family circumstances bind individuals to their communities in the same way that it perhaps did in the past. In addition high rates of private renting or moving house may reflect different neighbourhood characteristics in university towns, and different economic cycles. Similarly, our definition of areas was based on the scale at which all the contextual data were available, namely LSOA. We recognise that the scale at which neighbourhood effects are most important may vary although a recent review of neighbourhood effects across outcomes found little theoretical or empirical guidance on which scale different effects might operate (Knies et al., 2021). However, in an analysis of neighbourhood deprivation and life satisfaction, there was little evidence of the association varying at different scales (Knies et al., 2021). We explored each neighbourhood characteristic in separate models and therefore didn't investigate how relationships would change with simultaneous consideration of neighbourhood or individual socioeconomic variables. Finally, while the analytical sample was relatively large in this context, stratified analyses were inevitably based on smaller numbers and formal tests of statistical interaction, which are known to be under-powered (Brookes et al., 2001), may have been particularly impacted by this. This may be particularly true for our area-level variable 95% had fewer than 5 individuals within the LOSA and, although there is no specified cut off for individuals between level units when using multilevel models, this may have limited our ability to accurately assess variability at that level.

5 Conclusion

Inequalities in AL, an objective measure of cumulative stress on the body, are observed for both individual socioeconomic position and objective and subjective neighbourhood characteristics. These associations are stronger for objective measures of neighbourhood, and for overall measures rather than specific domains. However, having a higher socioeconomic position may protect against the negative impacts of poor neighbourhood perceptions and conditions, which are more marked among those with lower socioeconomic position whether measured by education, income or occupation. Policies to reduce stress, wellbeing and wider health outcomes should consider both individual and neighbourhood circumstances, particularly when both are unfavourable.

Funding

Understanding Society is an initiative funded by the Economic and Social Research Council (ESRC ES/M008592/1) and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. EW and JO are funded by the Medical Research Council (MC_UU_00022/2, MC_UU_00022/4) and Scottish Government Chief Scientist Office (SPHSU17, SPHSU19). MB is funded by ESRC (ES/S007253/1). The funders had no role in the study design, data collection, data analysis, data interpretation, or writing of the report.

Authors' contributions

EW and MB had the original idea for the study, which was developed with JO. EW carried out the statistical analyses. All authors critically revised the article, contributed to data interpretation and finalised and approved the manuscript.

Ethics approval and consent to participate

The University of Essex Ethics Committee has approved all data collection on Understanding Society main study. Approval for the collection of biosocial data by trained nurses in Waves 2 and 3 of the main survey was obtained from the National Research Ethics Service (Understanding Society - UK Household Longitudinal Study: A Biosocial Component, Oxfordshire A REC, Reference: 10/H0604/2).

Availability of data and materials

Data from the Understanding Society are available for download from the UK Data Service: Understanding Society: Waves 1–11, 2009–2020 and Harmonised BHPS: Waves 1–18, 1991–2009. SN: 6614, <http://doi.org/10.5255/UKDA-SN-6614-15> and Understanding Society: Waves 2 and 3 Nurse Health Assessment, 2010–2012. SN:7251. <http://doi.org/10.5255/UKDA-SN-7251-3>.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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