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ORIGINAL ARTICLE

Taking an intersectional approach to define latent classes of socioeconomic status, ethnicity and migration status for psychiatric epidemiological research

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Aims. Inequalities in mental health are well documented using individual social statuses such as socioeconomic status (SES), ethnicity and migration status. However, few studies have taken an intersectional approach to investigate inequalities in mental health using latent class analysis (LCA). This study will examine the association between multiple indicator classes of social identity with common mental disorder (CMD).

Methods. Data on CMD symptoms were assessed in a diverse inner London sample of 1052 participants in the second wave of the South East London Community Health study. LCA was used to define classes of social identity using multiple indicators of SES, ethnicity and migration status. Adjusted associations between CMD and both individual indicators and multiple indicators of social identity are presented.

Results. LCA identified six groups that were differentiated by varying levels of privilege and disadvantage based on multiple SES indicators. This intersectional approach highlighted nuanced differences in odds of CMD, with the economically inactive group with multiple levels of disadvantage most likely to have a CMD. Adding ethnicity and migration status further differentiated between groups. The migrant, economically inactive and White British, economically inactive classes both had increased odds of CMD.

Conclusions. This is the first study to examine the intersections of SES, ethnicity and migration status with CMD using LCA. Results showed that both the migrant, economically inactive and the White British, economically inactive classes had a similarly high prevalence of CMD. Findings suggest that LCA is a useful methodology for investigating health inequalities by intersectional identities.

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Introduction

Research addressing inequalities in mental health has generally explored such differences by using individual indicators of socioeconomic status (SES) or other key social identities, including ethnicity and migration status. The socioeconomic gradient observed for common mental disorder (CMD) is well documented (Lorant *et al.* 2003). A systematic review found overwhelming evidence for the association between indicators of low SES and symptoms of CMD in developed countries, with the most consistent associations for unemployment, less education and low income (Fryers *et al.* 2003; Jenkins *et al.* 2008; Butterworth *et al.* 2013). There are fewer studies examining the association between CMD with ethnicity and migration status. Although findings are not always consistent, studies generally find ethnic minorities have similar or higher levels of CMD than their ethnic majority counterparts (Williams *et al.* 1997; Weich *et al.* 2004) while migrants have been found to have fewer symptoms of CMD (Dey & Lucas, 2006). Whilst health inequalities by ethnic group appear to be reduced when adjusting for socioeconomic indicators (Nazroo, 2003), there still remains an independent health inequality that may be accounted for by discrimination and social exclusion (Williams, 1999).

SES is a broad term encompassing a number of constructs, but in epidemiological research it is typically

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assessed by a single item, such as social occupational class (SOC) (e.g., McFadden *et al.* 2009) or educational attainment (Cutler & Lleras-Muney, 2006). Relying on individual measures of SES does not account for short-term fluctuations or changes, such as underemployment (Feldman, 1996). Utilising a number of sources of information that can account more holistically for an individual's SES may be a more reliable approach. These other factors include education, housing tenure and household income, which have previously been used interchangeably as measures of SES even though they are based on different constructs (Geyer *et al.* 2006). A number of approaches have been used to create indices, which use multiple SES indicators to reflect a more holistic picture of SES, such as principal component analysis (Vyas & Kumaranayake, 2006; Psaki *et al.* 2014), yet as these indices summarise a number of variables into one continuous variable, they are still unable to describe and identify patterns regarding the intersection of these variables.

Epidemiological research that takes an intersectional approach can provide insight into the mechanisms of health inequality by identifying health burdens among those at different intersections of social position (Bauer, 2014). In particular, those identified to be in multiple disadvantaged social positions have been shown to be at more risk of reporting psychological distress than those in singly disadvantaged or privileged social positions (Grollman, 2014). Feminist theory, and particularly the concept of intersectionality (Crenshaw, 1991; Collins, 2000), proposes examination of multiple aspects of identity simultaneously to determine how privilege and disadvantage surrounding individuals' identities interlock and can impact on health. For example, the impact of becoming economically inactive on mental health may be very different depending on an individual's migration status. A commonly used intersectional method for quantitative analyses is latent class analysis (LCA). LCA can create a series of classes that allows for the study of not only multiple disadvantaged positions, but also those positions of privilege, as well as positions that occupy both (Nash, 2008). In quantitative analyses, simply controlling for any one of these social categories may lead to misleading conclusions, given that the experiences within these social categories is largely shaped by one's membership to other categories (Rosenfield, 2012; Garnett *et al.* 2014).

The current study uses community data from South East (Hatch *et al.* 2016, 2011), which compared with the national context, is not only diverse in terms of SES, but also in terms of both ethnicity and migration status. For example, 60.3% of Southwark's population identify as an ethnic minority compared with 19.5% of the UK population and the migrant population is also large, at 39% (Office for National Statistics, 2011). Both migration status and ethnicity are likely to intersect with SES indicators in different ways in this sample (Gazard *et al.* 2014). For example, ethnic minorities are more at risk of unemployment in South East London and migrants are less likely to be homeowners (Office for National Statistics, 2011).

The association between SES, ethnicity and migration status, used as individual indicators, with CMD is established. Therefore, the primary aim of this study is to develop understanding of these associations by using multiple indicators in LCA to take an intersectional approach. The South East London Community Health study (SELCoH) dataset, with its diversity across SES, ethnicity and migration status, represents an ideal opportunity to explore if different patterns of inequalities in mental health emerge using these multiple indicators simultaneously, in contrast to using individual indicators independently.

The objectives for this study are:

1. To define latent classes characterised by multiple indicators of SES;
2. To determine how the latent classes of SES change when intersected with ethnicity and migration status;
3. To describe the associations between the individual indicators (SES indicators, ethnicity and migration status) with CMD and then with the new multiple indicator (latent classes) measures.

Methods

Study design and participants

The SELCoH study is a community survey of randomly selected households from two boroughs in South East London, Lambeth and Southwark (Hatch *et al.* 2016). The survey assesses demographic and socioeconomic characteristics; physical and mental health symptoms; health service use; and a range of social stressors and psychosocial resources. Detailed information about the recruitment process for the study has previously been reported (Hatch *et al.* 2011, 2016). SELCoH I included 1698 adults from 1075 households interviewed from 2008 to 2010 (household participation rate: 51.9%, within-household participation rate: 71.9%). SELCoH II targeted 1596 participants who agreed to be re-contacted. The 1052 participants that were interviewed between 2011 and 2013 (response rate: 73%) will be analysed in the current study.

Measures

Common mental disorder

CMD was measured using the Revised Clinical Interview Schedule (CIS-R) (Lewis *et al.* 1992), a structured interview that asks about 14 symptom domains: fatigue, sleep problems, irritability, worry, depression, depressive ideas, anxiety, obsessions, subjective memory and concentration, somatic symptoms, compulsions, phobias, physical health worries and panic. A total CIS-R score of 12 or more is used to indicate the overall presence of CMD, as used in previous SELCoH studies (Hatch *et al.* 2011; Gazard *et al.* 2014).

Measures of SES

Three categories of SES were included in the LCA to account for an individual's SES; income and occupation, housing and educational attainment. For income and occupation we used SOC, employment status, household income, benefit receipt and debt (past year). SOC was measured by current occupation categorised according to the Registrar General's classification (Office of Population Cencuses and Surveys, 1980) into six categories: professional (I), managerial (II), skilled non-manual (III-NM), skilled manual (III-M), semi-skilled (IV) and unskilled (V). For this analysis, SOC was collapsed into four categories: professional & managerial (classes I and II); skilled (class III non-manual and manual); semi-skilled and unskilled (classes IV and V); and no SOC assigned. Employment status was reported and categorised as follows: full or part-time employment; student; unemployed; and other. Other employment status included temporary sick, permanently sick or disabled, retired, carer and at home looking after children. Gross annual household income was also reported and was collapsed into three categories (£0–£12 097; £12 098–£31 494; £31 495+). Binary variables for current benefit receipt (excluding state pension and child benefit) and debt in the past year (excluding mortgage) were also included in the analysis. For housing we used tenure type; own outright/mortgage, private rented, social housing, or rent free; and how many times participants had moved in the past 2 years (not moved or moved once; moved twice or more). For educational attainment, highest qualification obtained by the participant was recorded and were grouped into the following categories; no qualifications/GCSE, A-level, degree or above.

Migration status and ethnicity

In line with previous research, migration status was captured by asking participants their country of birth and length of stay in the UK to create four migration status categories; born in the UK, migrant 0–10 years, migrant 11–20 years and migrant 21+ years (Malmusi *et al.* 2010; Anderson & Blinder, 2011). Participants were asked to self-identify their ethnicity using UK Census categories. Ethnicity categories were collapsed into the following categories; White British, Black Caribbean, Black African, White Other, Non-White Other and Mixed ethnicity. The White Other ethnic group primarily includes participants from North Africa and other European countries while the Non-White Other group includes Indian, Pakistani, Chinese, Latin American and other Black and Asian groups.

Other demographic characteristics

Age, gender and marital status (single, married/cohabiting or separated/divorced/widowed) were also used to describe the resultant latent classes.

Statistical analysis

Latent class analysis

To meet the first two objectives of the study, two separate LCA analyses were conducted to define groups with similar SES profiles based on the eight measures of SES (model 1) and to define groups based on the same eight measures of SES plus migration status and ethnicity variables (model 2). All analyses were conducted in MPlus 6 (Muthén & Muthén, 2012) and accounted for clustering by household and data were weighted using sampling weights which accounted for: (i) within household non-response and (ii) sample attrition between SELCoH I and SELCoH II. LCA is an established data-driven statistical method, which allows for the classification of individuals in a sample based upon conditional probabilities (Hagenaars & McCutcheon, 2002). Individuals within a class will have a similar pattern of responses to a series of categorical variables. Parameters for the latent class models were estimated using maximum-likelihood techniques (Nylund *et al.* 2007). All models were inspected for replication of the log-likelihood value to increase confidence that the best fitting solution was found (Nylund *et al.* 2007).

Decisions on optimal number of latent classes for the two separate LCA analyses were informed by using the following goodness of fit statistics: Akaike's information criteria (AIC) (Akaike, 1987), Bayesian information criteria (BIC) (Gideon, 1978), sample-size-adjusted Bayesian information criteria (SABIC) (Sclove, 1987), entropy (Ramaswamy *et al.* 1993), the number of bivariate residuals (BVR) (Maydeu-Olivares & Joe, 2006) and the Lo–Mendell–Rubin likelihood ratio test (LMR–LRT) (Lo *et al.* 2001). Lower values for AIC, BIC and SABIC all indicate a better fit in LCA models. Entropy is a measure of the classification accuracy for an individual participant and higher entropy reflects better classification

(Ramaswamy *et al.* 1993). The number of BVR can be used to assess model fit with greater than four bivariate residuals suggestive of poor fit (Maydeu-Olivares & Joe, 2006). The LMR–LRT statistic was used to compare classes with similar values across the other goodness-of-fit statistics. BIC and SABIC are measures of model fit with penalisation for additional classes and recent research has shown these measures to be two of the most reliable indicators of best fit (Nylund *et al.* 2007). Where goodness of fit statistics were similar between classes, model selection was predominantly based on BIC/SABIC values and response probability profiles were inspected to see which solution contained the most informative classes (Nylund *et al.* 2007).

Missing data

Maximum-likelihood estimation was used to account for missing data, under the assumption of data missing at random (MAR), using all information that was available to estimate the full model. Any participants with full missing data were excluded from the models.

Comparing LCA models

After the identification of the classes, persons were assigned to their most likely class based on model probabilities (Collins & Lanza, 2013). Further analyses were then conducted in STATA 11 (Statacorp, 2009) and accounted for clustering by household and data were weighted for within household non-response and sample attrition between SELCoH I and SELCoH II. We report the unweighted frequencies and weighted percentages. To meet the first objective of the study, we described LCA model 1 with the SES and sociodemographic indicators. To meet the second objective, we then described LCA model 2 with the same indicators (plus ethnicity and migration status). The two multiple indicators (LCA models 1 and 2) were cross-tabulated to see how the LCA model changed after adding migration status and ethnicity.

Latent classes and CMD

To meet the third objective of the study, odds ratios (ORs) with 95% confidence intervals (CI) are presented for logistic regression models, which included CMD as the outcome and LCA model as the exposure, adjusted for age and gender.

Results

Class solutions

Goodness-of-fit statistics for both LCA models are presented in Table 1. For model 1, the AIC decreased from the two to seven class solution, the BIC decreased until the five class model and the SABIC decreased until the six class solution. Entropy was high for all solutions and the number of BVR was below the recommended threshold for the four to seven class solution. The six class solution was selected on the basis of the SABIC and interpretability of the data. For model 2, AIC decreased from the two to ten class solution. The SABIC decreased until the nine class solution (minimal decrease from seven to nine class solution) and the BIC decreased until the seven class solution. Entropy remained high for all solutions and the number of bivariate residuals was acceptable for the four to ten class solutions. Overall, goodness of fit statistics suggest the seven, eight or nine class solution to all offer a good explanation of the data. Based on the SABIC and BIC values, high entropy, and interpretability of the data, the seven class solution was chosen.

Model descriptions

The classes for models 1 and 2 are briefly summarised in Table 2 (full descriptions of classes for both models are provided in online Supplementary Tables 1 and 2). Based on these characteristics we assigned the following labels to the classes: Model 1; (1) 'Professional occupations, homeowners' (32.6%), (2) 'Professional occupations, renters' (4.7%), (3) 'Skilled occupations, renters' (22.6%), (4) 'Students, renters' (12.5%), (5) 'Economically inactive, renters' (19.5%), (6) 'Economically inactive, homeowners' (8.1%) and Model 2; (1) 'Professional occupations, homeowners, White British' (28.7%), (2) 'Economically inactive, renters, White British' (9.3%), (3) 'Students, mixed tenure, non-migrant, mixed ethnicity' (12.9%), (4) 'Skilled occupations, renters, non-migrant, mixed ethnicity' (14.2%), (5) 'Economically inactive, homeowners, mixed migration status, mixed ethnicity' (8.2%), (6) 'Professional occupations, renters, migrant, mixed ethnicity' (17.1%), (7) 'Economically inactive, renters, migrant, mixed ethnicity' (9.5%).

Changes to classes after adding migration status and ethnicity at SELCoH II

After adding migration status and ethnicity, there were changes to the six classes from model 1 and an additional class was introduced (see online Supplementary Table 3 for details). Class 1 'Professional, homeowners' from model 1, which was predominantly UK born and White British, was split into the 'Professional, homeowners, White British' (class 1) and the 'Professional, renters, migrant, mixed ethnicity' (class 6). Similarly, class 2 'Professional, renters' from model 1, which

Table 1. *Goodness of fit statistics for LCA models*

Model: number of classes	Model fit statistics AIC[a]	BIC[b]	SABIC[c]	E[d]	BVR[e]	LMR-LRT[f] p-value
			Model 1			
2 class	12 215	12 379	12 274	0.999	25	1941 (<0.001)
3 class	11 767	12 015	11 856	0.904	14	475 (<0.001)
4 class	11 391	11 723	11 511	0.882	0	469 (<0.001)
5 class	11 301	11 717	11 450	0.888	0	109 (<0.005)
6 class	**11 268**	**11 769**	**11 448**	**0.893**	**1**	**($p < 0.005$)[g]**
7 class	11 239	11 824	11 449	0.879	0	($p > 0.05$)[g]
			Model 2			
2 class	17 184	17 416	17 267	0.999	26	2020(<0.001)
3 class	16 685	17 036	16 811	0.921	15	537(<0.001)
4 class	16 309	16 780	16 478	0.890	2	538(0.766)
5 class	16 102	16 692	16 314	0.897	2	359(0.761)
6 class	15 907	16 616	16 162	0.909	2	251(0.764)
7 class	**15 741**	**16 569**	**16 039**	**0.916**	**3**	**250(0.768)**
8 class	15 658	16 605	15 999	0.916	3	211(0.801)
9 class	15 609	16 674	15 992	0.916	0	96(0.773)
10 class	15 577	16 763	16 003	0.921	0	77(0.779)

Model 1 – SES indicators only; Model 2 – SES indicators, migration status and ethnicity.
[a]Akaike's information criteria (AIC).
[b]Bayesian information criteria (BIC).
[c]Sample-size-adjusted Bayesian information criteria (SABIC).
[d]Entropy.
[e]Number of bivariate residuals.
[f]Lo–Mendell–Rubin likelihood ratio test (LMR–LRT).
[g]No adjusted LMR–LRT value reported – p value refers to LMR–LRT test.

was more mixed in terms of migration status and ethnicity, were split evenly into 'Professional, homeowners, White British' (class 1) and 'Professional, renters, migrant, mixed ethnicity' (class 6). The 'Skilled, renters' (class 3) from model 1 also split into two classes; 61.8% remained classed as 'Skilled, renters, non-migrant, mixed ethnicity' (class 4), while 28.7% were classed as 'Professional, renters, migrant, mixed ethnicity' (class 6) in model 2. Class 4, 'Student, renters', was very similar to class 3, 'Students, mixed tenure, non-migrant, mixed ethnicity', in model 2. Both student classes were predominantly UK born and mixed in terms of ethnicity. Class 5, 'Economically inactive renters', from model 1 was split into two classes; 'Economically inactive, renters, White British' (class 2) and the 'Economically inactive, renters, migrant, mixed ethnicity' (class 7) in model 2. Class 6, 'Economically inactive, homeowners' from model 1 remained largely unchanged in model 2, 'Economically inactive, homeowners, mixed migration status, mixed ethnicity' (class 5) in terms of SES, ethnicity and migration status.

Health outcomes by individual indicators and latent class models

Table 3 shows the prevalence of CMD by both individual indicators (entered separately) and multiple indicators (latent classes), as well as the associations between these indicators and CMD (adjusted for age and gender only). Only those with no assigned SOC were at increased risk of CMD in comparison to class I/II. Other SOCs were not associated with CMD. Similarly, being a student, unemployed or sick/disabled was associated with increased odds of CMD in comparison with those in employment. Low household income, low educational attainment, debt, benefit receipt and low household income were also associated with CMD. Notably, both debt and benefit receipt were associated with approximately four times the odds of CMD. In terms of tenure, living in social housing was associated with CMD compared with those who owned or mortgaged their homes. There were no associations between either ethnicity or migration status with CMD.

Table 2. *Description of latent classes from models 1 and 2*

Model 1 (SES indicators only)		Model 2 (SES, ethnicity and migration status)	
Class 1	*'Professional, homeowners'* Professional/managerial occupations (85%) High household income (93%), low debt (4%) and low benefit receipt (3%) High educational attainment (91%) Homeowners (69%)	Class 1	*'Professional, homeowners, White British'* Non-migrant (95%) and White British (86%) Professional/managerial occupations (84%), high household income (90%), low debt (6%) and benefit receipt (3%) High educational attainment (87%) Homeowners (67%)
Class 2	*'Professional, renters'* Professional/managerial occupations (64%) High household income (79%), low debt 6%) and low benefit receipt (10%) High educational attainment (73%) Private rented (86%) and high residential mobility (100%)	Class 2	*'Economically inactive, renters, White British'* Non-migrant (100%) and White British (97%) Economically inactive (100%), low household income (100%), high benefit receipt (68%) Low educational attainment (81%) Social housing (88%)
Class 3	*'Skilled, renters'* Skilled and semi-skilled occupations (67%), mixed household income and high debt (27%) Mixed educational attainment Private rented/social housing (79%)	Class 3	*'Students, mixed tenure, non-migrant, mixed ethnicity'* Non-migrant (77%) and mixed ethnicity (predominantly White British and Black African) Students (76%), high household income (66%) Mixed tenure
Class 4	*'Students, renters'* Students (76%) Medium level of debt (18%) and low benefit receipt (14.5%) Mixed tenure	Class 4	*'Skilled, renters, non-migrant, mixed ethnicity'* Non-migrant (75%) and mixed ethnicity (predominantly White British and Black Caribbean) Skilled and semi-skilled occupations (77%), mixed household income, high debt (31%) Low educational attainment (91%) Social housing (67%)
Class 5	*'Economically inactive, renters'* Economically inactive (100%), high debt (32%) and high benefit receipt (76.4%) Low educational attainment (62%) Social housing (84%)	Class 5	*'Economically inactive, homeowners, mixed migration status, mixed ethnicity'* Mixed migration status, mixed ethnicity (predominantly White British and White Other) Economically inactive (100%) High educational attainment (70%) Homeowners (89%)
Class 6	*'Economically inactive, homeowners'* Economically inactive (100%) and mixed household income No debt and low benefit receipt (12%) High educational attainment (70%) Homeowners (89%)	Class 6	*'Professional, renters, migrant, mixed ethnicity'* Migrant (93%) and mixed ethnicity (predominantly Black African, White Other, Non-White Other) Professional/managerial occupations (61%), high household income (72%), low benefit receipt (10%) High educational attainment (69%) Private/Local authority rented (67%)
		Class 7	*'Economically inactive, renters, migrant, mixed ethnicity'* Migrant (72%) and mixed ethnicity (predominantly Black Caribbean, Black African White Other and Non-White Other) Economically inactive (100%), low household income (92%), high debt (43%) and high benefit receipt (84%) Mixed educational attainment Local authority rented (80%)

Full descriptions of classes for both models are provided in online Supplementary Tables 1 and 2.

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Table 3. *Prevalence estimates, adjusted odds ratios (ORs) and confidence intervals for CMD by individual indicators and multiple indicators*

	Common mental disorder				
	n	%	OR[a]	(95% CI)	*p*
Individual indicators					
Social occupational class					
Class I/II	59	(14.6)	1.00		
Class III	25	(16.1)	1.12	(0.66–1.88)	0.679
Class IV/V	20	(20.5)	1.45	(0.81–2.59)	0.216
No SOC assigned	127	(31.5)	2.63	(1.81–3.81)	<0.001
Employment status					
Full/part-time employed	104	(15.8)	1.00		
Student	23	(26.6)	1.94	(1.07–3.49)	0.028
Unemployed	36	(36.7)	3.07	(1.86–5.06)	<0.001
Temporary sick/disabled	27	(67.3)	10.83	(5.38–21.83)	<0.001
Retired	28	(21.4)	1.47	(0.76–2.86)	0.257
Looking after children	13	(24.0)	1.34	(0.69–2.63)	0.380
Household income					
£0–£31 494	121	(29.7)	2.39	(1.69–3.38)	<0.001
£31 495+	80	(15.1)	1.00		
Any debt					
No	154	(17.3)	1.00		
Yes	77	(46.6)	4.27	(3.00–6.07)	<0.001
Any benefits					
No	124	(15.7)	1.00		
Yes	107	(41.9)	3.79	(2.76–5.21)	<0.001
Tenure					
Own outright/mortgage	65	(15.5)	1.00		
Rent/private	47	(20.8)	1.46	(0.93–2.30)	0.104
Rent/council	103	(30.5)	2.32	(1.60–3.37)	<0.001
Other	8	(20.2)	1.39	(0.60–3.21)	0.446
Moved in past 2 years					
Not moved or moved once	208	(22.3)	1.00		
Moved twice or more	16	(19.4)	0.86	(0.46–1.62)	0.507
Educational attainment					
No qualifications/GCSE	78	(31.2)	2.56	(1.77–3.71)	<0.001
A Level	72	(27.2)	2.06	(1.42–2.99)	<0.001
Degree or above	81	(15.1)	1.00		
Ethnicity					
White British	109	(20.7)	1.00		
Black Caribbean	19	(21.7)	1.01	(0.57–1.79)	0.968
Black African	25	(18.5)	0.85	(0.50–1.43)	0.532
White Other	41	(28.2)	1.48	(0.95–2.29)	0.080
Non-White Other	27	(27.8)	1.40	(0.85–2.31)	0.180
Mixed	10	(18.6)	0.92	(0.44–1.92)	0.821
Migrant status					
Born in the UK	142	(21.5)	1.00		
Migrant (0–10)	23	(17.9)	0.75	(0.44–1.28)	0.292
Migrant (11–20)	27	(25.1)	1.15	(0.70–1.91)	0.579
Migrant (21+)	37	(26.3)	1.34	(0.83–2.16)	0.234
Multiple indicators (LCA)					
Model 1 (SES only)[b]					
Class 1	49	(13.8)	1.00		
Class 2	5	(10.3)	0.82	(0.26–2.62)	0.735
Class 3	50	(20.0)	**1.59**	**(1.00–2.51)**	**0.048**

Continued

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Table 3. *Continued*

	Common mental disorder				
	n	%	OR[a]	(95% CI)	*p*
Class 4	26	(25.0)	**2.48**	**(1.33–4.62)**	**0.004**
Class 5	84	(41.5)	**4.89**	**(3.05–7.76)**	**<0.001**
Class 6	17	(16.9)	1.40	(0.73–2.70)	0.312
Model 2 (SES, ethnicity, migration status)[c]					
Class 1	41	(13.2)	1.00		
Class 2	42	(41.1)	**5.04**	**(2.81–9.06)**	**<0.001**
Class 3	28	(25.5)	**2.06**	**(1.13–3.74)**	**0.018**
Class 4	33	(20.6)	1.66	(0.97–2.83)	0.063
Class 5	15	(14.3)	1.13	(0.57–2.22)	0.732
Class 6	30	(16.2)	1.25	(0.72–2.16)	0.436
Class 7	42	(44.9)	**5.24**	**(2.99–9.20)**	**<0.001**

OR, odds ratio; CI, confidence interval.
Weighted percentages to account for survey design; frequencies are unweighted and may not add up due to missing values.
[a]Individual and multiple indicators adjusted for age and gender only.
[b]**Model 1 classes:** Class 1 – Professional, homeowners; Class 2 – Professional, renters; Class 3 – Skilled, renters; Class 4 – Students, renters; Class 5 –Economically inactive, renters; Class 6 – Economically inactive, home owners.
[c]**Model 2 classes**: Class 1 – Professional, homeowners, White British; Class 2 – Economically inactive, renters, White British; Class 3 – Students, mixed tenure, non-migrant, mixed ethnicity; Class 4 – Skilled, renters, non-migrant, mixed ethnicity; Class 5 – Economically inactive, homeowners, mixed migration status, mixed ethnicity; Class 6 – Professional, renters, migrant, mixed ethnicity; Class 7 – Economically inactive, renters, migrant, mixed ethnicity.

In model 1 (SES only), the adjusted analyses indicated that the 'Economically inactive, renters' (class 5) had almost five times the odds of reporting CMD in comparison to the 'Professional, homeowners' (class 1). The 'Skilled, renters' (class 3) and 'Student, renters' (class 4) also had increased odds of CMD. The 'Economically inactive, homeowners' (class 6) did not have an increased risk of CMD.

In model 2, both the 'Economically inactive, renters, White British' (class 2) and 'Economically inactive, renters, migrant, mixed ethnicity' (class 7) had five times the odds of reporting CMD in comparison to the 'Professional, homeowners, White British' (class 1). The Students, mixed tenure, non-migrant, mixed ethnicity' (class 3) also had increased odds of CMD.

Discussion

Using an intersectional approach allowed us to identify groups who were differentiated by varying levels of privilege and disadvantage. For example, within the economically inactive sample there was both an advantaged and disadvantaged group that had different associations with CMD. The diversity of the SELCoH sample in terms of SES, ethnicity and migration status provided a unique opportunity to study the intersection of such social identities that, to the authors' knowledge, has not been performed before. This builds upon studies that have used multiple SES indicators in LCA (Savage *et al.* 2013; Fairley *et al.* 2014). Adding ethnicity and migration status further differentiated between groups; for example, 'Professional, homeowners' (class 1) split into two groups who differed by migration status. Economically inactive classes with multiple levels of disadvantage (e.g., low education and receipt of benefits) were the most likely to report CMD symptoms. In model 2 (including ethnicity and migration status), it was the 'Economically inactive, renters, migrant, mixed ethnicity' (class 7) and 'Economically inactive, renters, White British' (class 2) who had the greatest odds of CMD.

Using an LCA approach allowed us to define more cohesive social groups and subsequently the reference group in the regression analyses was also likely to be a more homogenous group, which increases the validity of the analyses. The combination of these social indicators in LCA analysis produced classes that represent privileged, mixed and disadvantaged positions, reflective of the study sample. The 'Professional, homeowners, White British' (Class 1) is perhaps more representative of privileged position compared with its component individual social status indicators: professional/managerial occupations, being a homeowner or being White British. This privileged position translates into a lower prevalence of CMD (13.2%) in comparison with what has previously been identified by the individual social statuses (e.g., 20.7% in the White British ethnic group and 15.5% in those who own/mortgage their home) in this sample.

Reported associations for single indicators of SES and CMD in this study are similar to what have been previously reported, with similar effect sizes for unemployment (Ford *et al.* 2010), lower income and less education (Fryers *et al.* 2003). Using LCA to combine multiple indicators of SES highlights nuanced differences that could not be uncovered using other methods that combine indicators into a continuous variable, such as principal component analysis (Vyas & Kumaranayake, 2006; Psaki *et al.* 2014). For example, while being economically inactive was associated with CMD using data from the Adult Psychiatric Morbidity Survey 2007 (Ford *et al.* 2010), this study identified further differences in economically inactive classes by tenure, with the 'Economically inactive, renters' (class 5) being at increased risk of CMD, while there was no increased risk of CMD for the 'Economically inactive, homeowners' (class 6). This may also relate to the other advantages in the latter group, e.g., higher educational attainment. This study can therefore tell us more about the complexities of mental health risk in those who are currently economically inactive.

Analyses of the individual SOC indicators did not find that those in skilled or semi-skilled occupations had higher odds of CMD compared with those in professional and managerial occupations; however, in the LCA analyses those individuals in the skilled or semi-skilled occupation class were more likely to have a CMD. This suggests that this mental health association is unlikely to just be about the type of employment, but may result from other vulnerabilities that are associated with being in a lower income occupation, including factors around housing tenure. Notably, the student classes in both LCA models were associated with increased odds of CMD, with effect sizes similar to the individual SES indicator findings. This supports previous findings suggesting that depression is more common in university students compared with the general population (Ibrahim *et al.* 2013).

No associations were found for individual indicators of ethnicity and migration status with CMD in this study. This is consistent with previous studies conducted in South East London (Hatch *et al.* 2011; Gazard *et al.* 2014) but inconsistent with the findings nationally (Weich *et al.* 2004), which may be a result of demographic differences by study area. Nuanced differences in mental health emerged by including indicators of ethnicity and migration status in the LCA. On adding ethnicity and migration status to the models, two distinct migrant classes emerged; 'Professional, renters, migrants, mixed ethnicity' (class 6) and 'Economically inactive, renters, migrant, mixed ethnicity' (class 7). Only the less privileged migrant class had increased odds of CMD. This is consistent with the wider literature which suggests a key role for SES factors in explaining any ethnic inequalities in health (Darlington *et al.* 2015) and differences in health at the intersection of ethnicity and migration status (Smith *et al.* 2009; Gazard *et al.* 2014). Another potential explanation for differences between these classes is whether the decision to migrate was by force or choice. Forced migration, often based on economic circumstances, can lead to differences in power relations and increased exposure to adversity and discrimination experiences (Castles, 2003). Given evidence for the role of both stressful life events and discrimination in accounting for differences in CMD for ethnic minorities (Karlsen & Nazroo, 2002), migrants (Hatch *et al.* 2016) and those from low SES backgrounds (Fuller-Rowell *et al.* 2012), further research is needed to understand the role of such inequalities in CMD at the intersection of SES, ethnicity and migration status.

This study found that both 'Economically inactive, renters, migrant, mixed ethnicity' (class 7) and 'Economically inactive, renters, White British' (class 2) had increased odds of CMD compared with the 'Professional, homeowners, White British' (class 1). *Post hoc* tests did not indicate a difference in odds of CMD for class 7 in comparison to class 2 (results available from authors). This difference may have been expected given the higher educational attainment of the migrant class and previous research, which has associated being a migrant with lower risk of CMD (Dey & Lucas, 2006). However, the equal effect sizes could have been explained by the increased risk associated with higher levels of discrimination in ethnic minority groups being counteracted with the advantages of higher levels of education.

Strengths and limitations

This study analyses data from a large representative community study, including a diverse sample of migrants and ethnic minorities. Seventy-three per cent of the sample was retained in SELCoH 2, with sample attrition more likely in participants who were younger, male and unemployed, but not in those with a CMD (Hatch *et al.* 2016). A limitation of the study is that we were limited to exploring associations between classes and symptoms of CMD rather than individual symptom domains, such as depression, due to small cell sizes. However, this study is novel in using LCA to examine the intersection of SES, ethnicity and migration status. A limitation is that due to the classes being specific to the population of interest then the results may not be generalisable to other urban contexts or the national context. However, this can provide a methodology for taking an intersectional approach in other contexts and we think that this method may be particularly useful in studying diverse urban contexts.

Conclusions

This is the first study to examine the intersections of SES, ethnicity and migration status together using LCA, which additionally examines associations with CMD. Findings restricted to multiple indicators of SES identified two economically inactive classes, only one of which had increased odds of CMD (those who were also renters with low education). This approach was more informative than relying on SOC alone, which would have categorised individuals in both of these classes as unclassifiable. Findings including both ethnicity and migration status showed that both 'Economically inactive, renters, migrant, mixed ethnicity' (class 7) and 'Economically inactive, renters, White British' (class 2) had a similarly high prevalence of CMD. This work has shown that using multiple indicators in LCA is a useful methodology for investigating health inequalities by intersectional identities and in uncovering more nuanced differences in diverse settings. The findings of this research are particular to the diverse urban setting of the study area and may be related to risk and resilience factors that are unique to urban areas, such as ethnic density (Das-Munshi *et al.* 2010; Schofield *et al.* 2011), more accessible health services (Casey *et al.* 2001) and increased income inequality (Galea *et al.* 2005). Future research should consider how these factors contribute to health inequalities at the intersection of SES, migration status and ethnicity in other urban settings and national contexts.

Supplementary material

The supplementary material for this article can be found at https://doi.org/10.1017/S2045796017000142.

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Conflicts of interest

None.

Ethical standards

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. Ethical approval for SELCoH I was received from the King's College London Research Ethics Committee for non-clinical research populations (CREC/07/08-152) and for SELCoH II was received from the King's College London Psychiatry, Nursing and Midwifery Research Ethics Committee (PNM/10/11-106).

Availability of data and materials

Data available on request. For further details, the reader is encouraged to contact the corresponding author.

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