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The Impact of Stigmatised Deprivation on Loneliness

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Abstract

Loneliness and social isolation are a cause and symptom of poor psychological health, while they also have secondary impacts on physical health, employability

and educational outcomes. For a multitude of reasons, these phenomena are challenging to evaluate and understand in tandem; this can be attributed to the latent nature of loneliness and the wider sensitivity and stigma surrounding mental health. Comparatively less is known about the relationship between stigmatised deprivation (i.e., various forms of deprivation that can lead to social exclusion) and loneliness. To address this gap, the current study examines the impact of *stigmatised deprivation* on the prevalence of loneliness across London, UK. Specifically, we consider two increasingly prevalent forms of stigmatised deprivation: food insecurity and energy insecurity. We develop a hierarchical machine learning model to evaluate the relationship between a wide range of health and socioeconomic features and loneliness among a large sample of London residents (n=2886). Model results indicate that including stigmatised forms of deprivation increases loneliness prediction accuracy. In practice, this corresponds to potential improvements in understanding the drivers of loneliness, as well as how the condition might be remedied. Finally, we suggest policy recommendations in terms of how reducing stigmatised deprivation could also lead to broader mental health benefits.

Keywords: Loneliness, Social Isolation, Stigmatised Deprivation, Machine Learning, Hierarchical Modelling

1 Introduction

It has been estimated that over 9 million people in the UK feel lonely either often or all the time [1]. Loneliness and its psychological impacts can affect anyone: the young or elderly [2–4]; those working full-time, part-time or the unemployed [5, 6]; those in varied household composition such as living alone or as a single parent [2, 7]; male, female and non-binary genders [8, 9]; those of differing sexual orientations [10, 11]; and people across a range of deprivation levels [12–15]. The phenomenon transcends social boundaries and, according to the *Campaign to End Loneliness*[1], in 2022 49.63% of all adults in the UK (25.99 million people) reported feeling sometimes, often or always lonely, with 7.1% of citizens experiencing loneliness all the time.

Loneliness has been shown to generate a host of negative effects over time. It has serious impacts on the physical and psychological health of individuals [16, 17]; but it can also be highly damaging to the economic conditions of a nation as a whole, with the cost of loneliness to employers recently estimated at more than £2.5 billion per

year in the UK alone [18]. Studies also suggest that loneliness is associated with chronic disease and increased mortality rates [19], with compromised immune functioning and poor cardiovascular health also being related [20]. There is further evidence to suggest that those who are more lonely are more likely to engage in risky health behaviours such as smoking or substance abuse [19].

Although a relationship between deprivation and loneliness has been previously recognised [14, 21, 22], the exact nature of that relationship and its consequences for the lived experience of loneliness remains underexplored. In particular, while there is a clear link between disposable income and the opportunities for social interaction, far less attention has been paid to specific forms of economic instability. This is perhaps surprising given the impact loneliness has on psychological health [23, 24], we hypothesise that this may be due in part to the *stigma* that surrounds exact forms of deprivation such as *food* and *energy insecurity* [12, 25, 26] which in turn have specific driving affects for loneliness. McNeeley [27] proposed that the stigma surrounding such conditions exacerbates challenges in eliciting accurate data, as respondents often feel embarrassed or ashamed.

Deprivation of this nature is not uncommon: a recent survey of 8630 Londoners published by the Greater London Authority [28] estimated that not only were 8% of London's population 'often' or 'always' lonely, but that 19% of these respondents were unable to keep their house warm and 18% were forced to use food banks to survive. Of the 26% of London's population that were socially isolated (i.e. not able to rely on someone close to them if they had a serious problem), 40% were also unable to heat their home, and 42% relied on food banks.

In this study, we investigate the impacts of *Stigmatised Deprivation* on loneliness, via an individual-level analysis of loneliness and its potential drivers (both socio-demographic and psychological) based on a new survey of 2,886 respondents across London, UK. Building upon the core definition of stigma established by Link and

Phelan [29], and refined by Andersen et al. [30], we define stigmatised deprivation as: any form of economic insecurity where an individual experiences perceived social exclusion or shame when engaging in support to reduce deprivation impact. Food and energy insecurity are examples of such deprivation, reflecting the four key elements of stigma proposed by Andersen et al. [30]: *labelling*, *linguistic separation* (e.g. food secure vs food insecure), *negative stereotyping* via the mechanism of social exclusion [26, 31]), and *power asymmetry* due to reliance on social support (e.g. food banks, free school meals or universal credit).

Previous work exploring relationships between complex phenomena such as food insecurity and loneliness has either been qualitative, focusing on very specific sub-populations (e.g. old age pensioners, single mothers) [32–34], restricted to investigating the impact of individual variables in isolation [4, 33, 35], or limited to examination of relatively coarse, national-level statistics (albeit still showing strong effect sizes[12]). As such, there is currently limited research examining the impact of food and energy insecurity at individual levels, despite the importance of understanding specific drivers of loneliness to support informed routes to intervention.

This work aims to quantitatively extend hypotheses generated in the previously discussed qualitative studies, by first isolating individual forms of stigmatised deprivation from general deprivation scores and then setting these features against contextual factors such as socio-demographic, behavioural and environmental variables. AI-modelling is then used to analyse the relationship between variables and loneliness. This modelling approach allows researchers to consider whether food and energy insecurity are symptoms of a more general psychological experience of deprivation, or identify whether the effects of food and energy insecurity hold specific driving effects, given the stigmatised nature of these features. Specifically, the applied AI-modelling approach enables the analysis of the granular effects of these features over traditional statistical approaches such as linear regression and structural equation modelling,

which typically examine variables in isolation and cannot adequately capture the complex interactions between multiple socio-environmental factors that may moderate the relationship between stigmatised deprivation and loneliness.

Do those, for example, who experience less social cohesion, differing geographical locations, varying access to public transport, limited access to green space and/or living conditions in highly dense populations suffer effects differently [35–39] in particular, we ask:

1. Can food and energy insecurity impact loneliness at an individual level?
2. Does this impact occur in addition to the relationships with income?
3. Are effects moderated or co-occurrent with other social features (i.e. variables that can moderate or exacerbate that relationship)?

1.1 Background

Loneliness is defined as the subjective perception of a discrepancy between the desired and true social relationships in terms of companionship, connectivity, or intimacy [40]. This study focuses on the subjective emotional experience of loneliness, i.e. the experiences associated with loneliness defined by Weiss [41], rather than the objective experience of how often people are alone. The nuances in the experience of loneliness make it difficult to measure, and over time loneliness can have a number of serious negative effects, impacting physical and mental health outcomes [16, 17] while remaining latent. Furthermore, acquiring accurate estimates is difficult due to the stigma associated with loneliness and its prevalence being higher in poorer areas [42, 43].

Despite these challenges, loneliness is still a highly prevalent issue, with the UK Government producing a range of reports showing the negative effects of loneliness across the population [44–49]. These reports show how loneliness has been linked to earlier deaths on a par with smoking or obesity, increased risk of coronary heart disease, stroke, depression, cognitive decline and an increased risk of Alzheimer's [44].

Studies typically focus on specific population subgroups, including university students, patients presenting at GP practices with comorbidities, and elderly residents in care homes [50–52]. There are some limited examples of successful community interventions that enable communities to engage via social prescribing [48], which reduces feelings of social isolation and loneliness. However, 'Public opinions and social trends, Great Britain: personal well-being and loneliness', a dataset published by the Office of National Statistics (ONS), reports a range of social trends showing a steady increase in self-reported loneliness over time (see Figure 1).

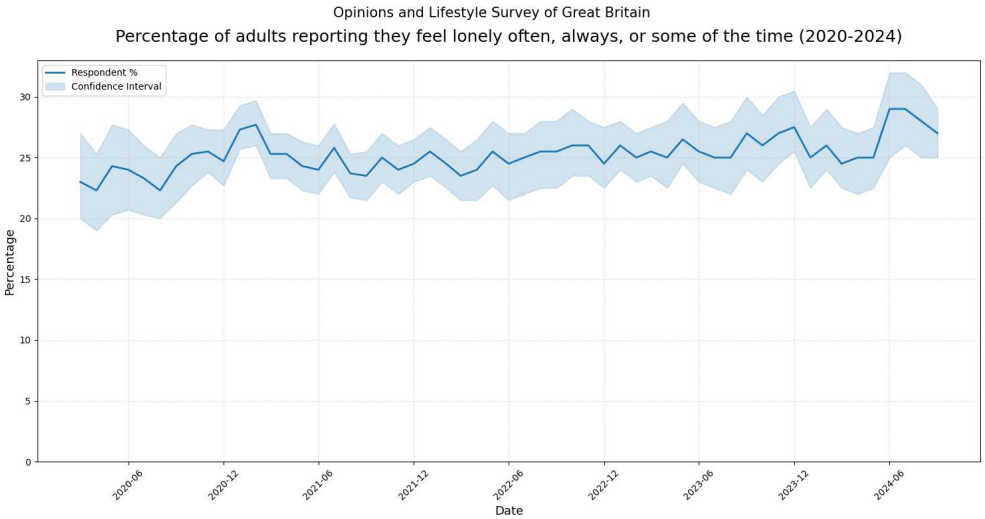

Figure 1: Public opinions and social trends, Great Britain: personal well-being and loneliness (October 2021 - September 2024

This steady increase in loneliness is likely due to strong links between loneliness and social infrastructures. Factors such as poor access to housing, transportation, limited access to green space and increasing deprivation limit social cohesion, combined with limited social support and weakened economic opportunities, which have a deleterious effect on experienced loneliness [53]. This is particularly pertinent as social support and provision continue to stagnate and decline in the UK while mental health concerns

endure and rise[43, 54]. This relationship between loneliness and social infrastructures is a concern that the UK Government has acknowledged in 2023 [48], finding the factors that contribute towards loneliness include physical health, deprivation and social care provisions. Deprivation can manifest itself in several ways, whether food and energy security are present or not; it is not just a lack of income that leads to deprivation but the consequences of an increased cost of living which enables this cycle of deteriorating physical and mental health.

Food insecurity has serious long-term health consequences, including inadequate nutrient intake, diet-related chronic disease, and magnified physical and mental health issues [55]. The financial hardship commonly experienced by those in food insecurity also limits their ability to socialise, leading to feelings of social isolation [33]. A 2023 ONS report found that adults reporting 'moderate-to-severe' depressive symptoms were over three times more likely to report experiencing food insecurity than adults with 'no-to-mild' depressive symptoms[13].

The mental health consequences of food insecurity are known to be highly sensitive to social contexts, Elgar et al. [12] concludes that the psychological health consequences of food insecurity are nuanced and moderated by a range of variables. In settings where food insecurity is less common and potentially more stigmatised, there are increased mental health consequences. As such, identifying which factors increase a person's propensity to loneliness and how behavioural, environmental, and demographic variables interact to moderate this relationship is important for creating more effective governmental policies, thereby increasing the efficiency and efficacy of assigned resources to reduce loneliness.

The relationship between food insecurity and loneliness [32] is also not unique, as loneliness co-occurs with other forms of deprivation. Energy insecurity is a concept that reflects hardships with the cost and quality of household energy and is defined as the inability to meet basic household energy needs [56]. Several studies show the

relationship between energy insecurity and social isolation [13, 14, 21, 57, 58]. Energy insecurity results in increased feelings of anxiety, depression, stress, and worry about keeping warm [57]. Those facing energy insecurity feel social stigma about their economic hardship, which in turn exacerbates conditions of social disadvantage. A 2023 ONS report [13] found that adults reporting moderate-to-severe depressive symptoms were over twice as likely to experience energy insecurity as adults with no-to-mild symptoms. There is a clear connection between deprivation and loneliness; however, it is still unclear whether these are symptoms of a more general, psychological experience of deprivation or whether the effects of food and energy insecurity (particularly stigma) hold specific driving effects.

There is limited research into the application of machine learning (ML) models to understand the features that impact loneliness. This research gap is two-fold, methodological approaches typically rely on qualitative methods or a lack of quantitative approaches that elicit the features that impact loneliness, due to studies primarily looking at ageing populations, the generalisability of the findings is limited. There is a range of data that can be evaluated to understand loneliness. Methods involve the statistical analysis of self-reported survey data, although the application of Natural Language Processing (NLP) methods to evaluate elicitations of loneliness in text data has proliferated. Typically, these text data are generated on social media platforms such as X (previously Twitter) or Reddit [59–62]. Other data streams include sensing technologies, including smartphones, Fitbit and Bluetooth data[63–65].

Ejlskov et al. [66] found that positive wellbeing, an absence of health problems and being married were strong predictors of lower loneliness using Random Forest methods to understand the relationships between 49 covariants and loneliness in individuals aged 68 or above. Kearns et al. [22] applied multinomial linear regression on cross-sectional survey data to understand loneliness and deprivation, finding that feelings of social connectedness and the ability to rely on family and friends reduce

feelings of loneliness while stressors such as deprivation, crime rates and poor governmental social support increased experiences of loneliness. Altschul et al. [50] applied Gradient-boosted modelling to understand the difference in predictors of loneliness amongst two age groups, 45-69 and 70-79 years of age, finding that emotional stability and household composition (living alone) contributed towards experiences of loneliness. Structural equation modelling (SEM) has been applied to show the relationship between stress and loneliness to be bi-directional over time [36], while Gerino et al. [51] found loneliness influences mental health and physical quality of life in Italian adults aged 65–90.

2 Methods

2.1 Data Sample and Procedure

Ground-truth data concerning loneliness were collected by Olio for the study via a survey disseminated to participants across 82.7% of London's geographical extent, UK. To ensure adequate coverage of economically secure and insecure participants, participants were drawn from the social sharing platform *Olio*, which has over 7 million registered users worldwide and is active across 51 countries as of 2023. The platform allows its users to list household items that they want to give away via their mobile device, to reduce waste and allow other users to request and then collect said items.

The survey was delivered to London-based users via a mobile-app, and completed by (n=2,886) participants in Greater London between 22nd November 2022 and 5th December 2022. Respondents received a £5 reward for completing the survey. A careful survey sampling strategy was applied, implementing quota constraints for socioeconomic status, as informed by the Indices of Multiple Deprivation (IMD) score of respondents' home areas (where the user was registered), defined as one of the 983

administrative areas of London, called MSOAs (See Figure 2)[1] and based on activity on the Olio Platform, participants had to have been active on the platform in the 6 months prior to data collection, and all data was strictly anonymised prior to receipt by researchers. All methods were performed in accordance with the relevant guidelines and regulations.

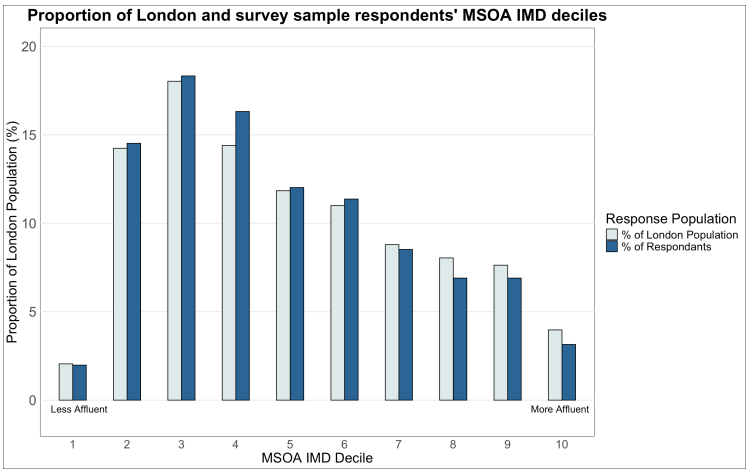

Figure 2: Proportion of survey sample respondents compared to Proportion of London and survey sample respondents' MSOA IMD deciles from 1 (most deprived) to 10 (least deprived)

2.2 Measures

The survey primarily captured insight across three themes: food insecurity via the USDA Food Security Survey Module, energy insecurity via the 2015 Residential Energy Consumption Survey (RECS) [67], and Loneliness from the three-item Revised UCLA Loneliness Scale [68]. Demographic questions were also included to capture information related to income, age, household composition and employment. The full list of survey questions can be seen in Supplementary file A.

[1] Middle Layer Super Output Areas (MSOAs) are a geographic hierarchy designed to improve the reporting of small area statistics in England and Wales, and on average a neighbourhood of 2,000 households with an average population size of 7,800

Two approaches are typically used when measuring loneliness: direct and indirect measurement. Direct measures make specific reference to loneliness i.e. *How often do you feel lonely?* [69, 70]. Direct loneliness measures are often composed of a single item, in comparison to indirect measures which use a range of questions related to a respondent's subjective social experience *How often do you feel that you lack companionship?* or *How often do you feel isolated from others?* [71].

The revised UCLA Loneliness scale was selected following the UK government's recommended approach as suggested by the ONS [72]. In order to keep survey completion time to a reasonable duration, a subset of questions were included from this scale. The measures 'How often do you feel left out?' and 'How often do you feel isolated from others?' were merged into the question *'How often do you feel isolated from others/left out?'*, as suggested by an independent UK government report on loneliness that found that respondents often interpreted the question 'How often do you feel that you lack companionship?' differently.

The authors note that this varies from the ONS practice of using the 3-item UCLA loneliness scale, plus a single direct loneliness question. However, due to the sensitive nature of the survey and its relationship to stigmatised insecurity measures, it was felt to be inappropriate to ask a direct loneliness question which also accounts for the suggestions by McNeeley [27] about conducting surveys around sensitive topics. The full survey questions can be seen in the supplementary material. A composite score of loneliness was calculated by assigning a numerical value to the responses for the two retained UCLA Loneliness Scale questions (Hardly ever or never = 1, Some of the time = 2, Often or always = 3) and computing a loneliness score of between 2 and 6 (See Figure 4). A binary feature, 'Loneliness', was assigned to respondents based on their composite score; those respondents with scores of 4 and less were classified as 'Not Lonely', while those with scores of 5 and above were classified as 'Lonely'.

2.3 Feature Engineering and Selection

A range of machine learning classifiers were tested in their ability to model participant loneliness, using 21 independent variables drawn from a range of prior literature (listed in Table 1), and broadly split across two domains:

- **Environmental Variables:** geospatial features representing the neighbourhood characteristics of a participant's home region (e.g. population density, rail linkage, living environment scores), gathered via either open government (ONS) or Transport for London (TfL) data, and linked to home locations via geospatial lookup.

- **Socioeconomic Variables:** a range of individual features including income, deprivation, age, household composition, employment status, and education, self-reported within the survey.

Table 1: List of features generated from the self-reported survey and national data sources

Feature	Data source	Description
Environmental		
Indices of Multiple Deprivation (IMD) Score	ONS	Poverty ranking as defined by the IMD score provided by the UK ONS
Living Environment Score	ONS	Living environment score as defined by the by the UK Office of National Statistics
Population Density	ONS	Population density of the respondents LSOA
Bus/coach Linkage	Geospatial	Distance from the LSOA to the nearest bus/coach stop
Tram/Metro/ Linkage	Geospatial	Distance from the LSOA to the nearest tram/metro access
Rail Linkage	Geospatial	Distance from the LSOA to the nearest train station
Access to Green Space	Geospatial	Distance in meters from the closest green space
Socioeconomic		
Unable to Rely on Friends and Family	Survey	The degree to which the respondent can turn to friends and family when in need
Financial Anxiety	Survey	Extent of worry about housing/rent payments
Unemployed	Survey	Whether the individual considers themselves unemployed
Not Working (Looking After Child or House)	Survey	Whether the individual's ability to work is impacted by caring responsibilities
Disability	Survey	Whether the individual's ability to work is impacted by disability
Age	Survey	The reported age of the participant
Gender	Survey	The reported gender of the participant
Physical or Mental health Conditions/Illnesses	Survey	Self-reporting of ongoing illness, physical or mental health problems
Household Composition	Survey	Single/living alone with children (under 18)
Energy Insecurity	Survey	The degree to which the individual struggles to pay for fuel/energy
Food Insecurity	Survey	The degree to which the individual struggles to pay for food/meals
Food bank usage	Survey	If the respondent has needed to use a food bank
Energy Anxiety	Survey	Self-reported concern/worry about their ability to pay for energy
Income	Survey	Self-reported income range of the participant

2.4 Modelling Approach

In order to investigate the array of factors impacting loneliness, while also allowing for a range of moderating interactions between variables, a non-parametric framework was selected. Analysis was structured around a binary classification task, optimising random forest models to predict individuals as lonely or not-lonely based on a potential set of 21 input covariates (features) as described in Table 1. To understand the impact of key features, and to ascertain their incremental benefits in assisting the prediction of loneliness, a systematic, hierarchical approach was implemented. Level-1 models used all 21 available features. Level-2 models used 20 available features omitting either food insecurity (Level-2a) or energy insecurity (Level-2b) from the dataset. Finally, Level-3 models used 19 features, omitting both stigmatised deprivation variables.

For each level, data were randomly assigned into training (70%) and test (30%) sets prior to model investigation. Random Forest models were then rigorously optimised via a 5-fold cross-validation approach, grid searching across model hyperparameters (*no. of estimators, maximum depth, splitting criterion, maximum features used in each tree, and minimum sample splitting for nodes*). A mean validation accuracy metric was used to obtain an optimal parameterisation, which was then used on the full training set to produce a best-of-class model for that level. Finally, classification accuracy was measured on the held-out test set.

All levels were trained using the same data points. To account for class imbalance, these were sampled from the full data to form a stratified set of 1000 observations (500 lonely observations and 500 non-lonely observations). Downsampling was preferred on this occasion to oversampling methods, such as Synthetic Minority Over-sampling Technique (SMOTE), in order to avoid use of synthetic data points (approaches such as SMOTE can be highly useful in situations with well-defined feature distributions [73], but can add risk of overfitting - and generate challenges in interpretation of model predictions, synthetics being less representative of real-world observations - a

factor potentially important in domains such as health and social care [74]). Our full approach is illustrated in Figure 3.

To ensure robust results and account for the stochastic nature of non-parametric modelling using Random Forests, the complete experiment was exhaustively re-run 5 times. Each iteration of the experiment utilised a different random seed, which was held consistent across hierarchical-levels analysed in each iteration. This resulted in a total of 20 models, 5 for each hierarchical-level. To assess models produced at each level, and hence the independent impact of the stigmatised deprivation variable, accuracy losses were analysed against a model with all the features (Level-1). A Friedman test was applied to identify significant differences in performance (and model accuracy distributions), with a *post-hoc* pairwise comparison being applied via a Bonferroni-corrected Wilcoxon signed-rank test.

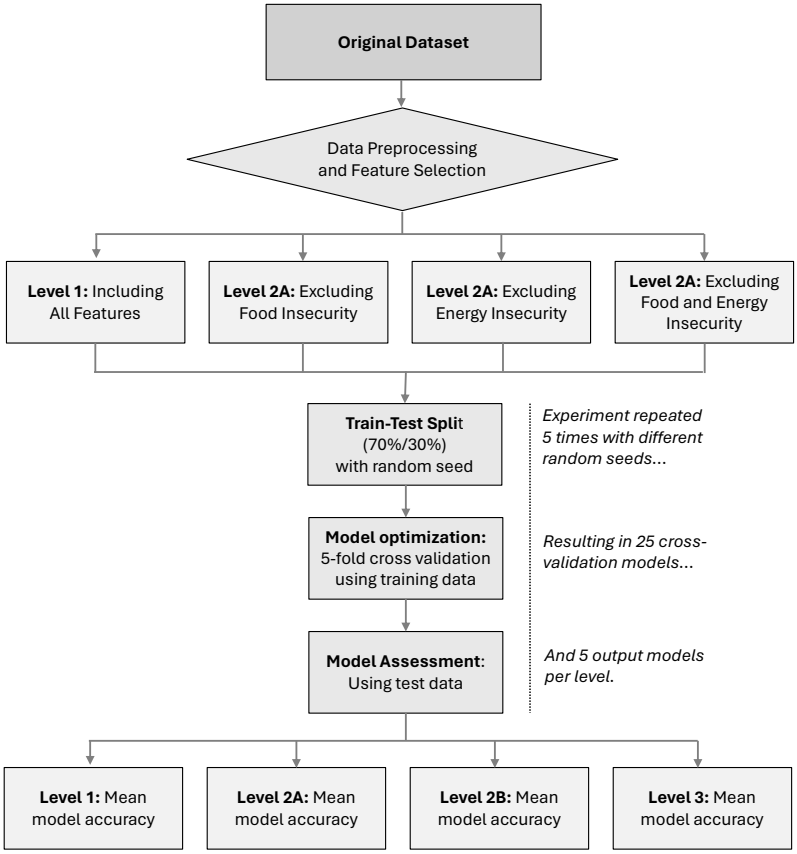

Figure 3: Hierarchical Modelling workflow, comparing four model versions (Level-1: all features, Level-2A: no food insecurity, Level-2B: no energy insecurity, Level-3: no food or energy insecurity). Each Level has 25 models produced during cross-validation, and 5 optimised output models that are tested.

2.5 Variable Importance Analysis

A non-parametric machine learning approach was then used to understand feature importance and interaction effects between covariates without explicit *a priori* definition of their relationships (which can be challenging in traditional techniques such as SEMs). This approach provides the capacity to apply advanced feature importance

methods to resulting models alongside SHapley Additive exPlanations (SHAP) analysis. Random forest models, in particular, allow the use of Model Class Reliance (MCR) analysis [75], a recently developed variable importance method that can provide deeper insights into the impacts variables have on predicting loneliness. When discussing the potential application of machine learning methods to understanding psychological phenomena, Yarkoni and Westfall [76], emphasised the need for explainability of models. However, running variable importance tools such as SHAP on one arbitrary model can generate misleading results due to i. the stochastic nature of machine learning algorithms; and ii. The fact that different, equally-performing models can arbitrarily use different feature combinations to generate the exact same prediction accuracy. Which model's explanation is 'correct' is unclear.

The MCR approach was introduced by Fisher et al. [77] to address this challenge, computing feature importance *bounds* across *all* optimal models (called the 'Rashomon Set') rather than for a single model solution alone. This is useful in investigating psychological phenomena, where direct observations themselves are not possible and proxy drivers must be examined. We utilised MCR to compute the permutation feature importance bounds each of our input variables had in predicting loneliness; calculating the minimum (**MCR-**) and maximum (**MCR+**) impact each feature can have on prediction accuracy, across all instances of the model class. While initially implemented for use with support vector machines, Smith et al. [75] adapted MCR to random forest classifiers and regressors. In this study, we extended Smith et al's work for use with hierarchical modelling, following a similar ablation approach used in Dolan et al. [78]. To understand the contribution of independent variables in each level, the optimal model across all experiments was identified, and both SHAP values and MCR importance bounds were calculated. MCR and SHAP plots were then used to assess which features contribute the most towards the model prediction of loneliness.

3 Results

3.1 Survey Results

Analysis of the composite loneliness scores revealed that 20.9% of respondents (n=590) were identified as lonely, while 79.1% (n=2,232) were not (see Figure 5). Results support conclusions drawn by NHS England [15], reporting that those who are in areas with the lowest IMD Deciles (those who are more deprived) report being often or always lonely more than those in the higher deciles. A clear socioeconomic gradient emerged in our data, with a higher prevalence of loneliness in less affluent areas characterised by lower IMD scores (see Figure 6).

A relationship between more severe loneliness and food insecurity, energy insecurity, poorer health and foodbank usage proposed within the Greater London Authority survey of London [28] is also reflected in the survey data (See Figures 7, 8, 9). The association between deprivation and loneliness was particularly pronounced when examining stigmatised deprivation variables. Among respondents classified as having very low food security, 77.4% (n=359) reported feeling lonely (See Figure 7); whereas 85.6%(n=88) of those experiencing very low energy security also reported loneliness (See Figure 8).

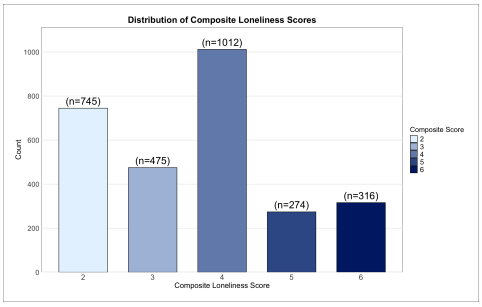

Figure 4: Composite loneliness scores range from 2 (lowest) to 6 (highest), representing increasing levels of loneliness.

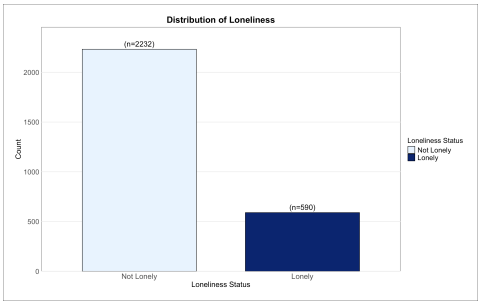

Figure 5: Distribution of Lonely vs Not Lonely Respondents

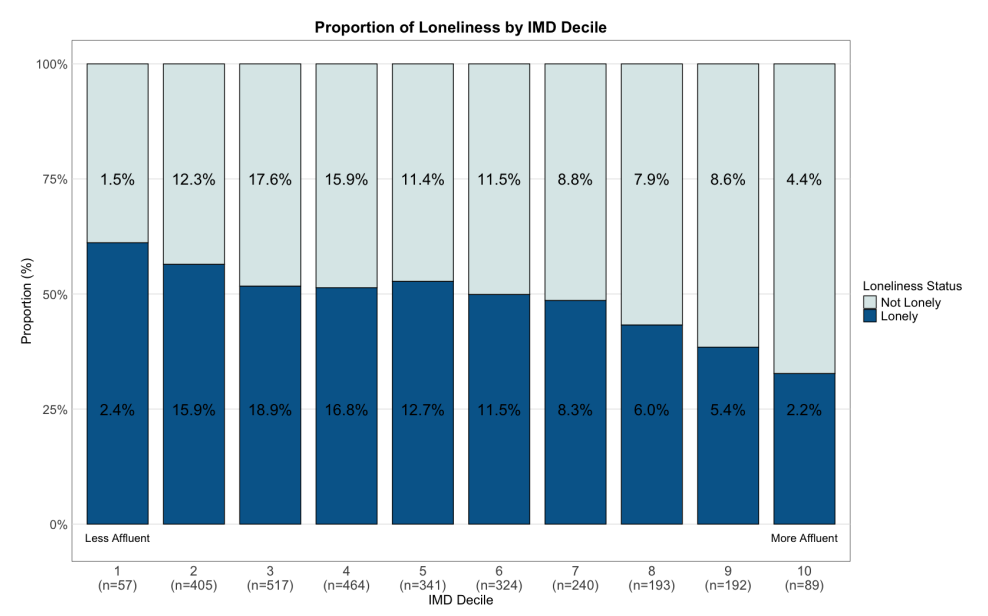

Figure 6: IMD deciles disaggregated by Loneliness. Lower IMD deciles represent less affluent individuals, and higher IMD deciles represent more affluent individuals.

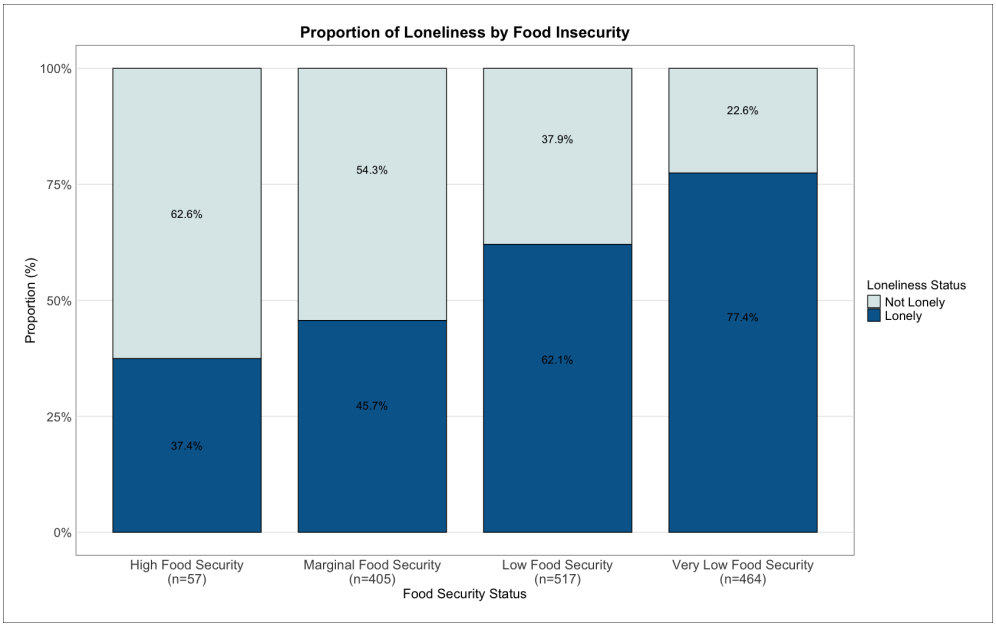

Figure 7: Association between food security status and loneliness. The proportion of loneliness increased with worsening food security status, from high food security to very low food security.

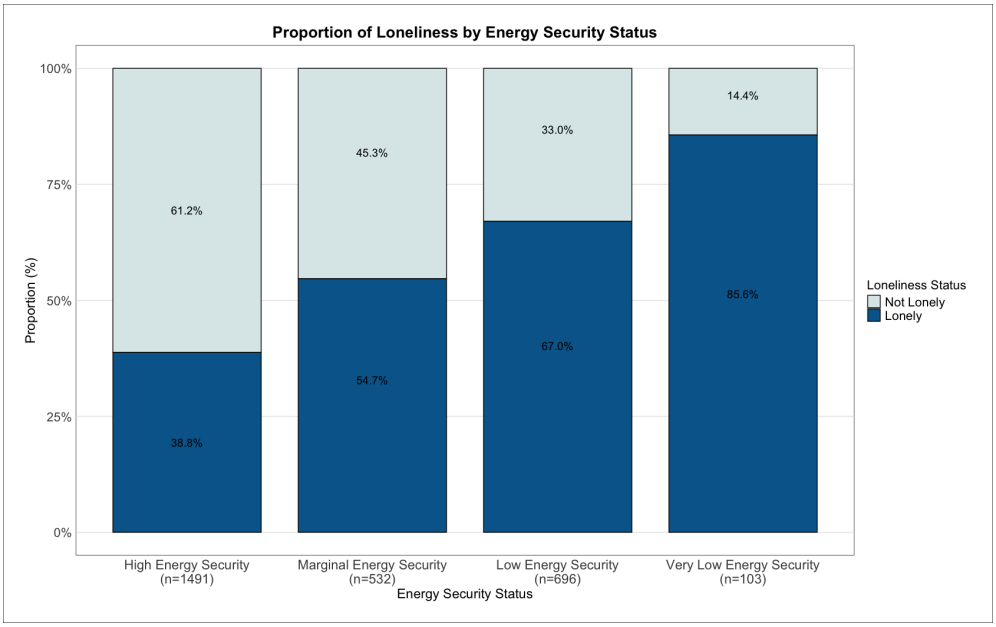

Figure 8: Association between energy security status and loneliness. The proportion of loneliness increased with worsening energy security status, from high energy security to very low energy security.

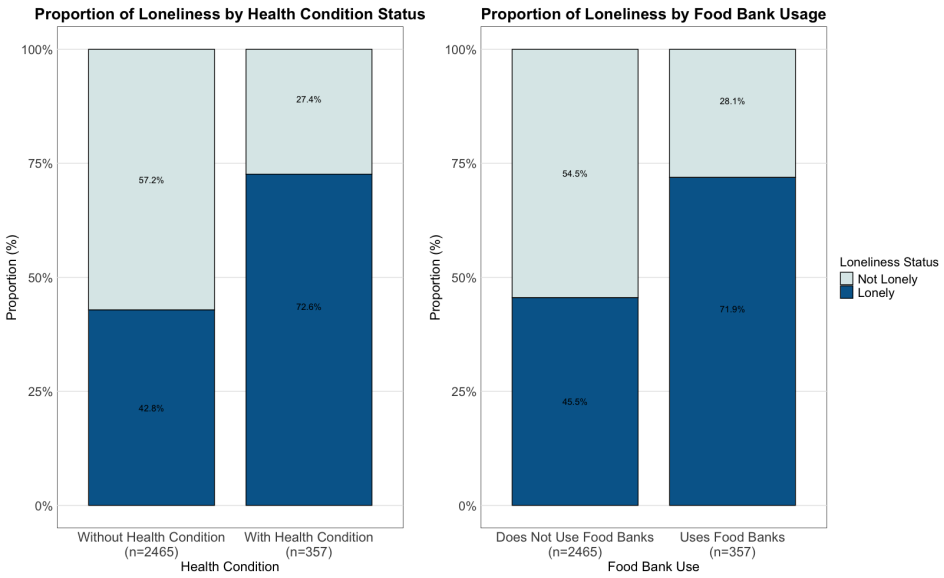

Figure 9: Comparison of loneliness proportions across health conditions and food bank usage. The left panel shows health condition disaggregated by loneliness. The right panel shows food bank usage disaggregated by loneliness.

3.2 Modelling Results

Our analysis compared four treatment levels to evaluate how different stigmatised deprivation features impact the prediction of loneliness. For treatment 1 (Level-1) the optimal treatment for level-1 had a mean test accuracy score of 69.6%; for treatment 2 (Level 2-A), with *food insecurity* excluded, the mean test accuracy of the treatment decreased to 68.2%; for treatment 3 (level 2-B), with *Energy Insecurity* excluded, the test accuracy of the treatment differed less, achieving a score of 69.3%. For treatment 4 (Level-3), where both *Food and Energy Insecurity* were excluded, the mean test accuracy of the model dropped to 67.3% - reflecting a 2.32% drop in predictive power.

To assess if the unique role of energy and food insecurity was significant, a Friedman test was applied, revealing significant differences across levels ($\chi^2(3) = 12.97$, $p = .002$). Post-hoc analysis using Wilcoxon signed-rank tests with Bonferroni

correction ($\alpha = .0083$) showed significant differences between Level-1/Level-2A, Level-1/Level-3, Level-2A/Level-2B, and Level-2B/Level-3 pairs (See Table 3 and Table 4). These findings indicate that removing stigmatised deprivation features (particularly in Level-2 and Level-3) had a substantial negative impact on model performance compared to Level-1, while Level-2B maintained relatively similar performance levels to the base model. This indicates that some food insecurity holds greater informational content over energy insecurity alone in predicting loneliness, but that both hold unique explanatory strength over and above basic deprivation statistics.

Table 2: Model Performance Summary: Comparative Analysis of Treatment Models Against Base Configuration

Treatment Level	**Mean CV Accuracy%**	**Highest Test Accuracy%**	**Mean Test Accuracy%**	**Accuracy Loss from Baseline%**
Level 1	70.24	73.63	**69.60**	0.00
Level 2A	69.59	71.33	**68.24**	-1.36
Level 2B	70.68	71.00	**69.28**	-0.32
Level 3	69.41	70.33	**67.28**	-2.32

Note. CV (Cross-Validation). Complete model results, including model parameters, are provided in the supplementary material.

Table 3: Results of Friedman Test

Analysis Type	**Test Statistics**
Friedman Test	$\chi^2(3) = 12.97$, $p = .002$

Across all models, features related to stigmatised deprivation are shown to contribute towards the prediction of loneliness. While income and income-related worry played a role in predicting loneliness, the inclusion of more granular deprivation features, particularly food insecurity, aid in increasing model accuracy. These findings raise important questions about the relationship between specific forms of deprivation and loneliness, which we explore in detail in the following discussion.

Table 4: Post-hoc Pairwise Comparisons Using Wilcoxon Signed-Rank Tests

Comparison	**Z-score**	**Effect Size (r)**	***p*-value**
Level-1 vs. Level-2A	−3.84	0.54	$< .001^{***}$
Level-1 vs. Level-2B	−1.18	0.17	.239
Level-1 vs. Level-3	−4.93	0.70	$< .001^{***}$
Level-2A vs. Level-2B	−2.81	0.40	$.005^{**}$
Level-2A vs. Level-3	−1.75	0.25	.080
Level-2B vs. Level-3	−4.10	0.58	$< .001^{***}$

Note. Significance levels: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$
Bonferroni-adjusted alpha level = .0083

4 Discussion

Both SHAP and MCR analysis was used to unpack the drivers of these results. Plots for Level-1 (Figure 10) showed that the features contributing to accurate loneliness predictions the most were *unable to turn to friends and family*, *food insecurity*, *illness* and *energy insecurity*. The **MCR+** and **MCR-** values for *Food insecurity* are larger than *illness*, which shows that across all the MCR treatment evaluations, *food insecurity* was a better predictor of loneliness than *illness*. The SHAP plot (Figure 10) for Level-1 indicates the directionality of the feature in the context of a positive prediction of loneliness; being unable to turn to friends and family contributes towards a positive prediction of loneliness. Other contributing features included *income* and *worry about energy payment*. Some feature impacts are context-dependent, evaluating the SHAP plot for features such as *distance to railway access*, which shows no clear directionality in the prediction of loneliness. This suggests possible interaction effects with other features or a non-linear relationship with the target variable, creating less discernible SHAP distributions.

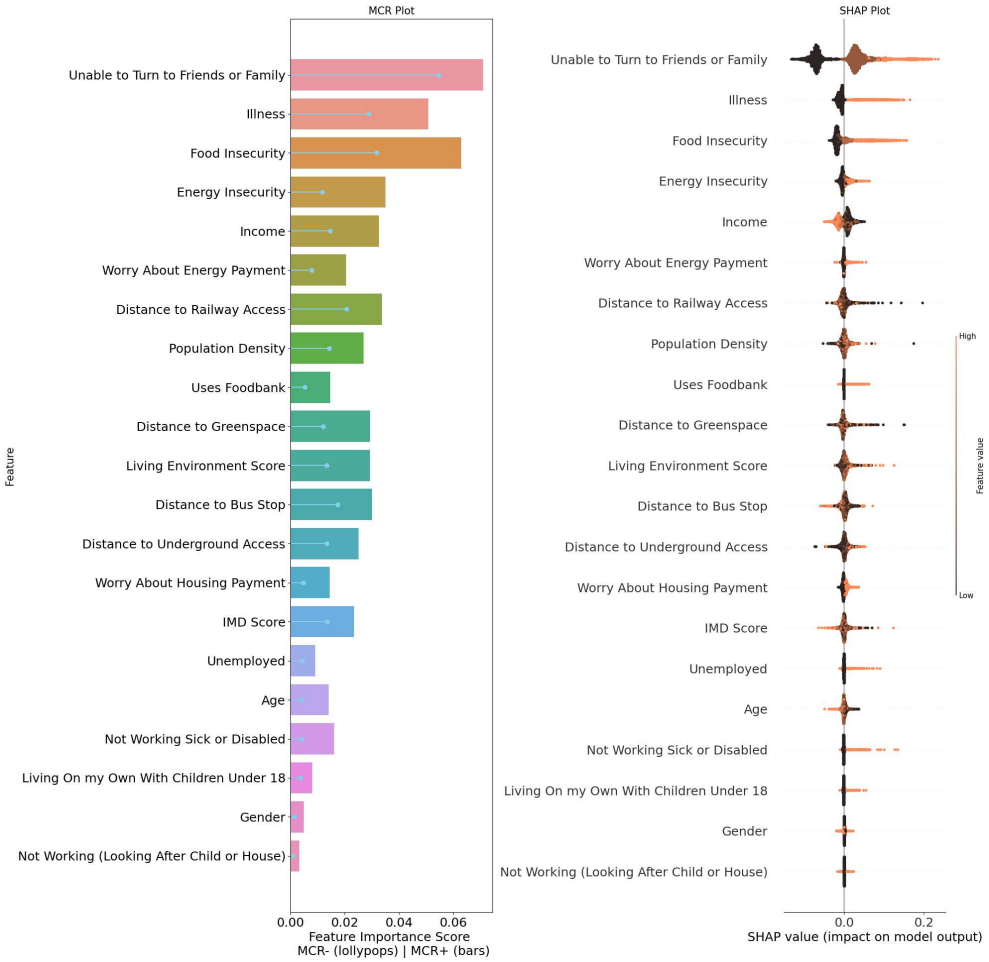

Figure 10: Level-1: MCR and SHAP Plots for All covariates. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.

Evaluating the MCR and SHAP plots for Level-2A, *unable to turn to friends and family* and *illness* still remain the highest contributing features. However, there were changes in the subsequent contributing features, including *energy insecurity*, *Income*

and *population density*, suggesting an increase in their impact on the model prediction (See Figure 11). The minimum MCR value for *income* and *illness* is higher than that of *energy insecurity* showing that income has a higher minimum impact on the prediction of loneliness

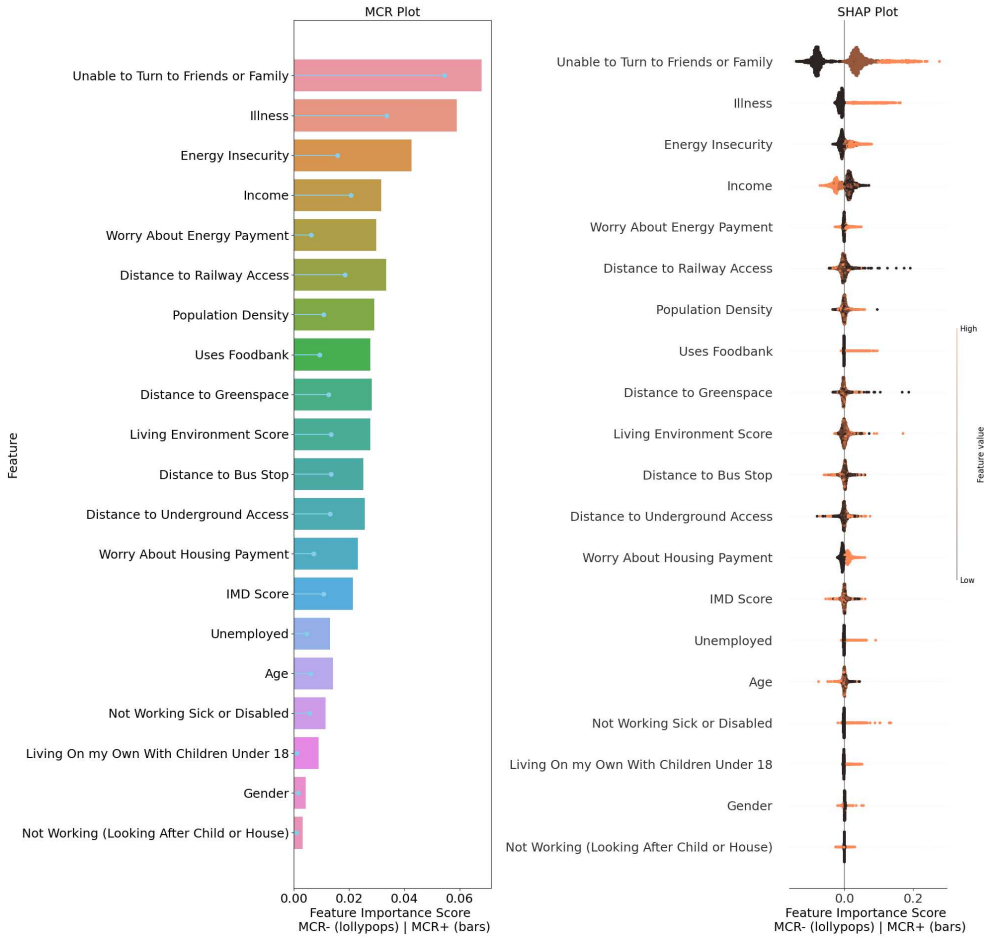

Figure 11: Level-2A: MCR and SHAP Plots Excluding Food Insecurity. The left plot displays minimum (MCR-) and maximum (MCR+) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.

The Level-2B analysis revealed that the model's test accuracy remained relatively unchanged from the Level-1 model, suggesting that energy insecurity had minimal impact on loneliness predictions when controlling for social reliance (being Unable to Turn to Friends and Family). Given the moderately positive relationship shared between food and energy insecurity, the food insecurity feature is likely already capturing / superseding information present in the energy insecurity feature. Examining the feature importance metrics (Figure 12) *food insecurity*, *illness*, and *income* still remain the highest contributing features. When comparing the MCR scores for the stigmatised deprivation characteristic *energy insecurity* in Level-2A, the MCR for *food insecurity* is higher than both *illness* and *income*. However, the lower accuracy score of Model-2B compared to Model-2A suggests that *food insecurity* is a more significant predictor of the experience of loneliness than *energy insecurity* in this sample.

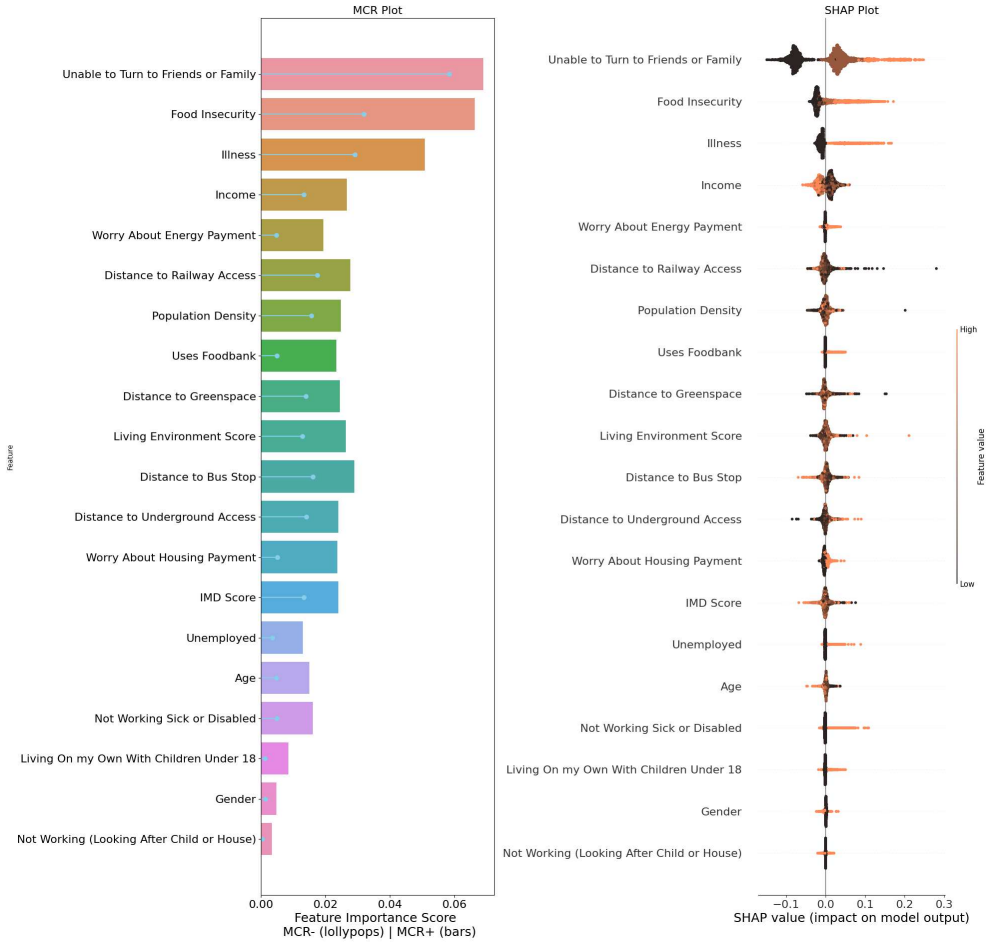

Figure 12: Model-2B: MCR and SHAP Plots Excluding Energy Insecurity. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.

Analysis of Level-3 MCR and SHAP plots (see Figure 13) demonstrates that *unable to turn to friends and family* remains the strongest predictor of loneliness, followed by *illness* and *income*. Features representing stigmatised deprivation, particularly *food insecurity*, contribute to the model's ability to capture subtle variations

in loneliness predictions. However, the dominant influence of social support availability (measured through the ability to turn to friends and family) emphasises a crucial distinction between social isolation factors and the psychological experience of loneliness itself. Notably, when food and energy insecurity are excluded from the model, 'Illness' shows increased importance, with larger MCR+ and MCR- values compared to Level-2A. This shift suggests that physical and mental health-related challenges may have more direct effects on loneliness when not considered alongside stigmatised deprivation indicators.

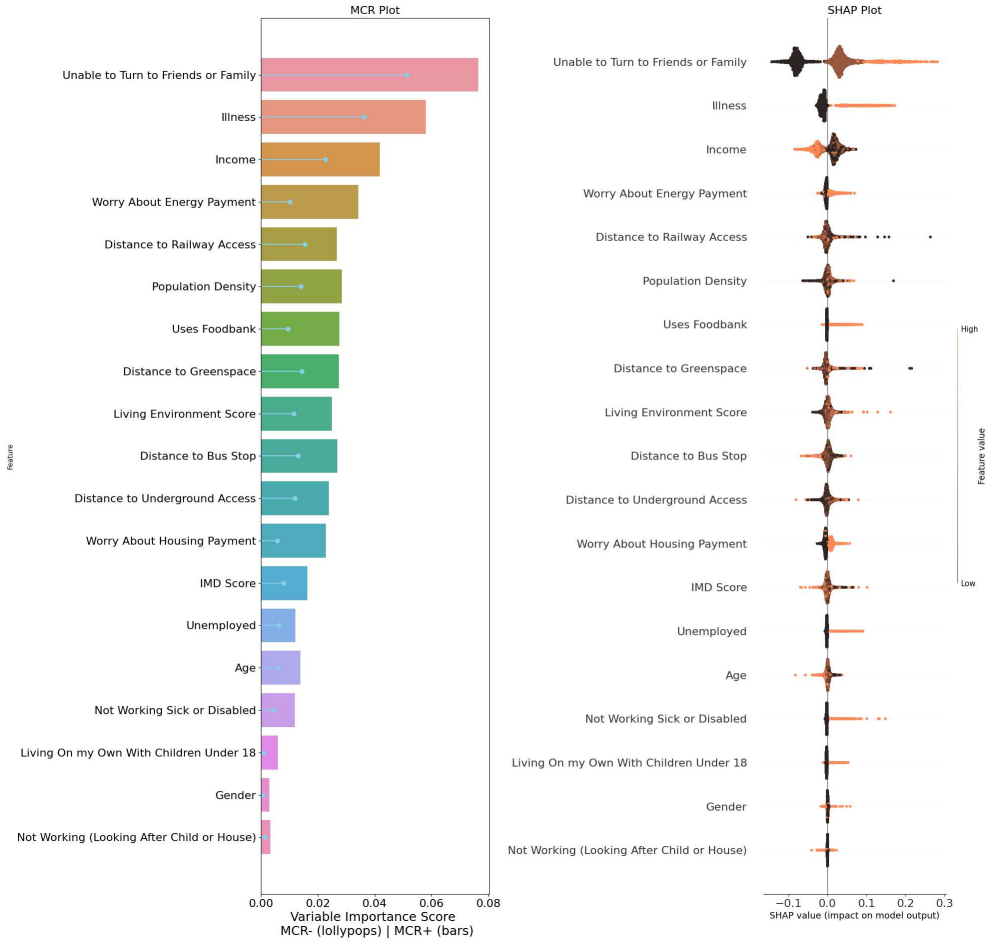

Figure 13: Level-3: MCR and SHAP Plots Excluding Food and Energy Insecurity. The left plot displays minimum (**MCR-**) and maximum (**MCR+**) feature values across optimal models. The right plot shows SHAP summary results for the top 20 predictive features, with point position indicating SHAP value magnitude and direction, and colour representing feature value intensity.

Overall, the model results show factors that limit autonomy, such as lower income, stress around unaffordable housing or energy costs, and limited access to transport, contribute towards an experience of loneliness. The feature *unable to turn to friends*

and family remained consistently at the top of the feature importance plots suggesting that despite the impact of stigmatised deprivation, having the social support of friends and family is more impactful in the prediction of loneliness. Furthermore, the prevalence of the *illness* feature across all treatments indicates that poor mental or physical health is a consistent predictor of loneliness.

These results offer evidence that experiences of stigmatised deprivation specifically can exacerbate experiences of loneliness. However, the question remains why this is the case of loneliness, and below we propose several hypotheses for this, worthy of future attention:

1. **Social Stigma Related to Deprivation and Social Resources**: People experiencing food insecurity may feel ashamed or embarrassed about their situation, leading them to withdraw from social interactions to avoid judgement or scrutiny from others [26, 33, 55, 79]. Food insecurity can cause feelings of shame and stigma, with those who use food banks and other social support mechanisms reporting experiencing feelings of loneliness and social isolation due to the perceived stigma [25, 26]. There is also a consideration for those who live in more affluent areas where food and energy insecurity are less common, who may experience more stigma related to experiencing such deprivation. Food banks operate on a 'deficiency model' that prioritises providing food for the individual person rather than facilitating the chance to eat with others, which in turn would reduce the stigmatised nature of food insecurity and mitigate against the psychological health impacts of stigmatised deprivation. This is likely exacerbated in areas with less social resources such as food banks, poorer quality social housing, and higher deprivation which contribute towards an increase in loneliness [22].

   When evaluating Level-3 in which the stigmatised deprivation features were removed, features including*living environment score* and *IMD Score* align with the

literature that shows how governmental support and remedial resources contribute towards feelings of loneliness.

2. **Limited Social Opportunities**: In some cases, individuals facing food insecurity may refrain from participating in social events or gatherings where food is the central focus due to fear of being unable to contribute or partake [55]; this idea is also reflected in the ability of individuals to participate in non-food related social events due to limited disposable income[17, 80–82].

   It is also suggested that limited mobility (specifically access to transport) in older people contributes towards feelings of loneliness [64]. This is reflected in the results of each model, where access to various transportation types was a contributing factor, with those further away from transport access points being predicted as lonelier more often, although the directionality of the feature's contribution remains unclear.

3. **Health Impacts**: It is clear that loneliness has an effect on an individual's mental and physical health [13, 40, 83]. While these results do not necessarily show causality, there is likely a bi-directionality between illness and loneliness, and further research could be done to understand the heterogeneity that may be present within the illness feature.

This study provides further evidence that the experience of loneliness is multifaceted. The features that were determined to be most important across the experiments align with previous studies [22, 59, 66]. This study builds upon previous work by examining loneliness at a more granular level compared to coarse national studies [12] while also capturing a broader population compared to work that focuses on older adults [4, 50, 66]. The modelling approach undertaken provides a more nuanced insight into the relationship between loneliness and stigmatised deprivation and health.

5 Limitations

A limitation of this study that should be acknowledged is the digital nature of the data collection approach. Olio is a digital platform that operates on a mobile smartphone; therefore, the data sample, while representative of London's IMD, does not include those who do not use the Olio platform or who have and can use a smartphone, as this requires a minimum level of media literacy.

This work attempts to identify the impact of stigmatised deprivation (i.e. specific experiences of deprivation) which lead to increased experiences of loneliness, not specifically the direct experience *of* stigma on loneliness.

While this study attempts to generate more generalisable insights about the lived experience of loneliness, rather than focusing on specific demographics such as age. However, these findings may not be generalisable when evaluating populations where social status and class may be less relevant than in the UK.

6 Conclusion

It is clear from the annual reports published by the ONS [45–48], the Campaign to end loneliness [1] and Public opinions and social trends datasets [49] that there is still a steady increase in the percentage of the population that experiences loneliness.

Our findings demonstrate that stigmatised deprivation, particularly food insecurity, impacts loneliness at an individual level. This not only corroborates previous qualitative research on how stigmatised deprivation affects the experience of loneliness [32, 33, 84], but emphasises the distinct nature of such challenges versus income deprivation alone. While the predictive power of these forms of deprivation only adds 2.32% accuracy to models of loneliness, this reflects an estimated 200k individuals in the UK who could be better identified as at risk (2.28% of the 9m people estimated to be lonely either often or all the time in the UK [1]).

However, the relationship between stigmatised deprivation and loneliness may be mitigated through the ability of an individual to socially rely on friends and family, which can be seen consistently across all treatment SHAP and MCR plots.

Stigma-related factors in loneliness modelling significantly affect model accuracy, further confirming the known psychological and social factors surrounding loneliness. However, the feature importance metrics suggest that despite how stigmatised deprivation carries unique psychological and social implications beyond general financial hardship, having a social network one can rely on is more impactful in reducing loneliness. Identifying how social isolation varies with deprivation should thus be the primary focus of policymakers looking to intervene. The challenge of social connection (or lack thereof) could likely be addressed through different initiatives, depending on whether the person is, for example, experiencing food insecurity and therefore lacks the opportunity to eat with other people. Showing a psychological health impact of stigmatised deprivation is the increased experience of emotional loneliness.

Social and environmental features, particularly area deprivation levels and access to green space, emerged as critical moderators of loneliness that moderate the relationship between deprivation and loneliness. Mental and physical illness also appeared as a strong predictor of loneliness across all the defined treatments, providing further evidence for the link between poor health and loneliness.

By examining loneliness across all age groups rather than just older adults, our findings reveal broader patterns in how stigmatised deprivation affects social isolation. By incorporating the spectrum of IMD scores alongside specific measures of stigmatised deprivation, our study offers a crucial context for understanding how various forms of stigmatised deprivation impact loneliness. It is important to note that our sample was limited to London's population. Further exploration is needed into the specific differences between those experiencing mental health concerns versus those with physical illnesses, as this granularity was not present in the dataset analysed.

Despite ongoing collaborations between UK government departments and charities to reduce loneliness through local initiatives, public opinion and social trends data show a steady increase in loneliness across the UK population. Our findings suggest that expanding these efforts to a national-level analysis would enable more effective targeting of interventions by better capturing how factors including stigmatised deprivation and access to services influence loneliness patterns across different regions across the UK.

Supplementary information.

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Declarations

- Funding:

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- Conflict of interest/Competing interests: Not Applicable

- Ethics approval and Consent to participate:

  Ethics approval for the study was via the University of Nottingham ethics panel (Faculty of Social Sciences, NUBS, review reference: 201829095.

  Informed consent was collected from each participant before completing the survey.

- Consent for publication:

  Not Applicable

- Data Availability:

  The data collected and analysed in this study can be found online at the following Github Repository https://github.com/GregorMilliganUoN/Exploring-the-Independent-Impacts-of-Stigmatised-Deprivation-on-Loneliness

- Materials availability

  For the purpose of open access, the author has applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version of this paper arising from this submission. Code availability:

  The code developed for this paper can be found online at the following Github Repository https://github.com/GregorMilliganUoN/Exploring-the-Independent-Impacts-of-Stigmatised-Deprivation-on-Loneliness

- Author contribution:

  Gregor Milligan: Conceptualization; Data Curation; Formal Analysis; Investigation; Methodology; Writing – Original Draft Preparation; Writing – Review and editing.

  James Goulding: Conceptualization; Data Curation; Support Analysis; Investigation; Methodology; Writing – Original Draft Preparation; Writing – Review and editing.

  Elvira Perez Vallejos: Conceptualization, Data curation, Writing – review & editing.

  Liz Dowthwaite: Conceptualization, Data curation, Writing – review & editing.

  Georgiana Nica-Avram: Writing – Review and editing (equal).

  John Harvey: Writing – Review and editing (equal).

  Torran Semple: Writing – Review and editing (equal).

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