# Assessing relative contribution of Environmental, Behavioural and Social factors on Life Satisfaction via mobile app data

Gregor Milligan[1,2], John Harvey[1], Liz Dowthwaite[3], Elvira Perez Vallejos[3,4], Georgiana Nica-Avram[1], James Goulding[1]

[1]N/LAB, Nottingham University Business School, University of Nottingham, UK
[2]Horizon CDT, University of Nottingham, UK
[3]Horizon Digital Economy Research, University of Nottingham, UK
[4]School of Medicine, University of Nottingham

***Abstract*—Life satisfaction significantly contributes to wellbeing and is linked to positive outcomes for individual people and society more broadly. However, previous research demonstrates that many factors contribute to the life satisfaction of an individual person, including: demography, socioeconomic status, health, deprivation, family life, friendships, social networks, living environment, and the broad range of behaviours enacted by the person, such as helping or volunteering. Consequently, it is challenging to disentangle the factors that contribute most significantly to life satisfaction, and thus more importantly, inform public policies designed to help foster positive wellbeing. We analyse primary survey data (n=2849) on self-reported life satisfaction in relation to a range of self-reported and observed variables associated with wellbeing. Specifically, we draw on a massive paired dataset related to use of a food sharing application in London, to augment the analysis using additional socioeconomic, environmental, and behavioural variables. Through a random forest machine learning approach and variable importance measures, we evaluate how a range of factors, that are often only evaluated individually, provide relative contributions towards life satisfaction. Result reveal that factors such as employment and social reliance contribute most significantly towards the experience of life satisfaction.**

***Index Terms*—Wellbeing, Life Satisfaction, Machine Learning, Deprivation, Variable Importance**

## I. Introduction

Life satisfaction (LS) is a significant indicator of wellbeing, linked to a range of positive outcomes across both individuals and society as a whole. Due to the many potential factors which can impact upon life satisfaction there exists a correspondingly large body of research on the relationship between potential indicators and LS. Alongside a wide range of academic research studies (see, for example, [1]–[3]), national governments have increasingly targeted use of subjective wellbeing and LS metrics not only in decision-making processes, but as an overarching tool for post-hoc policy assessment [4]. In this work we leverage a large ground-truthing survey, alongside behavioural features drawn from mass mobile phone app datasets, to shed light on which factors might be impairing life satisfaction the most - with the goal of augmenting the evidence base to help support public policy decision making.

Wellbeing, which has been defined as the state of *ideal psychological experience and functioning* [2], is a complex phenomena to model. It is both dynamic and contextual in nature, influenced by a variety of factors – including physical health, mental health, emotions, relationships, and social environment [5] – that adapt and change both seasonally and over lifetime trajectories. Contributing factors interact with each other in complex ways, generating feedback loops that can either improve or worsen wellbeing [6]–[8]. Given the wide range of variables able to influence LS at both an individual and national level, and the potential applications to policy and decision making, agreement of how exactly wellbeing should actually be measured, at scale, has become a key challenge, which we first detail below.

## II. Wellbeing Measures

Two prominent philosophies of wellbeing have been established in the literature: subjective (hedonic) wellbeing [9] and eudemonic wellbeing [1], each based on a contrasting contextualization of human nature. The *subjective* approach to wellbeing (SWB) equates the wellbeing of an individual to the level of happiness or pleasure they experience. [9] clarifies the three contributing factors of this interpretation as: (1) *High positive affect*, including emotions such as excitement, contentment, or interest; (2) *Low negative affect*: including emotions such as distress, guilt or fear; and (3) *Life Satisfaction*.

The *eudemonic* approach to wellbeing (EWB) is defined as the degree to which people are able to be their most 'authentic selves' [1]. This approach aims to incorporate greater nuance than solely considering happiness and LS, by also considering wellbeing as related to the actualisation of an individual's potential, albeit such a concept being very hard to reify. This is underpinned, however, by the observation that not all outcomes that produce pleasure are congruent with wellbeing [10]. Martela and Sheldon (2019) elaborate that wellbeing should be considered as a combination of not only *how* a person is feeling, but also *why* the person feels a certain way and *what* the person is doing to feel that way.

In this study, which examines life satisfaction quantitatively, we conceptualise wellbeing through the *eudemonic activity model* (EAM) as "*a common core for connecting eudemonic and subjective wellbeing*" [10]. While the EAM reflects a tripartite approach to wellbeing – grounded theoretically on the assertion within self-determination theory (SDT) that all people share the evolved need for autonomy, competency, and relatednes – it was developed for practical purposes [2]), and specifically the difficulty of comparing EWB studies, due to the diverse range of competing EWB measurement strategies. "*Doing well*" and "Feeling well" are the two pillars of the EAM; with the latter derived from the eudemonic concept of motivations and activities that lead to self-realisation and the pursuit of excellence. "*Feeling well*" itself can be divided into two sections: Psychological need-satisfaction and SWB, with concepts including feelings of autonomy, competence, and relatedness, i.e. SDT and their causal link to the constructs in the SWB, particularly LS (see Figure 1).

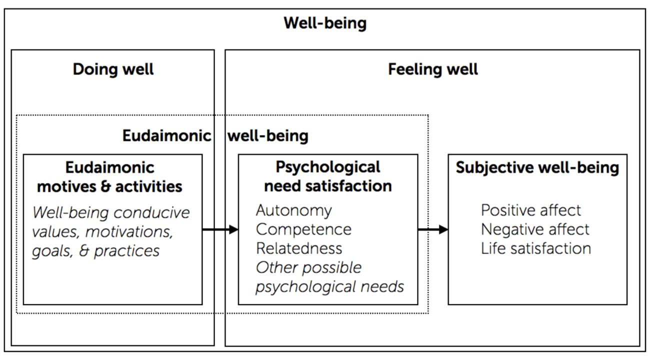


Fig. 1. The Eudemonic Activity Model

In the past, standardised research instruments have generally been used to collect and evaluate wellbeing metrics at both individual and population levels. The most common instruments for such assessment have traditionally been self-reported wellbeing surveys, although their usage has been subject to scepticism due to well-evidenced biases in self-reported data [11]. For wellbeing this is particularly prescient issue, with additional scepticism being raised due to the pressure an individual faces to conform to the societal expectation of happiness. However, it has also been noted that such pressure to conform is also present in qualitative measures such as interviews [12] - and that social desirability, being a substantive feature of an individual's personality, is closely linked to an individual's SWB, and therefore should not be wholly discounted as a source of error when evaluating wellbeing [13].

A range of prominent measures exist to measure SWB, including the Warwick-Edinburgh Mental wellbeing Scale (WEMWBS), and its short variant, the Short Warwick-Edinburgh Mental wellbeing Scale (SWEMWBS) - wellbeing instruments that measure the subjective wellbeing and functioning of the respondent [14]. The Scale of Positive and Negative Experience (SPANE) has also been used to evaluate subjective wellbeing, specifically, the range of positive and negative experiences a respondent faces and the balance of these experiences [15]. LS, in particular, is often measured using a single item measure such as "on a scale of 0 to 10, how would you rate your overall life satisfaction?" (0 = not at all satisfied to 10 = extremely satisfied) [16] or "How satisfied are you with your life as a whole?" (7-point Likert scale from 1 = extremely dissatisfied to 7 = extremely satisfied) [9].

The multitude of wellbeing instruments and measures used by researchers illustrates the challenging nature of capturing wellbeing. Yet this also emphasizes the need to take a multi-pronged approach, as leveraged in this work, modelling well-being via a range of variables (such as socio-demographic, geographic and behavioural factors) in an attempt to evaluate LS through a wider lens. The concept of LS has previously been linked to socio-demographic, geographic and behavioural characteristics, such as physical health conditions [4], deprivation factors such as food and energy insecurity [7], [8], loneliness, employment and household composition [17]. However, these have not previously investigated holistically, within a single model framework - nor has their *relative importances* been examined.

## III. Factors of Life Satisfaction

In this work we take a hypothesis-generating and machine learning approach to modelling contributors to LS. This allows us to consider a wide range of factors that can impact LS simultaneously, with variables drawn from both self-reported outcomes and linked big datasets, characterised by the following domains:

### *A. Socio-economic Factors of Life Satisfaction*

Employment status and the security of a job have previously been evidenced as affecting wellbeing with unemployment in particular being pernicious to wellbeing [18]–[20]. It is generally accepted that unemployment has a deleterious effect on individual subjective wellbeing [21]. Factors that could lead to a difference in life satisfaction within sub-populations of employed people could be due to for instance high job insecurity [20]. Unemployment is associated with lower subjective wellbeing and life satisfaction and is linked to other contributing factors of lower life satisfaction such as deprivation and social isolation [18], [22], [23].

The implications of such variables are not just damaging for the individual, but at scale can impact economic growth as a whole [24]. Unemployment can additionally lead to a rise in deprivation, and knock-on challenges such as food and fuel insecurity, where an individual can't afford to buy food or pay for energy to heat their home or cook food. Thus a low LS can lead to a vicious cycle, and a continual longitudinal decline in wellbeing [5]–[8]). Such insecurity can also lead to a decrease in social participation, limiting a person's ability to engage socially due to either cost or stigma [17], [25], further increasing social isolation and loneliness [23].

There is a clear relationship between social participation and inclusion and LS leading to increased happiness, confidence, self-esteem and SWB general mental health [26], [27], indicating the need to model social inclusion when understanding wellbeing. Social inclusion can take several forms such as engaging in a community or religious group [28], visiting family and friends [29] and generally being part of a social network. Being part of a dense social network improves LS and an individual's sense of belonging [30]; and while not always true, being part of a sparse social network generally correlates to lower overall self-reported scores of LS. Other significant socio-economic factors that impact LS are noted in the literature, including: Age [31]–[33]; Income [34]; Diet [35]; and wider environmental factors such as public transport access, crime and greenspace access [25], [36], [37].

### B. Environmental Factors of Life Satisfaction

Environmental factors have been shown to contribute to an individual's LS, including the quality and size of amenities and extent of greenspace in a local area [38]. There are a range of factors that contribute to the use of such greenspace, including the quality of its maintenance, size and diversity [39], [40], the ability of local communities to physically travel to such greenspace via personal or public transport [29], [39], [41], and the public perception of the location the greenspace is situated (for example in areas with a higher crime can impact the usage [42]). Those who live closer to greenspace such as parks are purported to have higher life satisfaction, and it is has been suggested in isolation that the quality of the greenspace is of key importance [40].

More generally, limited access to transport can have a negative effect on LS, with different modes and quality of transportation options having varying effects on life satisfaction for different people [29]. It has also been suggested that the actual experience of transport is influential, alongside indirect effects such as the facilitation of social engagement (e.g. visiting family or friends) and enablement of travel to work [29]. An individual's ability to get around independently is also likely to affect their sense of autonomy [43], [44] - but also potetnially impactful is the ability to find solitude when needed. The relationship between SWB, particularly LS, and population density is complex and ambiguous. It is suggested that higher population density can lead to increased stressors, such as noise, traffic, and housing challenges. However, other research suggests that there may be some indirect positive effects of a higher population such as higher social cohesion [45]–[47].

### C. Social Behaviour and Life Satisfaction

In addition to the socioeconomic and environmental contexts in which a person lives, LS is also potentially affected by the social behaviours enacted by the person. There is evidence to support the contention that prosocial behaviours such as donation and/or volunteering can play a protective role for individuals and increase their well-being in the face of otherwise unsatisfactory life conditions [48] [4]. However, the relationship is not deterministic and is likely moderated by demography, among other factors [49]. The literature on behavioural factors relating to life satisfaction is less well developed than other streams, due to the challenges of obtaining related variables (a situation the use of big-datasets reflecting naturalistic behaviours may help to improve). However, in this work, due to the use of mobile app data drawn from a popular food sharing platform, we are able to link a range of behavioural factors. For example, following existing work such as [50], we can analyse whether a person *donates* to or *takes* a lot of food from other people, whether they volunteer to help others, and whether they interact in tightly-knit community groups or sparsely connected networks. Previous work has shown some people who participate in food sharing are in food insecurity [51], typically meaning they participate differently in the social groups that form, and this adds an important dimension to the study as we know that food insecurity, like most other forms of deprivation, has a corrosive effect on life satisfaction [52].

## IV. Machine Learning to Understand wellbeing Factors

Although there exists extensive literature exploring the impact of a number of factors on LS such as employment, deprivation, social mobility and age individually, there is little consensus on the relative importance of such factors in supporting wellbeing [3]. A methodological approach able to provide insight into the relative importance features is the application of machine learning methods, an approach previously underutilized in wellbeing research [3], [33].

While previous studies have employed traditional linear models to identify that age, gender, and sleep are important factors in wellbeing [53], understanding of the interactions and priority of different factors is unclear. The efficacy of machine learning models to evaluate the significance of age as a factor of LS has been examined in [33], through the analysis of the German Socio-Economic Panel. This work found that although there is a dip in life satisfaction around the age of 50 further analysis was needed to understand the interplay of other factors such as income and education. Further [54] applied both linear models (Ordinary Least Squares and Least Absolute Shrinkage and Selection Operator) and tree-based methods (Random forests and Gradient Boosting) to the German Socio-Economic Panel (along with UK household survey data and the US Gallup Daily Poll data) to evaluate the factors affecting wellbeing across different contexts. In an effort to extract meaningful features, permutation importance and pseudo partial effects were examined; finding that poor health, frequency of worry, and age, were significant factors across the three datasets evaluated. Importantly, the non-linearity of these effects was noted, with tree-based machine learning approaches outperforming conventional linear models [55].

We build upon this nascent literature by modelling a self-reported single-item LS measure against a combination of domain features previously suggested to correlate with LS

(*Age, Income, Worry, Deprivation and Employment*), aiming to provide a holistic overview of the factors that contribute to LS. Given the potential issues within self-reported measures of personal circumstance, this offers a potentially more objective overview of the factors contributing towards LS. A range of features were engineered, including behavioural measures derived from linked big-data sets, and cutting-across several domains indicated in the current literature. To understand which factors are most influential we use a non-linear tree-based model (random forest) with evaluation focusing on feature importance established using SHAP values (SHapley Additive exPlanations) [56].

## V. Experimental Method

### A. Data

Ground-truth data concerning LS were drawn from a survey disseminated amongst London-based users of *Olio*. Olio is a food-sharing platform centred around users listing items of food that they want to give away via their mobile device, such as surplus produce from their garden, leftover food, or food that is nearing its expiration date [57]. Other users can then browse listings, request items and exchange what they need or want, with the platform underpinning a social network of 7m registered users as of 2023. The survey was delivered via the Olio mobile-app platform, and completed by 2,849 users across 983 MSOAs[1] in Greater London between 22nd Nov 2022 to 5th Dec 2022. The survey sampling strategy involved the application of quota restraints for socioeconomic status (informed by the IMD score of respondents' home area, according to their corresponding MSOAs). Figure 2 illustrates the representatives of the survey in terms of distribution across London LSOA IMD deciles.

Along with a single item self-reported *life satisfaction* [9], the survey collected a range of socio-demographic (e.g., age; gender; household income; household characteristics), economic (e.g., food insecurity; energy consumption habits; housing; anxiety associated payments) and social characteristics (e.g. reliance on family, friends or charities, isolation, neighbourhood cohesion). In addition to survey response items, participants were additionally linked to two other datasets. The first was environmental and geospatial data reflecting their locality (e.g. access to greenspace, population densities, neighbourhood crime levels, access to transport, etc), sourced from official UK's statistical providers such as the Office of National Statistics (ONS). The second data source was provided via a data donation process [58] administered in a strict privacy-preserving fashion, with consenting participants linked to a range of behavioural and network features reflected in their Olio app usage, and resulting social network on the platform (e.g. network centrality, activity, etc.)

[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

### B. Feature Selection and Engineering

In order to investigate the relative importance of factors correlated with life satisfaction, we first constructed a binary classification task to identify individuals with low versus medium or high life satisfaction, optimizing a machine learning model that employs 69 features drawn from three broad domains of individuals' exposomes i.e. the socioeconomic, environmental, and behavioural exposures that an individual encounters throughout life:

- **Environmental:** geospatial features that represent the neighbourhood characteristics of a participant's home area, linked via a geospatial lookup.
- **Socio-economic:** reflecting a range of individual features including income, deprivation, age, marital status, household composition, occupation, and education, self-reported within the data collection survey.
- **Behaviourally derived:** Features derived from the way consenting participants use the Olio application to perform a variety of tasks, and via network analysis of their interactions on the platform.

All independent variables/features underwent a traditional data cleansing process, with standard scalar functions applied to numerical variables, and categorical variables being one-hot-encoded. A complete list of input variables is described in Appendix Table 1.

The dependent variable, "Satisfaction with life", was produced by first ordering and then partitioning individuals into three equally sized groups (tertiles) based on the survey item response (which accommodated values in the range $[1-10]$). This generated three classes reflecting *Low*, *Medium*, and *High* life satisfaction. Medium and High classes were merged for binary classification treatments. Due to the heavily left-skewed distribution of the responses (see Figure 3) any response below 7 was therefore designated "Low life satisfaction", and responses values 7-10 designated as "Medium or High life satisfaction". This binary split was selected due to the focus on understanding factors contributing towards a lower-than-average life satisfaction score within this sample.

### C. Modelling

A 25% sample (712 individuals) from the total dataset was separated out to form a randomized test set, with the remaining 80% (2137 individuals) of the data being used as the experimental training dataset. In order to employ a balanced dataset for model optimization, the High/Medium class is down-sampled, resulting in a total training dataset of 1425 individuals. A Random Forest Model was then optimized using the training dataset, employing a full grid-search and five-fold cross-validation. The grid-search allows exploration of the parameter space (splitting criterion, maximum depth, maximum features used in each tree, minimum sample splitting for nodes, and total number of estimators), with the optimal mean validation accuracy used to select the optimal model. The final model is then applied to the test dataset to examine accuracy, precision and recall scores, followed by variable importance analysis via SHAP.

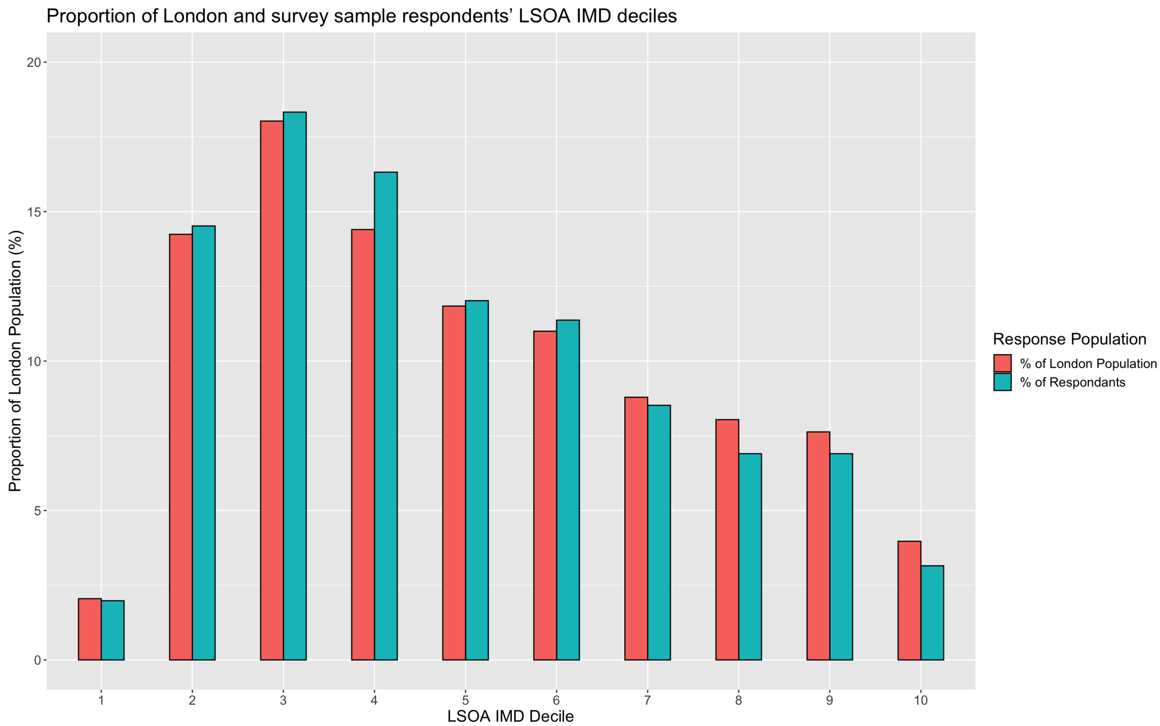


Fig. 2. Proportion of London and survey sample respondents' LSOA IMD deciles

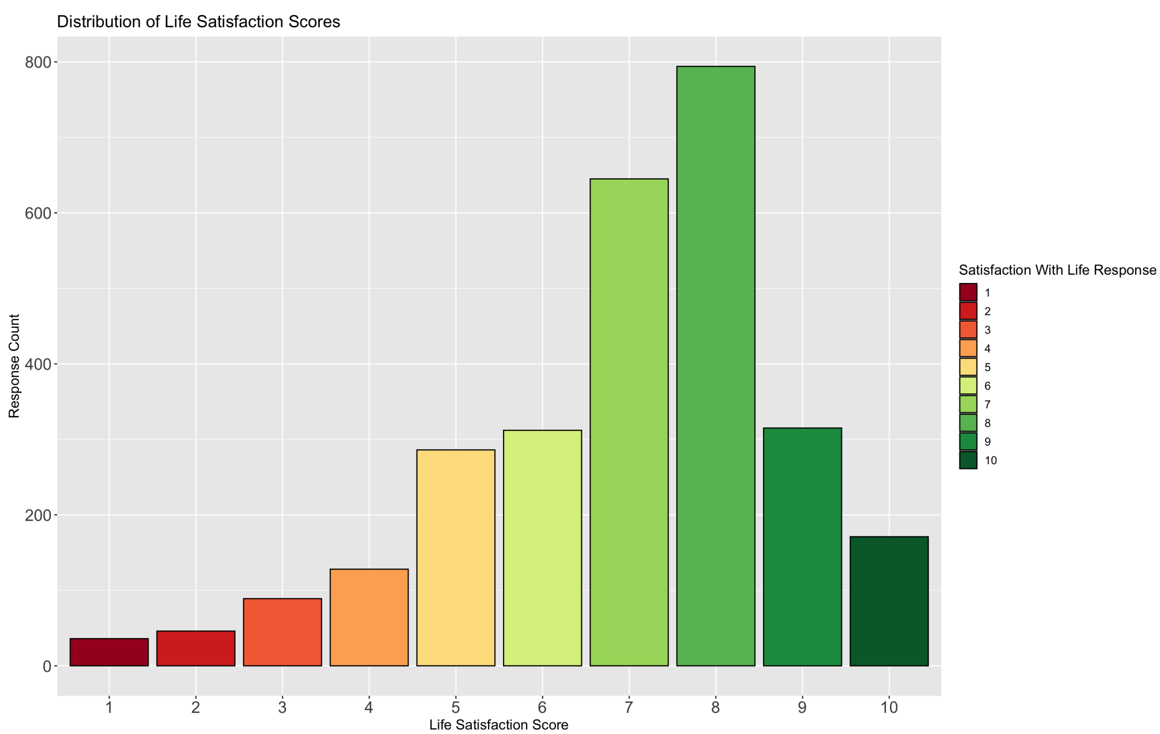


Fig. 3. life satisfaction distribution

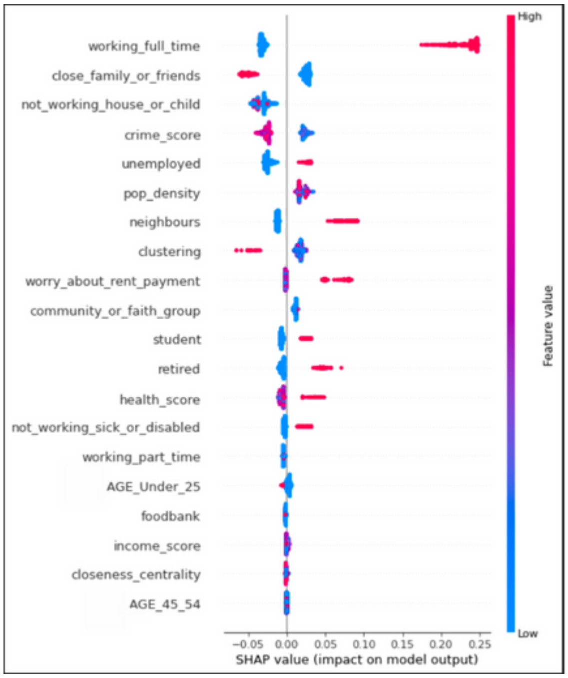


Fig. 4. SHAP Feature Importance

## VI. Results

An optimal test accuracy of 0.68 (mean 0.72 validation accuracy) was found for a Random Forest composed of 1000 estimators with a maximum depth of 5, using automated detection of maximal features and splitting via gini index at each node, with a minimum sample splitting level of 3 participants in each. This is accompanied by a recall of 0.68, a precision of 0.69 and an f1-score of 0.68. Results compare favourably to a dummy classifier (accuracy of 0.5), reflecting significant results (p-value, $< 0.01$) despite a relatively limited number of psychological and physical health variables in the analysis. Variable importance analysis results for the optimal model are illustrated in Figure 4.

## VII. Discussion

This work investigates the relative contribution of environmental, behavioural and socio-economic factors on LS and wellbeing via the analysis of mobile app data (behavioural data from a food-sharing platform) and combined, gathered and engineered a range of features across several domains indicated in the current literature to understand which factors are most significant. The SHAP plot illustrated in figure 4 highlights the 20 highest contributing features for predicting life satisfaction, and serves immediately to demonstrate the wide range of contributing factors at play. The height of each bar represents the magnitude of the SHAP values and the colours indicate whether the feature increased (red) or decreased (blue) the model's prediction. With factors spread across three feature domains, as expected, variable importance results indicate that LS is related to correlated factors across environmental, socio-economic and behavioural characteristics. It is important to note that care must be taken when interpreting this analysis as the SHAP does contain correlated features.

As previously hypothsized, the socio-economic factors shown to be significant in this model tend to be factors related to deprivation such as *crime* (crime score), *health* and *income* scores (which are often combined to define the overarching index of multiple deprivation scores or IMD Score). While it is widely known that these forms of deprivation contribute towards both LS and wellbeing [4], with full time employment being the most influential factor, they dominate but do not completely compose the top rankings. Further socio-economic factors include *employment status* and *employment tenure status* (full-time and unemployed). This is consistent with previous studies analysing the impact of socio-economic factors on LS [18], [22], [23].

A range of social factors were also shown to be important in the model. Primarily, factors related to social reliance such as access to a *community or faith group* or *close family and friends*. Two social network features were also determined to be important in the model, the clustering coefficient features (a measure of how densely connected a survey respondent on the Olio platform was connected to other users) and closeness centrality which indicates how close a survey respondent is to all other users in the app network. The relationship between the embeddedness of an individual in a social network is also in line with previous literature on LS factors [30].

The factors that have been shown to be significant contributors towards LS are related to certain aspects of the EAM, particularly social factors such as employment and geographic factors *crime score, population density*, and worry about a *lack of income*, *paying rent*, *foodbank usage* may diminish people's sense of autonomy and competence. Being part of a community or faith group is related to having particular values, and several of the others may relate to practices such as working patterns. These outputs support the findings made by the ONS' evaluation of national wellbeing [4] showing that financial worry, employment security, employment satisfaction, and community belonging all contribute towards wellbeing and LS.

Some considerations should be made when evaluating the data collected and results of the model, primarily that the survey was sent out to respondents at the outset of the UK energy and cost of living crisis, this could place an unseen emphasis on certain features such as unemployment, income, and financial worry. Further to this only one model class has been applied during this study but this will be expanded upon in future work through the application of Model Class Reliance (MCR) to understand variable importance.

To conclude this study provides insight into the factors that contribute LS, a multi-pronged approach was taken to consider the socio-economic, environmental and behavioural features of 2,849 individuals through the combination of survey responses and behaviours on a food-sharing app. This work attempts to provide some initial insight in tackling the challenges of understanding and ordering the factors that contribute towards LS suggested by [3].

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## VIII. Appendix

TABLE I
ABRIDGED LIST OF FEATURES GENERATED FROM BOTH SELF-REPORTED AND BIG-DATA SOURCES

| Feature | Data source | Description |
|---|---|---|
| **Environmental** | | |
| poverty level | ONS | poverty ranking as defined by the IMD score provided by the UK ONS |
| employment level | ONS | employment_score ranking as defined by the IMD score provided by the UK ONS |
| income level | ONS | income_score ranking as defined by the IMD score provided by the UK |
| educational facilities | ONS | educational ranking as defined by the IMD score provided by the UK ONS |
| crime levels | ONS | crime_score ranking as defined by the IMD score provided by the UK |
| barriers to servies | ONS | ranking of barriers to local services as defined by the by the UK ONS |
| living environment | ONS | living environment_score as defined by the by the UK Office of National Statistics |
| health levels | NHS | Risk of premature death/impairment of quality of life through poor physical health |
| foodbanks | Geospatial | Number of foodbanks extant in the LSOA |
| ethnicity | Geospatial | percentage of the local community non-wite (pct_non_white) |
| 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 |
| green space | ONS | Average population per park or public garden or playing field |
| high-rise housing density | ONS | Number of flats in built up area with gardens |
| neighbourhood comparison | Self-reported | Relative deprivation compared to neighbouring communities |
| **Social** | | |
| neighbours | SURVEY | the extent to which a participants interacts with neighbours |
| friendship | SURVEY | the level of activity with close family or friends |
| social engagement | SURVEY | level of engagement with community or faith groups |
| financial anxiety | SURVEY | extent of worry about housing/rent payments |
| unemployed | SURVEY | whether the individual considers themselves unemployed |
| working$_{f}ull_{t}ime$ | SURVEY | whether the individual is in full time employment |
| retired | SURVEY | whether the individual is retired or not |
| caring | 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 |
| student | SURVEY | indication of engagement in higher-level education |
| gender | SURVEY | the reported gender of the participant |
| illness | SURVEY | self-reporting of ongoing illness or health problems |
| household composition | SURVEY | single/children/married/shared occupancy |
| social isolation | SURVEY | the extent to which an individual can turn to friends and family |
| fuel security | SURVEY | does the individual struggle to pay for fuel/energy |
| pre payment | SURVEY | does the individual use a pre-payment meter for energy |
| food security | SURVEY | does the individual struggle to pay for food/meals |
| housing | SURVEY | self-reported level of housing |
| epc rating | SURVEY | official EPC energy rating of home, as assigned by the UK government |
| energy anxiety | SURVEY | self-reported concern/worry about ability to pay for energy |
| income range | SURVEY | self-reported income range of the participant |
| **Behavioural** | | |
| social activity | OLIO | |
| number of added messages on the OLIO platform social reach | OLIO | number of added comments for food listings on the OLIO platform |
| donation behaviours | OLIO | number of donated food listings on the OLIO platform |
| closeness centrality | OLIO | the extent to which a user is connected to other users |
| clustering | OLIO | the extent to which a user is part of a social clique |
| embeddedness | OLIO | the extent to which a user is embedded within the OLIO network |