Exploring the spatial disparities in gambling risk and vulnerability

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Summary

Gambling harm disrupts the health and wellbeing of the individuals, as well as families, communities and societies around them. Despite the growing recognition that gambling harms are socially and geographically uneven in its occurrence and impacts, there is limited empirical knowledge about the factors underlying the disparities. Here, we quantitatively profile nationwide gambling survey using series of small area geodemographic data. Results from this granular analysis are synthesized to devise a composite indicator of gambling risk and vulnerability that can be mapped to provide new insights into public health strategies to tackling gambling harms in a more effective manner.

KEYWORDS: gambling harm, public health, risk index, overlay analysis, geodemographics

1. Introduction

The gambling industry has grown considerably in the past few decades, largely led by the rapid diffusion of smartphones and Internet use, proliferating the opportunities for participation, such as via online betting (Robitaille and Herjean, 2008). In the UK, the industry attracts more than half of the adult population, yielding an annual revenue of £14.2 billion (Gunstone et al., 2019). Gambling harms have become more apparent, too, disrupting the health and wellbeing of individual and families that interferes with daily lives. Consequences include financial insecurity, domestic abuse, anxiety and depression, which are known to be socially and geographically uneven in its occurrence and impacts (Wardle et al., 2018).

Traditionally, excessive gambling has been conceptualised as a psychiatric disorder, diagnosed based on criteria defined by the measures such as Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and International Classification of Diseases (ICD-11) (Christopher, 2021). Accordingly, harms inflicted by gambling have often been attributed to weakness of the individuals, which led to articulation of 'responsible gambling' initiative as a mainstream solution. Not only does this perspective often pathologize and stigmatize those that are affected, it also overemphasises policy attention on the 'problem gamblers' at an individual level whilst neglecting the wider population that may be vulnerable to gambling harm (Christopher, 2021). Acknowledging the limitations of the 'responsible gambling' approach in tackling relevant harms, recent literatures have suggested a shift towards a public health discourse (Blank et al., 2021). The public health approach seeks to prevent harm at as 'upstream' as possible, which is to say that the preventative strategy should be targeted to the identified sub-populations that may be particularily vulnerable, more so than focusing on the individual cases.

This paper views gambling harm as a potential public health issue by blending a nationwide combining gambling survey with open datasets to try and understand the spatial and demographic

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factors underlying disparities in gambling risk and vulnerability in England. The paper further attempts to synthesise these results in creating a composite gambling risk and vulnerability indicator.

2. Data

Three types of data are combined to quantitatively analyse gambling harms. The first is a nationwide survey on gambling behaviour, commissioned by GambleAware. The GambleAware survey was carried out between November and December 2020 using online interviews conducted with YouGov's online research panel with response from 18,879 adults (Gunstone et al., 2019). It includes respondents' residential addresses aggregated by Lower Super Output Area (LSOA) level; and their self-identified level of experienced harm defined by the Problem Gambling Severity Index (PGSI) scale, ranging from 0 to 27. Indicated by PGSI score 8+, 410 out of 16,338 respondents in England were identified as a 'problem gambler'. The data was weighted to be representative of the Great Britain (GB) adult population.

The second type of data comprises two geodemographic classifications. Geodemographics is an 'analysis of people by where they live' (Brunsdon et al., 2011: 18). Public health campaigns are progressively adapting this method, namely in profiling and targeting prevention measures at the vulnerable segments of the society (Petersen et al., 2011). Here we use the 2011 Output Area Classification (OAC) and the Internet User Classification (IUC). OAC is a three-tier hierarchal classification that is built upon 60 socio-residential variables from the 2011 Census data (Vickers and Rees, 2007). The second-tier Group level is deployed in this study, which consists of 26 classes at the output area (OA) geography. It is deemed to be a useful tool to glean some general insights about the socio-residential attributes that may be associated with gambling harms. The IUC is a bespoke segmentation aimed at depicting differential patterns of online engagement amongst the GB population (Singleton et al., 2020). This is relevant, as more interaction with Internet likely puts an individual at greater risk from gambling harm, given the increased accessibility (e.g. online betting) and exposure to incentives (e.g. advertisement) (Robitaille and Herjean, 2008).

The third type of data focuses on neighbourhood conditions. Emerging evidence suggest that deprived neighborhoods facilitate higher risk of gambling harms, as the condition in which people live can affect their health and wellbeing, such as mental health, which is often associated with gambling activities (Rogers et al., 2019). We use the English 2019 Index of Multiple Deprivation (IMD), a composite indicator portraying seven domains of hardship experienced by the population within each LSOA (Longley et al., 2021). It has further been suggested that rates of problem gambling as defined by the PGSI are higher in areas near to gambling outlets, albeit that gambling behaviour in such locations is spatially heterogenous (Wardle et al., 2017). Research conducted in Australia also suggests that spatial accessibility of specific gambling venues is an important factor to be considered in the assessment of gambling risk (Young et al., 2012). Therefore, dataset on Gambling Outlet Accessibility (GOA) will be utilised in this study: one of the domains of the CDRC Access to Health and Hazards (AHAH) index, which can be used to differentiate between localities that are as more or less accessible to physical gambling outlets.

3. Methodology

To derive a basic understanding of endogenous and exogenous characteristics that determine gambling risk and vulnerability, 410 individuals with PGSI score 8+ were profiled according to the categorical indicators: OAC Group (**Figure 1**), IUC group (**Figure 2**) and IMD decile (**Figure 3**). As illustrated in Equation 1 below, a location quotient (LQ) was produced for each variable by dividing the proportion of problem gamblers within each category by the proportion of problem gamblers across the England sample.

$$LQ_i = \frac{\dfrac{p_i}{e_i}}{\dfrac{P}{E}} \qquad\qquad (1)$$

Where:

p_i = weighted count of problem gamblers in class i
e_i = weighted count of England respondents in class i
P = number of problem gamblers within England respondents
E = number England respondents

LQ<1 indicates a class with fewer-than-expected 'problem gamblers', whilst LQ>1 indicates a class with more-than-expected 'problem gamblers'. Here, the modal OAC Group was assigned to each LSOA to unify the geographical granularity. Furthermore, the calculated LQs were standardised into z-scores, which were then assigned to each LSOA in England, accordingly, based on the belonging group/decile. Similarly, the GOA values were also converted into z-scores. To create a composite gambling risk and vulnerability index, an overlay analysis was performed by aggregating the z-scores of the four indicators, which was then visualised into a risk map (**Figure 5**).

4. Results

The following bar charts present results of the profile analysis conducted on the GambleAware survey according to the geodemographic classifications, OAC Group and IUC group, respectively.

As seen in **Figure 1**, areas categorised as the *ethnic dynamics* (LQ=3.82) were identified to be most prone to gambling harm, followed by *challenged Asian terraces* (LQ=2.64). They commonly accommodate people with relatively high levels of unemployment, low qualification levels and non-white ethnic groups. **Figure 2** emphasises more on residents' differing levels of interaction with Internet, where the top two groups, *e-cultural creators* (LQ=2.23) and *e-withdrawn* (LQ=1.66), have contrasting characteristics. Whilst the former enjoys high levels of Internet engagement, especially for entertainment purposes, the latter group has the least online presence.
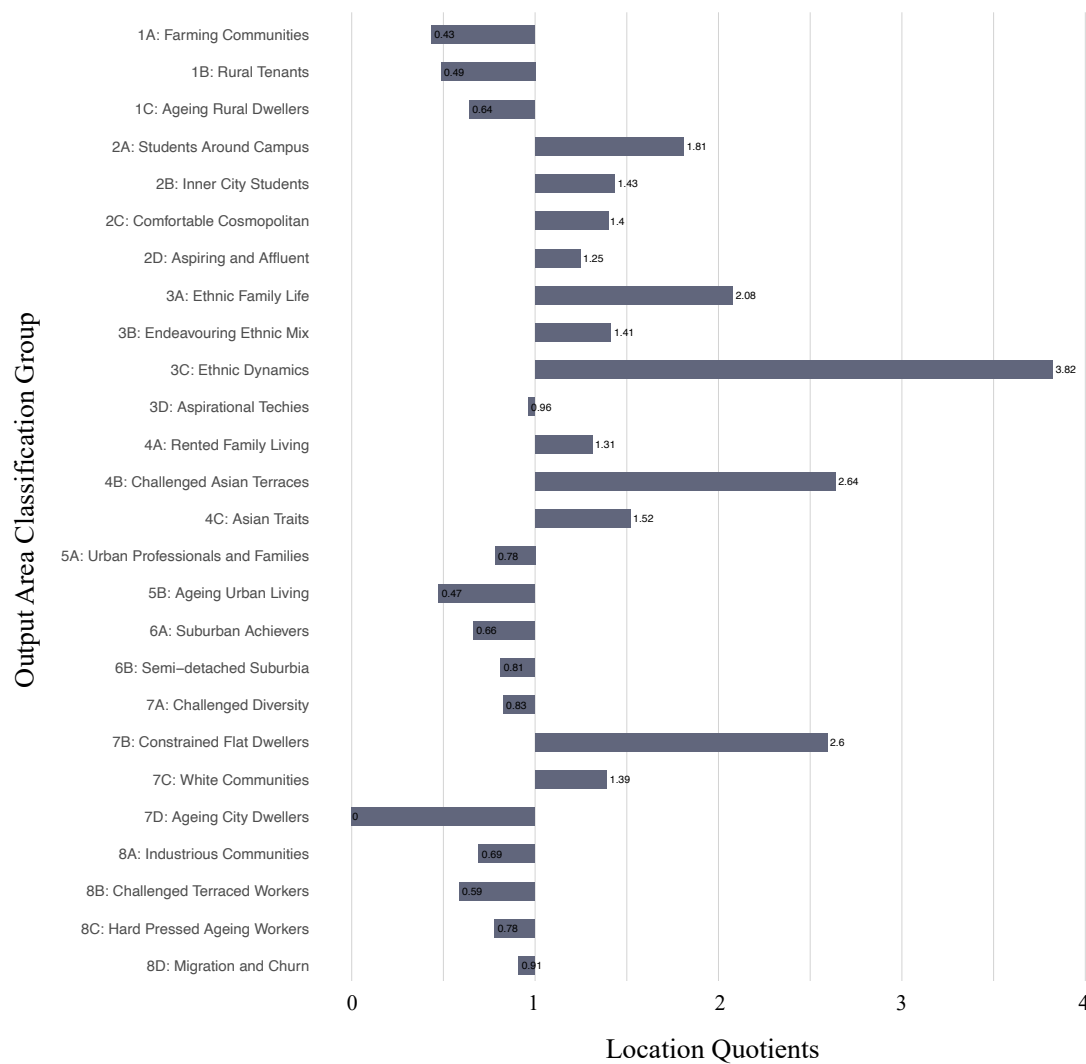
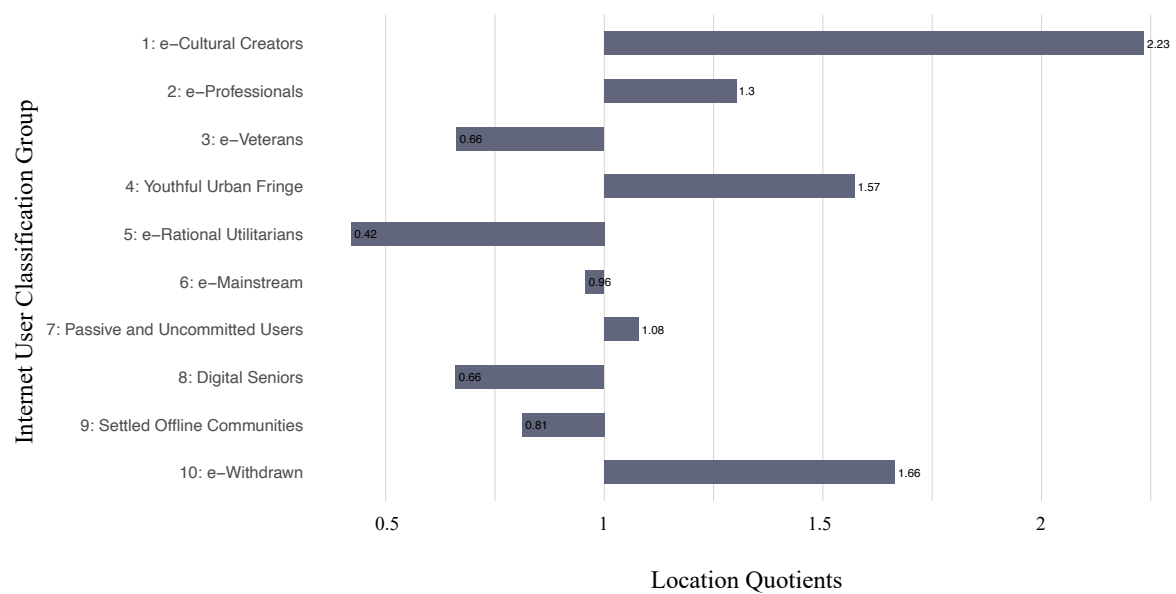**Figure 1** Location quotients produced for each Output Area Classification Group

Figure 2 Location quotients calculated for each Internet User Classification group

Figure 3 presents the LQs produced for each IMD decile. People living in deprived environments, especially in the localities of IMD deciles 3+ (LQ>1.35), were found to be more susceptible to gambling harms in relative to the England average.
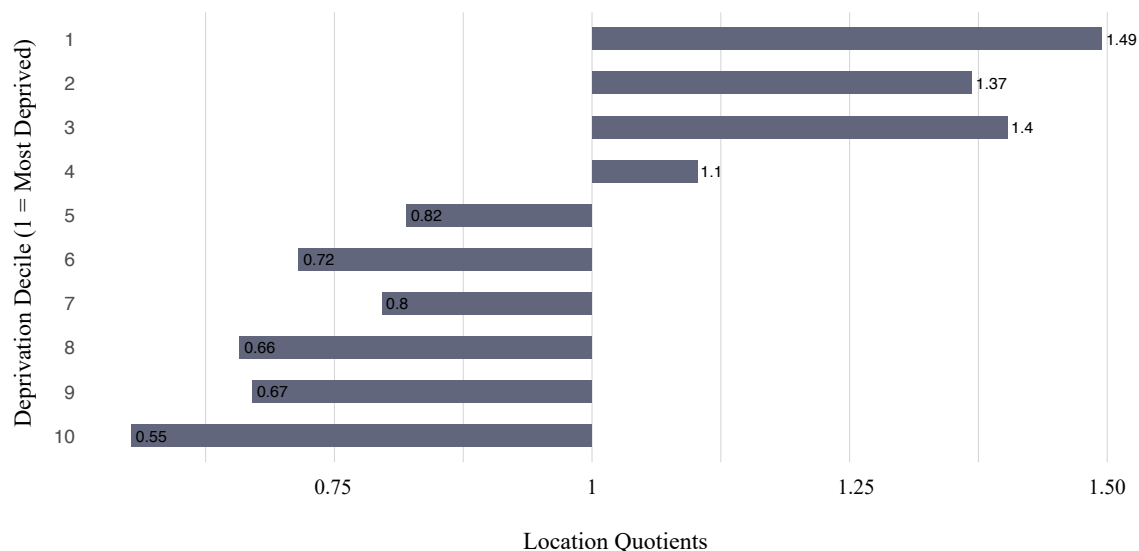

Figure 3 Location quotients calculated for each Index of Multiple Deprivation decile

The following maps present a gambling risk and vulnerability profile across England, derived by an overlay analysis based on four indicators: OAC Group, IUC group, IMD decile and GOA. **Figure 4** shows areas around Manchester, clipped from the full England map depicted in **Figure 5**.
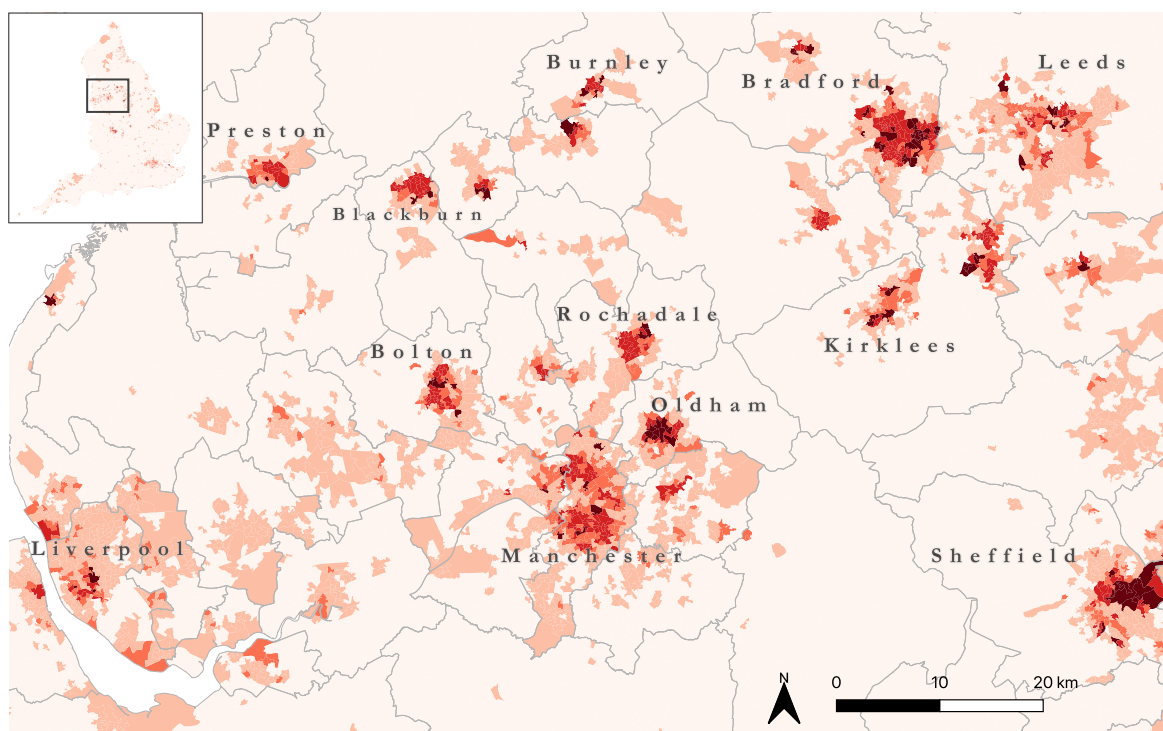

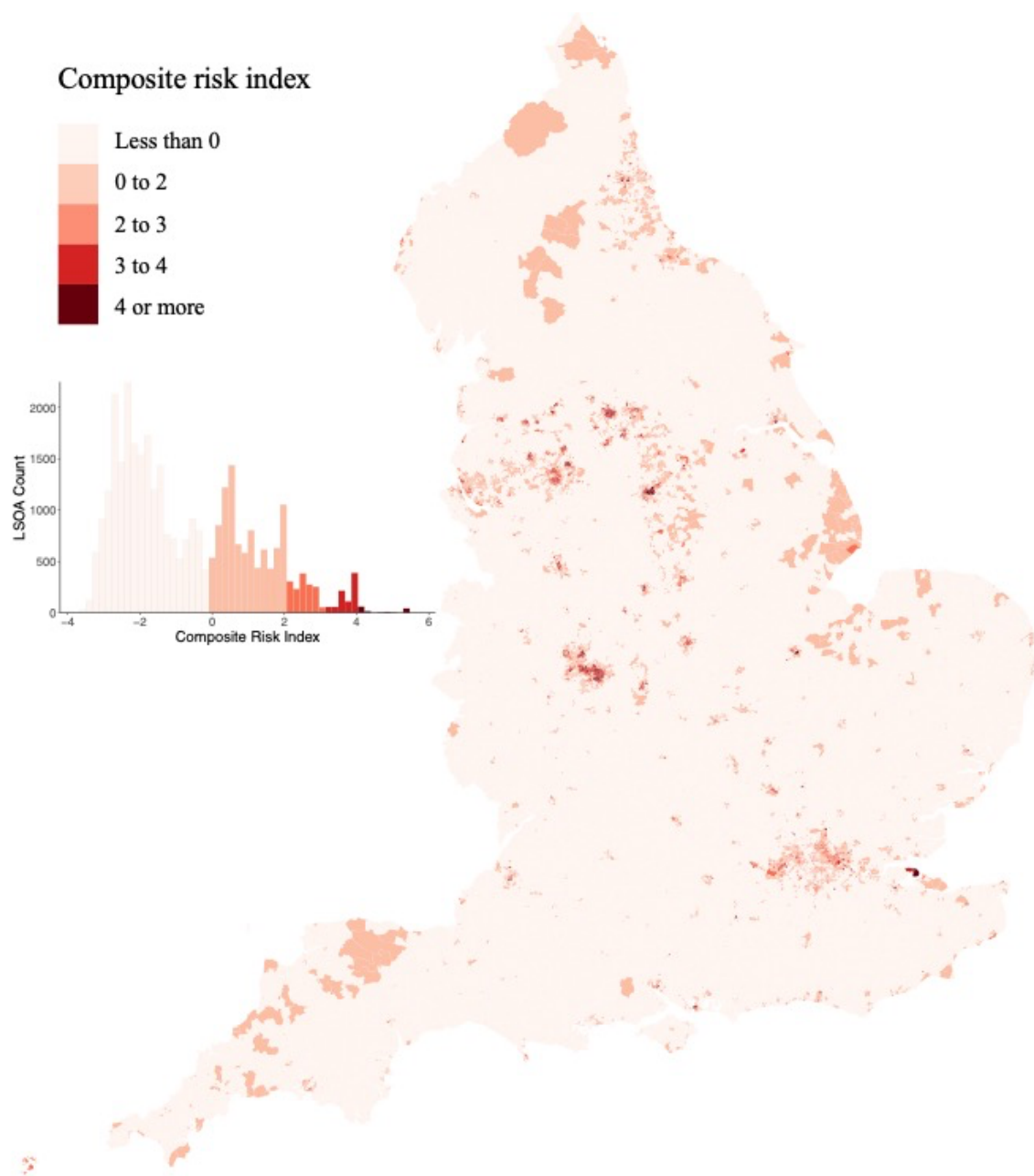**Figure 4** Geographies of gambling risk and vulnerability around Manchester, UK

Figure 5 Geographies of gambling risk and vulnerability in England at LSOA level

5. Conclusion

We have attempted to create a composite indicator of gambling risk and vulnerability in England upon synthesising the results of profiling the GambleAware survey with series of relevant geodemographic and spatial variables. Proposing explicitly spatial interventions to ameliorate gambling harms, this methodological framework provides a useful tool for public health community in understanding and shaping effective, evidence-based policies for prevention of the incidents at as 'upstream' level as possible. Moving forward, we hope to explore wider range of factors underlying disparities in gambling harm, such as comorbidities with other public health issues, to produce a more robust and extensive GB-wide indicator of gambling risk and vulnerability.

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Biographies

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Justin van Dijk is a Lecturer in Social and Geographic Data Science in the Department of Geography at University College London. His primary research interests are grouped around the analysis and visualisation of large-scale spatial data, urban mobility, socio-spatial inequalities, and geospatial data in general.