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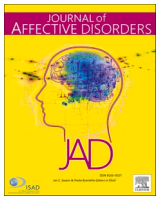

Research paper

Urban-rural differences in anxiety and depression in the UK, New Zealand, and Norway

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A B S T R A C T

As the global urban population surpasses 50 %, understanding the impact of urban environments on mental health is crucial. This study examines the relationship between urbanicity and the prevalence of depression and anxiety disorders in the United Kingdom (UK; $N = 449{,}232$), New Zealand ($N = 33{,}042$), and Norway ($N = 13{,}238$). This paper addresses a central limitation of previous research, which relied on dichotomous and varying definitions of urbanicity, by employing a continuous measure of urbanicity consistently across our three samples. Results revealed country-specific patterns: in the UK, a non-linear pattern showed a minimum in semi-urban areas but increased prevalences of anxiety and depression in both urban and rural regions; in New Zealand, only urban living was linked to a higher prevalence of anxiety, while depression rates remained consistent across settings; in Norway, increased mental health problems were associated with rural residency. These relationships were robust across various sensitivity analyses. Overall, the results underscore that there is *no universal association* between urbanicity and mental health; rather, the urban–rural gradient operates differently across countries. Future research should explore cross-national variation in urban environments toward identifying aspects of urban life that serve as favorable versus detrimental to mental health.

1. Introduction

In the past century, two significant societal trends have emerged: the rise in global urbanization, increasing from around 10 % in the 1920s to over 50 % in 2024 (UN-Habitat, 2016; United Nations et al., 2019; van der Wal et al., 2021), and the growing prevalence in mental health disorders such as depression and anxiety, which now rank among the leading contributors to the global burden of disease (Liu et al., 2024; Xiong et al., 2022). This begs the question of whether these two trends are related. Specifically, does the rise of cities contribute to the increased mental health burden?

A recent meta-analysis of UN-classified developed countries suggested that there is a higher prevalence of mental health disorders in urban areas (Xu et al., 2023b). However, the analysis also reveals heterogeneity between studies in the relationship between urbanicity and depression, even among those studies conducted in similar countries, cohorts, and time periods (Xu et al., 2023b). A central question is whether these inconsistent findings are due to a complex interplay between cities and mental health or whether they might stem from methodological differences between the studies.

Substantively, the heterogeneous relationship between urbanicity and mental health may arise from both rural and urban areas having unique sets of risk and protective factors related to mental health difficulties. For example, living in urban areas can expose individuals to various mental health stressors, including social stressors (e.g., economic inequality and exposure to crime; Finnemann et al., 2024), physiological stressors (e.g., increased sensory stimulation, noise, traffic, and air pollution; Hahad et al., 2024; Lederbogen et al., 2011;

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Bakolis et al., 2021; Xu et al., 2023a), and other urban-specific stressors (e.g., housing difficulties or increased rates of traffic accidents; e.g., Okkels et al., 2018). At the same time, urban environments also offer economic, social, and cultural opportunities that can positively impact one's mental health (Sugar and Kennedy, 2021). Likewise, a corresponding bidirectional relationship has been reported for rural settings. In particular, rural settings feature numerous mental health stressors (e.g., limited access to healthcare and increased mental illness stigma; Andrilla et al., 2018; e.g., Zhang et al., 2020; Fuller et al., 2001; Jones et al., 2011) and protective factors (e.g., greater access to green spaces and nature; de Vries et al., 2003). This plethora of risk and protective factors potentially varies between and within countries, which could be leading to the observed heterogeneity.

Beyond the substantive reasons, methodological factors might cause the inconsistencies in the literature, including different operationalizations of urbanicity (Arcaute et al., 2015; Huth et al., 2022; Openshaw, 1981). For example, urban-rural dichotomies may obfuscate possible non-linear relationships between urbanicity and common mental health disorders. Indeed, in support of this, Breslau et al. (2014) found a non-linear association between depression rates and urbanicity with the highest prevalence found in semi-urban areas between cities and rural areas. Such semi-urban effects might explain some of the heterogeneity in the literature if these areas are inconsistently classified as either urban or rural in different dichotomy-based studies such as in the recent meta-analysis (Xu et al., 2023b). To address this problem, it is important that urban research moves beyond simple urban-rural distinctions.

In this study, the aim is to advance our understanding of urban mental health through a large-scale analysis that overcomes these methodological limitations in the literature. First, this investigation uses an objective and continuous measure of urbanicity. Which enables flexible additive models that can probe non-linear relations between urbanicity and the prevalence of common mental disorders. The method is applied consistently to three large samples from the UK (N = 449,232), New Zealand (N = 33,042), and Norway (N = 13,238). Together, this makes for a comprehensive and nuanced study of the associations between urbanicity and two of the most common mental health disorders, depression and anxiety, using a consistent state-of-the-art measure that overcomes the so-called modifiable boundary problem (whereby spatial statistics depend on how areas are defined), and enables the detection of semi-urban effects through non-linear statistical modeling.

2. Methods

2.1. Study designs, participants, and procedures

In this preregistered study (AsPredicted reference: 190687, https://aspredicted.org/gzxy-pvzp.pdf), participants were obtained from three large-scale population studies conducted on adults from the UK, New Zealand, and Norway.

Adults from the UK were obtained through the UK Biobank, a large-scale prospective study of UK adults that was carried out from 2006 to 2010. The UK Biobank study invited over 9.2 million people who were registered with the National Health Service and lived up to 40 km from one of the 22 assessment centers to participate (Bycroft et al., 2018). Ethical approval for this study was obtained from the North West Multicentre Research Ethics Committee (reference: 16/NW/0274).

Adults from New Zealand were retrieved from The New Zealand Attitudes and Values Study (NZAVS), a longitudinal and nationally representative panel study that has been repeated annually since 2009 (Sibley, 2014; https://osf.io/75snb/wiki/home/). The NZAVS uses random sampling from the New Zealand electoral roll and employs follow-up strategies such as prize incentives to improve retention. The 14th wave was used, sampled between 2022 and 2023 and with 33,722 participants recruited via e-mail and postal follow-ups to those who did not respond to the initial email. A booster sample was added to refresh the cohort, particularly targeting younger participants aged 18–23. Ethical approval for this study was given by the University of Auckland Human Participants Ethics Committee (reference: UAHPEC22576).

Adults from Norway were obtained from the Critical Incidents and Psychological Adaptation (CIPA) study, an ongoing large-scale nationally representative study in which recruitment began in March 2023 (https://www.cipastudy.com/). The CIPA study consists of a random sample of adults recruited through Norwegian population registries, with the sampling procedure designed to sample participants from each region of Norway relative to the region's population size. Participants were contacted via email and invited to complete an online survey. Ethical approval for the CIPA study was granted by The Regional Committee for Medical and Health Research Ethics (reference: 522020).

2.2. Measurement

Respondents across all three studies provided information about their demographic characteristics, including biological sex and age (measured by years).

2.2.1. Psychiatric illness

The two outcome variables of this study include the presence versus absence of an anxiety disorder or major depressive disorder, respectively. For the UK sample, diagnostic data were obtained from hospital records based on the International Classification of Diseases 10th edition (WHO, 2019). For the New Zealand and Norwegian samples, self-reported diagnoses were measured by asking participants whether they had received a psychiatric diagnosis (and/or treated for any mental health condition; New Zealand sample) as assessed and provided by a healthcare professional, with data retrieved for major depressive and anxiety disorders. These self-reported measures for psychiatric diagnoses have been previously used in the literature (e.g., Ebrahimi et al., 2024) and found to be acceptable for assessing diagnostic status (Van Der Waerden et al., 2015; Veldhuizen et al., 2014).

Beyond these diagnostic measures, the relationships between continuous symptom measures of depression and anxiety available in the Norwegian data were examined using the sum-score of the validated instruments Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) and Generalized Anxiety Disorder Questionnaire (GAD-7; Spitzer et al., 2006), respectively. These questionnaires query about the participants' symptoms during the last two weeks, measured on a four-point Likert scale (0: *Not at all* to 3: *Nearly every day*). The results of these analyses are provided in the Supplementary Material 1 and 2.

2.2.2. Continuous measure of urbanicity

Our independent variable is a measure of urbanicity that follows from recent work by Finnemann et al. (2024), proposing a continuous and objective measure of urbanicity that avoids the difficulty of delineating urban, suburban, periurban, and rural areas, and surpasses the limitation of the urban-rural dichotomization. The measure, city-size-adjusted distance to the city center, is defined as

$$adjusteddistance_d = min\left(distance / \sqrt{n}\right)$$

First, the distance from a participant's residence to all city centers is calculated, where greater distances reflect a more rural location and shorter distances reflect a more urban location. Second, differences in city size are accounted for by dividing the distance by the square root of the city's population, n. This adjustment reflects the difference between being 10 km away from Leeds versus 10 km away from London; while the former would be considered countryside, the latter remains part of a dense urban area. This measure implies that distances from city centers correspond to different levels of urbanicity depending on the size of the city. For example, a value of $d = 0.1$ corresponds to radii of 4 km, 7 km, and 10 km for cities with populations of 200,000, 500,000, and 1 million, respectively. Similarly, a value of d = 0.3 corresponds to

distances of 12 km, 21 km, and 30 km for cities of the same population sizes. The most urban point in any city is its center, and this measure predicts increasing rurality as the distance from the city center grows, scaling according to the square root of the population size. Fig. 1 illustrates this with a contour plot that shows which distances and city sizes correspond to equal levels of urbanicity.

To compute the adjusted distance, the participants' home locations, city populations, and city center coordinates are needed. City populations and center coordinates were obtained from https://simplemaps.com/, which queries geographical information from various sources such as the UK National Geospatial-Intelligence Agency. The city data are also available through our Open Science Framework repository where all code is stored as well (OSF; link). In the UK, coarse-grained home location data is obtained from the UK Biobank. For New Zealand, participants' areas of residence are identified using meshblock data, with each meshblock typically covering around 20 dwellings. Distances are calculated based on the centroids of these meshblocks, which are provided by Stats NZ, the national statistics agency (https://www.stats.govt.nz/). In Norway, participants' home locations are associated with the centroids of four-digit postal codes, as reported by the participants, with these centroids sourced from GeoNames (http://download.geonames.org/export/zip/). Fig. 2 provides a visualization of participant urbanicity overlaid on country-specific maps. All preprocessing, analysis, and data visualization were done in the programming language R (R Core Team, 2020). Geographic results were obtained using the raster package (Hijmans, 2018).

The urbanicity measure was computed with respect to all city centers that have a population of more than 50,000 (see Supplementary Material 3 and 4 for sensitivity analysis using different cutoffs), resulting in 210 city centers in the UK, 15 in New Zealand, and 14 in Norway. Fig. 3 visualizes the distribution of urbanicity in the UK (left), New Zealand (center), and Norway (right). Note that the much narrower range of urbanicity in the UK is a result of 1) the sampling methodology of the UK Biobank, where only people living within a 40 km range from an assessment center, which were placed near larger cities, were invited to the study, and 2) the much larger population density of the UK in comparison to New Zealand and Norway.

2.3. Statistical analysis

The prevalence of depression and anxiety disorders was modeled as a function of urbanicity using binomial generalized additive models (GAMs; Wood, 2017). The non-linear effect of urbanicity was estimated with cubic spline expansions with four basis functions. The models were adjusted for linear effects of age and sex. The results are reported in the form of predicted values with 95 % confidence intervals. All models were fitted with the *mgcv* package (Wood, 2017).

The results were visualized using plots of predicted values with 95 % confidence bands. In the main results, adjusted distances from 0 to 0.05 are highlighted. Since the UK Biobank primarily samples within a radius of 40 km from assessment centers, 99.8 % of the sample falls within an adjusted distance of 0.05. Therefore, all plots focus on this range, even though models were estimated using the entire sample. The plots were created using ggplot2 (Wickham, 2016).

2.3.1. London

For the UK, separate analyses were conducted for London and the rest of the country. London's global status distinguishes it from all other cities in the sample due to its stronger international profile in finance, corporate headquarters, and international migration (Murray, 2022; Sassen, 2013). Its substantially larger population also poses statistical challenges, making it unsuitable for analysis alongside the rest of the UK. To ensure accuracy and avoid skewing the results, London was excluded from the main analyses and addressed separately, as detailed in Supplementary Material 5.

2.3.2. Robustness analyses

Three analyses were performed to examine the robustness of the findings. First, all analyses were repeated using cities with populations over 20,000, 100,000, and 200,000 inhabitants. Second, the main analyses were extended to more rural areas of Norway and New Zealand. Third, all analyses were repeated without controlling for age and sex.

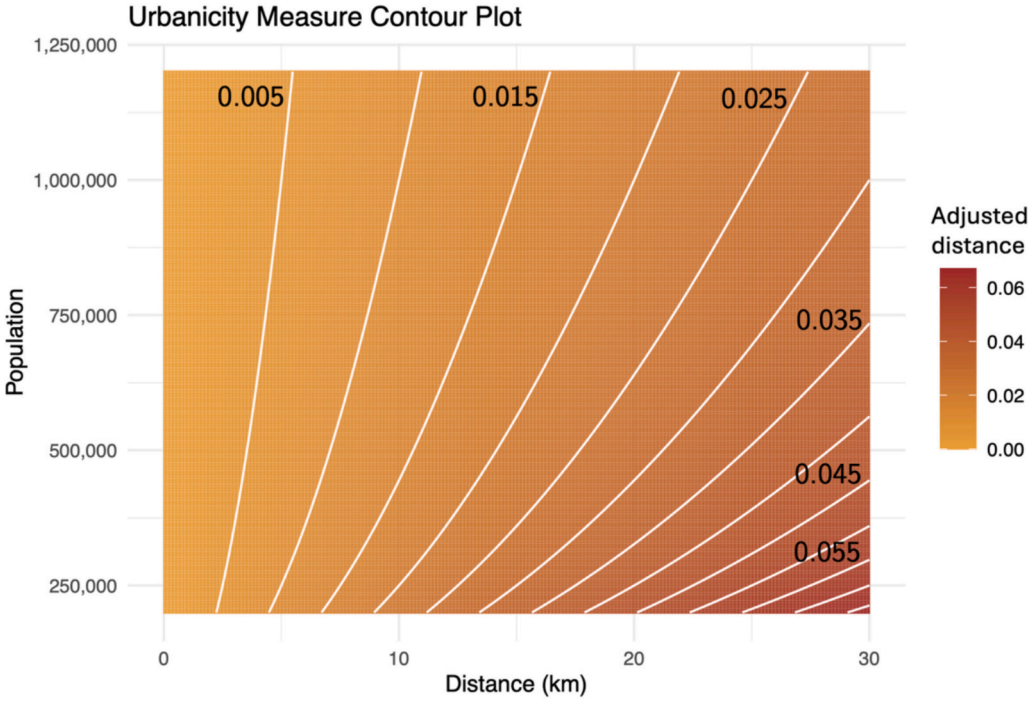

Fig. 1. Contour Plot of Distances of Equal Urbanicity Depending on Sizes of Cities
Note. Adjusted distance is based on how far participants live from a city and the city's population. Higher adjusted-distance values correspond with decreasing urbanicity. Thus, greater distances—especially from smaller cities—lead to decreased urbanicity (darker orange color).

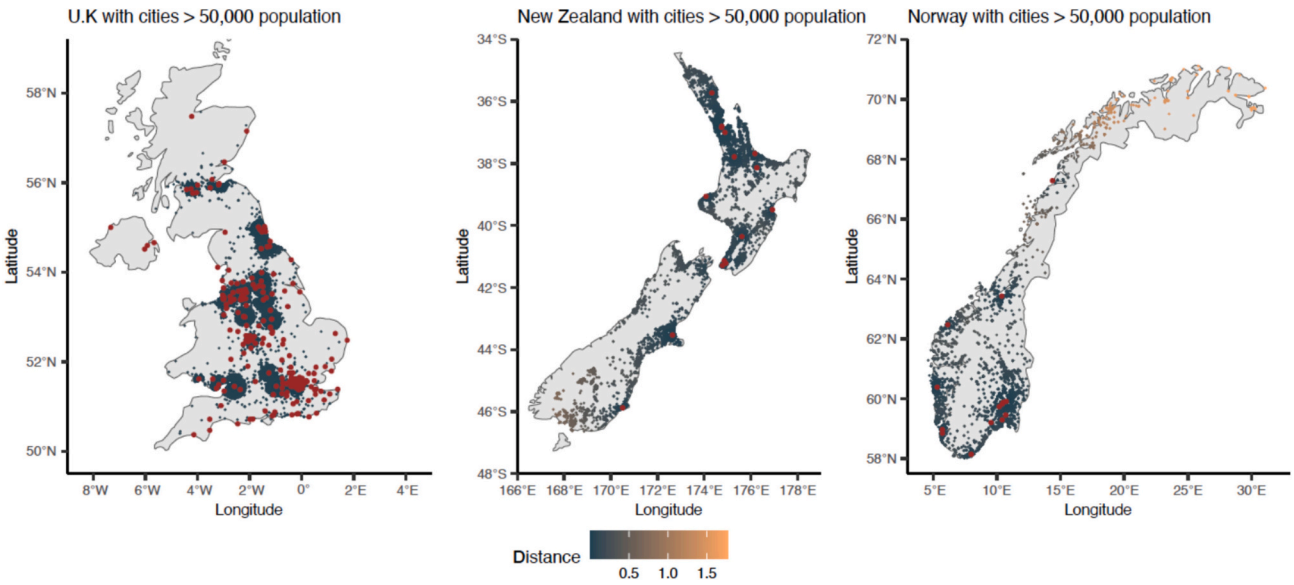

Fig. 2. Distribution of Participants in the UK (left panel), New Zealand (middle panel), and Norway (right panel)
Note. City centers are colored in red, and participants are colored by their adjusted distance score. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

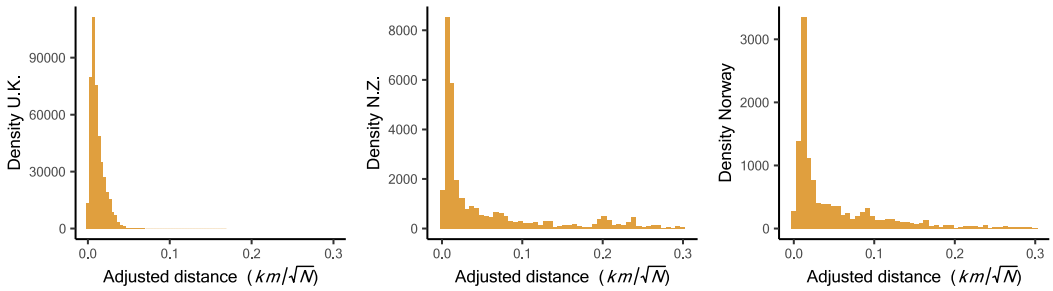

Fig. 3. Density of Observations for Adjusted Distances
Note. 934 (7.1 %) observations were removed from the Norwegian sample and 1504 (4.5 %) from the New Zealand sample due to our cut-off on the y-axis of 0.3. This cutoff was applied to enhance clarity in visual inspections. The y-axes differ across the figures.

2.3.3. Transparency and openness

The present study deviated from its preregistered protocol by using a self-reported diagnostic measure rather than a continuous symptom measure for the Norwegian sample. This deviation was opted for since self-reported diagnostic data was identified in the Norwegian dataset, allowing us to match the measurement of the New Zealand sample, and further enabling an investigation of psychiatric diagnoses rather than symptomatology in all three samples. The original pre-registered analysis for the Norwegian sample using the continuous symptom data is reported in Supplementary Material 1 and 2. The results were similar in both analyses, highlighting that this deviation did not affect the findings, and further demonstrating the robustness of the findings when using both continuous and binary outcome measures.

2.3.4. Exploratory analysis

The UK Biobank differs from our Norwegian and New Zealand samples by having a restricted age range from 40 to 70. To assess if associations between urbanicity and mental health disorders depend on age, analyses were run including interactions between age and urbanicity using generalized additive models with tensor product smooths. The tensor product allows us to model the interaction between two continuous variables while accounting for potential non-linear relationships in each variable separately.

3. Results

3.1. Sample characteristics

The UK sample consisted of 449,232 participants, out of 502,326 (89 %), who had complete responses on the measures required to be included in this study (i.e., available hospital records for diagnostic data and valid location information), including 244,968 (55 %) female participants, with a mean age of 56 (range: 40–69 years old). The majority of participants were White (364,423; 95.99 %), while 15,251 participants (4.01 %) belonged to ethnic minorities. Specifically, the ethnic minorities included 6157 Asian or Asian British (1.62 %), 4092 Black or Black British (1.08 %), and 5002 Other (1.32 %). The UK participants were divided into a London sample ($n = 88,833$; hereafter referred to as the London sample) and a UK without London sample ($n = 381,437$, hereafter referred to as the UK sample). Similarly, 33,042 out of 33,722 (98 %) participants from New Zealand had provided the necessary data (postal codes and self-reported diagnoses) to be included in the study, resulting in a sample of 20,825 female participants (63 %), with a mean age of 54 (range: 18–98 years old). The majority of participants were New Zealand European (27,624; 85.54 %), while 4671 participants (14.46 %) belonged to ethnic minorities. Specifically, the ethnic minorities included 1156 Asian (3.58 %), 3049 Maori (9.45 %), and 466 Pacific Nations (1.44 %). In the Norwegian sample, 13,238 of 13,436 (98 %) adults had provided the necessary information (postal codes and

self-reported diagnosis) to be included in this study, resulting in a sample of 7053 females (53 %), with a mean age of 51 (range: 18–89 years old). The majority of the NO participants were from the ethnic majority (12,289; 91.44 %), while 1147 participants (8.56 %) belonged to ethnic minorities. Among the ethnic minorities, the distribution included African (30; 0.22 %), European (914; 6.80 %), South/Latin-American or Caribbean (42; 0.31 %), Middle Eastern or North African (48; 0.36 %), Mid-Asian (22; 0.16 %), North American (20; 0.15 %), Oceanic (6; 0.04 %), and East/Southeast Asian (65; 0.48 %).

Although the models are estimated on the entire samples, results are visualized from $d = 0$ to $d = 0.05$ for comparability of all samples with the UK sample where this was the geographic boundary, as per the design of the UK Biobank study. 7961 (60 %) participants are located within this range in Norway, 22,120 (67 %) in New Zealand, and 448,358 (99.8 %) in the UK. Supplementary Material 6 and 7 visualize results at greater distances from city centers including 90 % of data for New Zealand and Norway.

3.2. Depression

Fig. 4 visualizes the estimated prevalence and 95 % confidence interval (CI) of depressive diagnoses as a function of urbanicity in the UK (left), New Zealand (center), and Norway (right). Each country presents a distinct relationship between urbanicity and depression; in the UK the prevalence of depression is U-shaped with a minimum at $d = 0.022$ km/$\sqrt{}$pop. In New Zealand, the prevalence of depression is independent of urbanicity. In Norway, the prevalence of depression is increasing as urbanicity decreases.

Specifically, in the UK the prevalence of depression is as high as 8.5 % [8.2 %, 8.9 %] (mean estimate and 95 % CI) in city centers ($d = 0$ km/$\sqrt{}$pop), reaching the minimum of 7.0 % [6.8 %, 7.2 %] at $d = 0.021$ km/$\sqrt{}$pop, and again increasing to a prevalence of 7.9 % [7.3 %, 8.6 %] in more rural areas ($d = 0.05$ km/$\sqrt{}$pop). In New Zealand, the prevalence of depression is 13.6 % [13.1 %, 14.2 %] in city centers and does not change when moving to more rural areas with an estimate of 13.5 % [13.0 %, 14.0 %]. In Norway, the prevalence of depression seems to be increasing from 7.4 % [6.6 %, 8.1 %] in city centers to 8.6 % [7.9 %, 9.2 %] in more rural areas.

Additional robustness analyses (Supplementary Material 3) verify that the patterns are robust to changing the city size cutoffs and to the exclusion of covariates. A small deviation is seen when controls are omitted for New Zealand, then urban-rural differences become stronger.

3.3. Anxiety

Fig. 5 presents the estimated prevalence and 95 % confidence bands for anxiety diagnoses across the UK (left), New Zealand (center), and Norway (right). In both the UK and Norway, the patterns observed are similar to those seen in the depression prevalence analysis. However, the pattern for anxiety prevalence in New Zealand diverges, showing an almost U-shaped relationship, with a minimum at $d = 0.017$ km/$\sqrt{}$pop.

Specifically, the prevalence of anxiety disorders in the UK is 6.1 % [5.9 %, 6.3 %] in city centers, decreasing to a low of 5.6 % [5.5 %, 5.7 %] at $d = 0.017$ km/$\sqrt{}$pop, before rising again to 6.0 % [5.5 %, 6.5 %] in more rural areas. In New Zealand, anxiety prevalence is highest in urban areas, at 12.2 % [10.9 %, 13.5 %], reaching a minimum of 9.9 % [9.3 %, 10.4 %] at $d = 0.017$ km/$\sqrt{}$pop, and then gradually rising to 10.5 % [9.8 %, 11.3 %] in rural regions. In Norway, the prevalence of anxiety appears to increase from 5.7 % [5.0 %, 6.4 %] in city centers to 6.9 % [6.3 %, 7.5 %] in rural areas.

Additional robustness checks (Supplementary Material 4) support that these patterns hold up under variations in city size cutoffs and when excluding covariates. Similar to what was observed for depression, excluding covariates for New Zealand results in a more pronounced association with urbanicity.

3.3.1. Exploratory results

In this exploratory analysis of the interaction between age and urbanicity, no significant effects were found. In New Zealand, the interaction between adjusted distance and age was not significant ($p = 0.347$), with similar non-significant results in the UK ($p = 0.298$) and Norway ($p = 0.125$).

4. Discussion

This study examined the relationship between urbanicity and two prevalent mental health disorders—depression and anxiety—across the UK, Norway, and New Zealand. Across the three countries, a continuous measure of urbanicity that captures semi-urban effects was *consistently* applied, thereby addressing a major source of variability in past research (Xu et al., 2023b). Despite this methodological alignment, our results reveal no universal pattern: in the UK, both urban and rural living were linked with higher rates of depression and anxiety; in Norway, only rural living was associated with higher self-reported rates of these disorders; and in New Zealand, no urbanicity effect emerged for depression, but anxiety appeared distinctly tied to urban residence. These findings persisted across different sensitivity analyses, underscoring that even a standardized definition of urbanicity does *not* produce a one-size-fits-all association with mental health.

In the UK, a non-linear association was identified, with an optimal distance between highly urban and rural areas with the lowest prevalence of both depression and anxiety. This “Goldilocks zone” was found at around 0.021 km/$\sqrt{}$ (pop) from city centers which corresponds to 9 km from a city of 200,000 inhabitants and 21 km from a city of 1,000,000 inhabitants. This association is in line with previous research on well-being, family satisfaction, and friendship satisfaction in the UK (Finnemann et al., 2024).

The presence of country-specific relationships despite a harmonized measure of urbanicity across the countries suggests that substantive differences underlie the heterogeneous associations between urbanicity

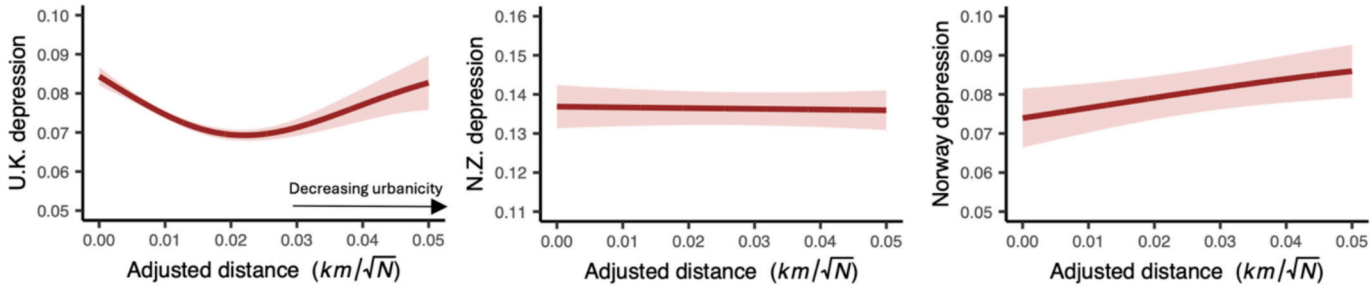

Fig. 4. The Prevalence of Depression as a Function of Adjusted Distances to City Centers in the UK, New Zealand, and Norway
Note. The y-axis displays the prevalence of depression, while the x-axis shows the city size adjusted distances from city centers with higher values reflecting participants living further from cities. For example, an adjusted distance of 0.01 corresponds to 4.5 km from a city with 200,000 inhabitants and 10 km from a city with 1,000,000 inhabitants. Similarly, an adjusted distance of 0.04 equates to 17 km from a city of 200,000 inhabitants and 40 km from a city of 1,000,000 inhabitants.

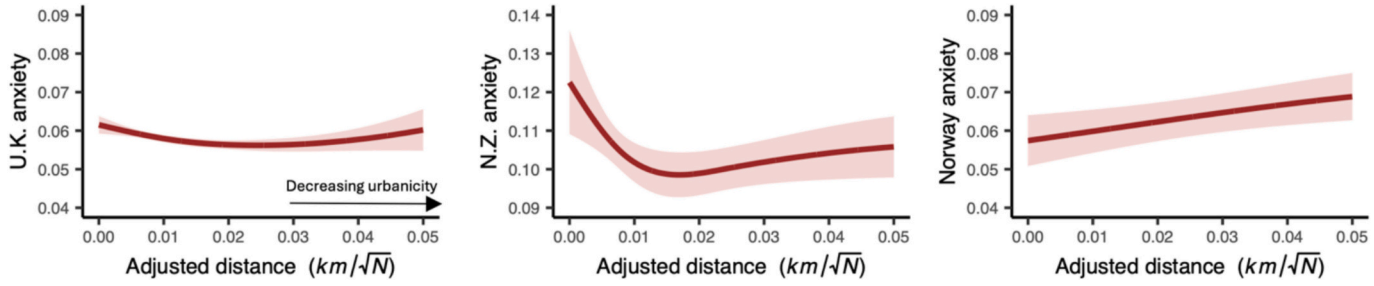

Fig. 5. Anxiety as a Function of Adjusted Distances to City Centers for the UK, New Zealand, and Norway

Note. The y-axis displays the prevalence of anxiety, while the x-axis shows the city size adjusted distances from city centers with higher values reflecting participants living further from cities. For example, an adjusted distance of 0.01 corresponds to 4.5 km from a city with 200,000 inhabitants and 10 km from a city with 1,000,000 inhabitants. Similarly, an adjusted distance of 0.04 equates to 17 km from a city of 200,000 inhabitants and 40 km from a city of 1,000,000 inhabitants.

and the prevalence of common mental disorders. Unravelling why countries exhibit different urban gradients in mental health is a complex question involving a myriad of potential risk and protective factors that can differ between the countries. The following paragraphs explore potential explanations that align with existing literature but require further empirical investigation using a larger sample of countries.

Urban dynamics and inequality are intricately connected and offer potential explanations for socioeconomic disparities. Countries differ in income inequality, with New Zealand and the UK having Gini coefficients of around 0.32, indicating moderate levels of inequality across their populations (World Bank, 2024). In contrast, Norway, with a Gini coefficient of approximately 0.24, stands out as one of the most equal societies globally, largely due to its strong welfare system and emphasis on equitable income redistribution (World Bank, 2024). As inequality tends to be more pronounced in urban areas, this suggests that Norwegian cities are relatively less unequal (Arvidsson et al., 2023; Heinrich Mora et al., 2021). Lower levels of inequality have been linked to reduced crime, stronger social cohesion and stability, and improved psychological well-being (Burger et al., 2020; Kelly, 2000; Morrison, 2021; Pickett and Wilkinson, 2015). Additionally, research indicates that Norwegian cities generally maintain better air quality compared to other European cities (EEA, 2024; Eeftens et al., 2012), a factor previously associated with poor mental health outcomes (Cohen-Cline et al., 2015; Nutsford et al., 2013). In 2019, Oslo was further recognized as the European Green Capital for its success in sustainable urban development (Directorate-General for Environment, 2019). These factors suggest that Norwegian cities might provide a more supportive environment for mental health compared to those in the UK and New Zealand.

The patterns might also be due to differences in rural areas across the countries. Notably, the Norwegian mental health penalty across both disorders is in line with general health disparities between Norwegian rural and urban areas (Bremberg, 2020), likely caused by limited access to health and mental healthcare services in remote municipalities (Riksrevisjonen, 2021; SSB, 2024), which can leave mental disorders untreated and sustain them.

Beyond place-based factors such as job opportunities, green spaces, and access to mental health facilities, selection and composition effects also shape urban gradients. These effects refer to the systematic movement of psychologically vulnerable versus resilient individuals. For instance, the Goldilocks zone observed in the UK may result from resourceful families relocating to areas just outside cities, while demographics more vulnerable to depression and anxiety—such as racial, gender, and ethnic minorities—tend to favor urban living (Finnemann et al., 2024; Hoogerbrugge and Burger, 2022). Given this dynamic, a similar pattern might be expected in Norway and New Zealand. It remains unclear why the Goldilocks zone is only observed for the UK. Future research is needed to examine the demographic compositions of urban, semi-urban, and rural areas across the three countries to determine whether systematic differences exist in the concentration of psychologically vulnerable and resilient groups.

To pinpoint which rural and urban features drive the heterogeneous mental-health patterns we observed, we must refine our methodology: move beyond a single urbanicity index to large, cross-national cohorts capturing key physical, social and service-related variables. By pooling data from diverse countries and applying multilevel models, we can disentangle within- and between-country environmental effects and derive globally generalizable insights. At the same time, integrating qualitative and participatory methods—such as focus groups, interviews or photo-voice studies—will surface locally specific stressors that broad surveys may miss. This combined quantitative–qualitative strategy ensures we efficiently identify both universal and context-dependent drivers of mental-health risk.

5. Strengths and limitations

This study has several strengths, including the use of three large-scale population studies, an innovative continuous measure of urbanicity, supplementary analyses highlighting the robustness of the results, as well as conducting a cross-country comparison of the association between mental health and urbanicity. Nonetheless, several limitations must be noted. First, the UK Biobank data includes only residents living within 40 km of an assessment center, limiting the geographic coverage and range of urbanicity studied. This restriction may underrepresent highly rural areas, potentially biasing the findings toward more urbanized settings. The New Zealand and Norway data allow us to study depression and anxiety up to an urbanicity score of $d = 0.15\ km/\sqrt{n}$. In this highly rural region, Norway displays an increasing mental health prevalence and New Zealand shows a trend toward higher depression and anxiety rates. Future research should investigate UK rural mental health with better coverage of remote areas. Second, the UK Biobank sample includes only participants aged 40 years and older, excluding younger individuals who may have a higher risk of mental health problems (Sohn, 2022). To assess whether the different age ranges in the UK (40–70 years) compared to Norway and New Zealand (18–89 years) influenced the results exploratory analyses were run including interactions between age and urbanicity. These analyses revealed no significant interaction within ages 18–89 in Norway/New Zealand and 40–70 in the UK, indicating that the urbanicity–mental health association did not differ by age among the studied participants. However, since no UK participants under age 40 were included, we cannot rule out potential age-by-urbanicity interactions in early adulthood in the UK. Future research should incorporate cohorts spanning younger age groups to determine whether urbanicity effects in the UK vary across the full adult lifespan. Third, the low response rates in the UK (5.7 %) and New Zealand (16.6 %) studies raise concerns about self-selection bias. In line with this, the UK Biobank has a known healthy volunteer bias (Fry et al., 2017). Future research should implement strategies to improve response rates, such as increasing outreach efforts, offering incentives, or simplifying participation procedures, and conducting analyses to assess and adjust for potential self-selection bias would help mitigate

this limitation. Lastly, the measures of mental health disorders differed across the study populations. In Norwegian and New Zealand samples, psychiatric conditions were measured through self-reported diagnoses assigned by professionals, while these were measured through hospital records in the UK. Despite evidence for the validity of self-report measurement of mental disorders (Van Der Waerden et al., 2015; Veldhuizen et al., 2014), this difference might have impacted the results. However, a supplementary analysis investigated the difference between a diagnostic measure of mental disorders and a cut-off based self-report instrument approach (i.e., PHQ-9 and GAD-7), yielding identical findings. This suggests that the results are robust against such measurement differences. Still, future research should aim to link cohort data to national health registries in Norway and New Zealand to extract ICD codes and fully harmonize case definitions across all three samples.

6. Conclusion

This study used a consistent and continuous measurement of urbanicity to overcome an important limitation of the literature, where evidence synthesis was done across studies with a wide range of dichotomous urban-rural definitions. The present study's results indicate that the heterogeneity in the literature is not fully explained by varying urban-rural definitions. Instead, these results add to a growing corpus of evidence suggesting complex associative patterns between urban-rural living and mental health difficulties due to substantive place-based factors and the selective migrations of different demographics. Understanding both place and selection effects, as well as how they differ across countries, is central for developing effective health-promoting interventions and planning future urbanization.

CRediT authorship contribution statement

Adam Finnemann: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Nora Skjerdingstad:** Writing – review & editing, Writing – original draft. **Lydia G. Speyer:** Writing – review & editing, Writing – original draft. **Orestis Zavlis:** Writing – review & editing, Writing – original draft. **František Bartoš:** Writing – review & editing, Writing – original draft. **Reinout Wiers:** Writing – review & editing. **Han van der Maas:** Writing – review & editing. **Chris G. Sibley:** Writing – review & editing, Data curation. **Sverre Urnes Johnson:** Writing – review & editing. **Marieke A. Helmich:** Writing – review & editing. **Asle Hoffart:** Writing – review & editing. **Omid V. Ebrahimi:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Data curation.

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Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2025.119601.

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