



A Meta-Analysis of Neighbourhood Interventions on Subjective Wellbeing and Mental Health

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Abstract

Research in urban planning demonstrates that the built environment holds significant power to shape individuals' subjective wellbeing and quality of life outcomes. In contrast, a substantial body of psychological research suggests that circumstantial and geographical environments play a relatively minor role in explaining variations in happiness. To reconcile these contrasting findings, we conducted a meta-analysis to provide a quantitative synthesis. This study adopts a sequential design. First, we systematically search for and evaluate quantitative evidence from 54 studies examining 29 policy interventions. Based on the included studies, we then identify relevant covariates, focusing on the type of interventions, associated neighbourhood environments, population subgroups, duration, and methodological design, for a meta-regression analysis. Estimates from our meta-regressions reveal that place-based neighbourhood interventions are more likely to produce short-term mental health and wellbeing impacts compared to people-based interventions, such as subsidised residential mobility programmes. However, the wellbeing effects are unequally distributed among population subgroups. Girls are more likely to experience beneficial effects, while boys are more likely to experience detrimental ones. Additionally, the results from our meta-regressions suggest that among various types of neighbourhood environments, the social environment is more likely to be associated with neighbourhood effects than the economic environment.

Keywords Neighbourhood effects · Moving to Opportunity · Place-based interventions · People-based interventions · Happiness · Life satisfaction · Mental wellbeing · Mental health

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Introduction

The geography of wellbeing presents several paradoxical results. For instance, despite significant population movement to large urban agglomerations, people of very large cities tend to be less happy than those living in medium-sized agglomerations (Florida, 2017). This raises important questions: What can urban planning do to create ‘good cities’ (Lynch, 1984) where people feel at home? While poor policies can make people miserable, can well-designed policies actively boost happiness? Recent research in urban planning underscores the significant influence of the built environment on people’s perceptions (Sha & Cheng, 2024; Ziogas et al., 2023), behaviours (Herrmann-Lunecke et al., 2021), and quality of life outcomes (Wu et al., 2022), suggesting that happiness can be designed (Kourtiti et al., 2022; Mouratidis & Yiannakou, 2022). For example, in a review article, urban geographer Mouratidis (2021) identifies several pathways through which urban environments affect subjective wellbeing. One such a pathway is transportation. Improved transportation systems and easy access to nature and leisure facilities can promote active lifestyles, which in turn foster positive emotions (Richardson et al., 2013; Sallis et al., 2016). In a more recent study, Kourtiti et al. (2024) demonstrated that subjective urban wellbeing (termed ‘city love’) at the neighbourhood level is co-determined by both material artefacts such as good infrastructure, shopping amenities, and urban greenery (termed ‘body of the city’) and intangible factors like historical environment or social atmosphere (termed ‘soul of the city’). In summary, geography does matter when it comes to wellbeing.

Despite the seemingly self-evident relationship between neighbourhood environments and wellbeing, psychological research has shown that neighbourhood effects are weaker than commonly assumed. In a well-cited study, Lyubomirsky et al. (2005) reported that the majority of the variation of happiness is attributed to genetic and personality ‘set points’ (50%) as well as intentional activities (40%). Circumstances including geographical environment, demographic factors, and personal experiences, account for only 10% of the variation. While the modest role of the environment may seem surprising, these findings align with the ‘treadmill model of happiness’ (Brickman & Campbell, 1971; Kahneman, 1999), which postulates that humans are highly adaptive to change. People continuously adjust their expectations and aspirations, for example, through social comparisons (Easterlin et al., 2010). As expectations rise, levels of happiness may revert to their original baseline. This implies that any effects induced by environmental changes are likely to be transitory, and neighbourhood betterment may not necessarily result in sustained increases in subjective wellbeing (Foye, 2017; Hoogerbrugge & Burger, 2022). This conclusion sharply contrasts with the findings documented in the urban geography literature mentioned earlier, which emphasise the powerful influence of the built environment on wellbeing.

The debate over the existence of neighbourhood effects on mental health and wellbeing is important and is clearly related to the values of place-based policies targeting deprived areas. One example is the UK New Deal for Communities Programme. Implemented during the 2000s, the programme sought to improve the

living environments of 39 deprived neighbourhoods in England through a range of community-led initiatives, including job creation, crime reduction, and building renewal. In its evaluation report, the Department for Communities and Local Government (2015) – now the Department for Levelling Up, Housing and Communities – examined the physical and mental health impacts of the programme. The findings revealed that these effects vary across population subgroups and changed over time. This variability highlights the lack of consensus on the effectiveness of neighbourhood interventions in achieving wellbeing outcomes.

In addition to being empirically ambiguous, existing evaluations of urban welfare programmes are limited in three ways. First, most evaluations focus on a single programme. Large-scale initiative like the New Deal for Communities are expensive and multidimensional, addressing various aspects of the environments (e.g., physical, social, and economic) and often involving community inputs during the designing phase. In contrast, smaller, cost-effective programmes typically target only one type of neighbourhood environment—for instance, green and blue space. Therefore, it remains unclear what types of environmental changes in deprived neighbourhoods are more effective at improving wellbeing. For example, Bartik (2020) estimated that various place-based policies cost state and local governments in the United States approximately 50 billion US dollars per year, a figure that exceeds Slovenia's GDP in 2020 (about 48 billion USD, adjusted to 2015 constant prices, according to the World Bank (2023)). Given the enormous fiscal costs of these policies, identifying the most effective interventions is crucially important from a public finance perspective. Evidence-based insights can help policymakers design and implement programmes that meaningfully enhance people's wellbeing.

Secondly, as highlighted in our systematic literature review, neighbourhood renewal is not the only policy approach to improve wellbeing. People who move from one neighbourhood to another, for example, could be another source of change which can inform us about the impact of urban environments. At the policy level, rather than transforming the physical environment, subsidising individuals to move away from deprived neighbourhoods could be a faster and potentially more cost-effective strategy for improving quality of life. A prominent example of this “people-based” approach is the housing vouchers offered by the US Department of Housing and Urban Development (HUD), which assist low-income households to find affordable housing in the private market (Owens, 2017). As alternatives exist, the relative effectiveness of place-based versus people-based approach in enhancing wellbeing remains an important but largely unanswered policy question.

Finally, existing studies often scrutinize a specific type of subjective wellbeing outcome, which may contribute to disagreement in the literature. A key issue in the literature is the lack of consensus on how mental wellbeing should be defined and measured. As Diener (1984) and Bak-Klimek et al. (2015) have noted, wellbeing can be conceptualised in both positive and negative terms. Positive wellbeing encompasses positive thinking, feelings, and emotions, which include happiness and life satisfaction. In contrast, negative mental health refers to conditions such as mental illnesses, psychological distress, depression, and other mood and anxiety disorders (MAD). Some of the measures are self-assessed and subjective, while others rely on validated psychological scales

and are considered more objective. The drivers of positive and negative wellbeing may differ. They could be related to the mix of hazards and resources in a given environment. For example, using machine learning techniques, Wong et al. (2021) found that negative wellbeing outcomes are often linked to environmental risks, while positive wellbeing outcomes are more closely associated with enabling resources such as green capital. The ongoing debate between risk-based and resource-based approaches to neighbourhood environments offer valuable insights into how local context affect wellbeing and quality of life.

In summary, there is a pressing need for a more systematic evaluation of the impacts of neighbourhood environment on mental wellbeing. To address this, our study combines a systematic review with a meta-analysis to fill these critical knowledge gaps. Specifically, this research seeks to answer the following questions:

- What types of neighbourhood interventions have been evaluated in the academic literature?
- How are mental health and wellbeing defined and measured?
- Are neighbourhood interventions associated with mental wellbeing outcomes?
- Which policy approach, place-based or people-based, is more likely to yield positive wellbeing impacts?
- Which population subgroups are more likely to experience positive effects?
- What factors may explain the heterogeneity in findings?

We adopt a sequential approach to address the research questions, enabling us to identify sources of variations among studies and synthesise the existing literature. To answer the first two questions, we systematically search for relevant literature following the PRISMA guideline. After that, we synthesise and compare the identified studies and re-examine their findings using meta-regressions. This approach aims to produce more generalisable results derived from previous studies (Borenstein et al., 2009).

This paper is organised as follows. After this introductory section, the next section will detail our search strategy, following the PRISMA guidelines. In Sect. "Descriptive Results", we present our descriptive findings, highlighting two policy approaches: place-based and people-based policies. While the former focuses on actively transforming neighbourhood environments, the latter involves relocating people to new neighbourhood. Sect. "Meta-Analysis: Model and Variables" will outline the meta-regression methodology. Sect. "Effectiveness of Place-Based and People-Based Interventions" will look at whether the people-based or the place-based approach contribute to mental health and wellbeing, and identify which population subgroups are more likely to benefit. Sects. "People-Based Interventions" and "Place-Based Interventions" will focus on each policy approach in turn and identify relevant neighbourhood characteristics that explain neighbourhood effects. Sect. "Limitations" discusses limitations of the study and directions for future research. Sect. "Conclusions" concludes with a remark on the policy implications.

Literature Search

We searched literature from two databases, Scopus and the Web of Science, with search results restricted to journal articles written in English. We are interested in the extent to which interventions targeting deprived neighbourhoods can improve wellbeing outcomes. As many have been written, this study raises the bar and includes only studies based on a policy interventions that help us identify causal effects.

The following search strings were used: (program* OR project* OR policy* OR intervention* OR experiment* OR random*) AND (disadvantage* OR poverty OR deprived) AND (neighbo*) AND (well-being OR wellbeing OR happiness OR satisfaction OR distress OR mental). Web of Science returned 1768 records and Scopus 1229 records.

Inclusion and Exclusion Criteria for Screening

After eliminating duplicated records, we screened titles and abstracts based on several inclusion criteria. First, included studies must focus on the impacts of neighbourhood environments on mental health or subjective wellbeing. This excludes studies examining behavioural or cognitive outcomes such as walking, healthcare utilisation, delinquency, crime, academic performance, or employment. However, studies that address psychological illnesses, as defined by Diener et al. (2009) as psychological wellbeing, are included, as many studies rely on existing psychological scales to measure wellbeing. Second, studies must focus on interventions that induce changes in the physical environment or beyond. This includes residential mobility programmes if households are supported in moving to a new environment. However, we exclude interventions primarily based on psychological and counselling components, such as parenting training or psycho-emotional supports for specific groups (e.g. women, parents, and youth). Health infrastructure interventions, such as openings of new psychiatric clinics or related facilities, are also excluded. Third, studies must evaluate impact quantitatively. This excludes pure qualitative evaluations, protocols or pre-analysis plans, review articles, and essay-type contributions. Finally, we include only studies that use longitudinal or repeated cross-sectional data to assess the effect of an intervention. Findings based solely on cross-sectional comparisons using post-intervention data are excluded.

Iterative Search Approach

We adopted an iterative approach to ensure the inclusion of relevant programmes in the meta-analysis. Based on our literature search, we identified nine large-scale neighbourhood interventions and residential mobility programmes that have been evaluated in the academic literature. They are the Dutch District Approach (Netherlands), GoWell (UK), Gautreaux (US), HOPE VI (US), Moving to Opportunity (US), New Deal for Communities (UK), Section 8 housing vouchers (US), Well London (UK), and the Yonkers Project (US). Based on this new information, we followed the same literature

search and screening procedure using the specific programme names and the search string (well-being OR wellbeing OR happiness OR satisfaction OR distress OR mental) to include studies left out from the previous round of search. Google Scholar was also used in this stage to identify forthcoming articles. Based on the same inclusion criteria, after screening, 111 additional studies are retrieved for screening and 11 studies are included to the final list. In total, 54 studies are selected for the meta-analysis. Figure 1 displays the flow diagram outlining the literature search and selection process.

Coding

We coded the studies based on several characteristics, including authors, years of publication, article titles, journal titles, and fields of study. In line with our research questions, we also coded specific programme characteristics, such as the location of the programmes and the type of interventions. Additionally, we recorded how the authors measured wellbeing, the psychological scale used (when applicable), the methods employed, the findings, the population subgroup, and the included covariates.

We intended to include the standard error of the estimated effect sizes in our data. However, due to publication constraints, standard errors are not always reported, for instance, when effect sizes are displayed in a graph with their confidence intervals, standard errors are usually omitted. In some cases, only confidence intervals or p-values are provided in tables or in the text. Additionally, in many experimental studies, standard errors are not reported and could not be found even in the online appendices or working paper versions. Sample sizes are also sometimes omitted in subgroup analyses. Given these limitations and the fact that dependent variables are measured in various ways, we were unable to obtain the standardised effect sizes for further analysis. Consequently, following Card et al. (2010), we categorised the results in three groups: statistically significant beneficial effects, statistically non-significant effects, and statistically significant detrimental effects.

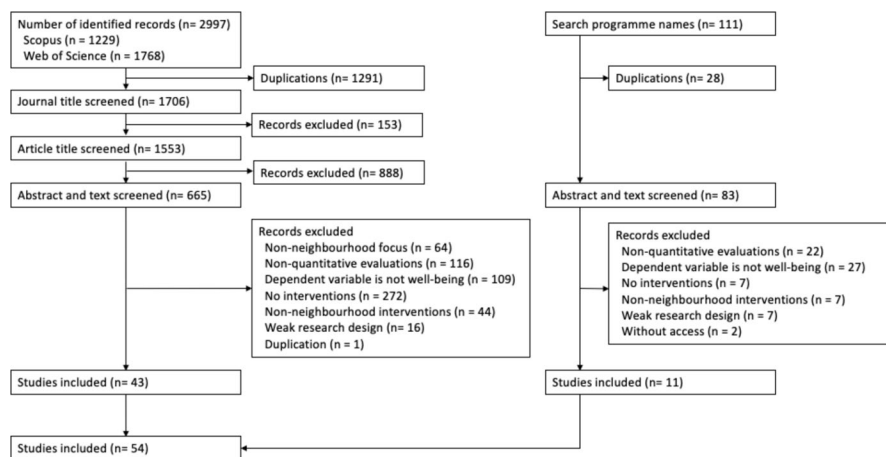


Fig. 1 Flow diagram of retrieved data

Descriptive Results

The list of studies is reported in Table 1. In total 54 studies, with the study ID for later in-text references, are included. Figure 2 plots the number of published studies according to the year of publication by programme types (place-based or people-based). Over time, there is a growing scholarly interest in the topic. The earliest papers (2 studies) were published in 2001. One is written by Tim Blackman, John Harvey, Marty Lawrence, and Antonia Simon, who studied the mental health impact of a neighbourhood renewal programme in Scotswood, Newcastle upon Tyne (UK). The other one is authored by Lawrence Katz, Jeffrey Kling, and Jeffrey Liebman, who evaluated the Moving to Opportunity programme in Boston in the US. Since then, the number of studies assessing the mental wellbeing impact of neighbourhood environment has increased. In terms of geographical focus, with only one exception—Westaway (2006), who studies a programme in South Africa—all studies are based on a case from an advanced economy. The most studied country is the US (32 studies), followed by the UK (10 studies), the Netherlands (4 studies) and Australia (2 studies).

Place-Based Versus People-Based Interventions

Two main types of interventions are identified: place-based (20 studies) and people-based (34 studies). While the former aims to transform the neighbourhood environments, the latter seeks to relocate people to new neighbourhoods. Place-based interventions are multidimensional efforts that aim to improve the physical, economic, and social environments of a neighbourhood. These projects often involve renovating or demolishing old buildings, introducing green infrastructure and adding recreational facilities after replanning. To improve safety, new streetlights are installed and policing is enhanced. Graffiti is removed and vandalised facilities are repaired. Social events are often organised to foster community cohesiveness, and residents receive information on new events and messages about healthy lifestyle. Local governments may also provide financial incentives such as tax breaks or subsidies, to encourage entrepreneurs and create new business and job opportunities to revitalise the economic environment. Typically, these projects are led by local residents to foster local ownership and community involvement. Examples include the Dutch District Approach in the Netherlands and the Go Well programme in Glasgow. While place-based interventions can be effective, they are expensive and often take years from planning to completion. Another popular form of place-based intervention is greening, which focuses on beautifying the natural and physical environments of neighbourhoods by planting trees and improving access to nearby green and blue spaces (e.g. South et al., 2018; Van den Bogerd et al., 2021).

People-based interventions primarily take two forms: governments either subsidise residents to relocate from disadvantaged neighbourhoods, or they allocate residential units to applicants through a housing programme, often via a randomisation process. Examples include public social housing allocation (Boje-Kovacs et al., 2023), transitional social housing (Chen et al., 2023), refugee resettlements

Table 1 List of studies

ID	Reference	Region	Intervention	Program Name
1	Blackman et al. (2001)	Newcastle upon Tyne	Place-based	-
2	Boje-Kovacs et al. (2023)	Copenhagen	People-based	-
3	Burrows et al. (2023)	New Orleans	Place-based	-
4	Byck et al. (2015)	Mobile, Alabama	People-based	HOPE VI
5	Chan et al. (2023)	Hong Kong	People-based	-
6	Chesher et al. (2023)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
7	Cooper et al. (2014)	Atlanta	People-based	-
8	Dunn et al. (2023)	Hamilton, Canada	Place-based	-
9	Egan et al. (2016)	Glasgow	Place-based	Go Well
10	Fauth et al. (2008)	Yonkers, New York	People-based	-
11	Foverskov et al. (2023)	Denmark	People-based	-
12	Frostick et al. (2017)	London	Place-based	Well London
13	Garg et al. (2013)	Oahu, Hawaii	People-based	Section 8
14	Gennettian et al. (2012)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
15	Glymour et al. (2016)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
16	Graif et al. (2016)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
17	Gubbels et al. (2016)	Netherlands	Place-based	Dutch District Approach
18	Jalaludin et al. (2012)	Sydney	Place-based	-
19	Jongeneel-Grimen et al. (2016)	Netherlands	Place-based	Dutch District Approach
20	Katz et al. (2001)	Boston	People-based	MTO
21	Kearns et al. (2020)	Glasgow	Place-based	-
22	Kearns et al. (2021)	Glasgow	Place-based	-
23	Kelagher et al. (2010)	Victoria, Australia	Place-based	-
24	Kessler et al. (2014)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
25	Kling et al. (2007)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO

Table 1 (continued)

ID	Reference	Region	Intervention	Program Name
26	Leventhal and Brooks-Gunn (2003)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
27	Leventhal and Dupéré (2011)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
28	Ludwig et al. (2008)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
29	Ludwig et al. (2012)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
30	Ludwig et al. (2013)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
31	Mehdipanah et al. (2014)	Barcelona	Place-based	-
32	Mohan et al. (2017)	Northern Ireland	Place-based	-
33	Moulton et al. (2014)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
34	Nguyen et al. (2013)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
35	Nguyen et al. (2016)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
36	Osypuk et al. (2012a)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
37	Osypuk et al. (2012b)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
38	Osypuk et al. (2019)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
39	Phillips et al. (2014)	Baltimore, Boston, Los Angeles, New York London	People-based	Well London
40	Rudolph et al. (2020)	Boston, Chicago, Los Angeles, New York	People-based	MTO
41	Rudolph et al. (2021)	Boston, Chicago, Los Angeles, New York	People-based	MTO
42	Rudolph et al. (2023)	Boston, Chicago, Los Angeles, New York	People-based	MTO
43	Ruijsbroek et al. (2017)	Netherlands	Place-based	Dutch District Approach
44	Sanbonmatsu et al. (2012)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
45	Schmidt et al. (2017)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
46	Schmidt et al. (2020)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
47	Schmidt et al. (2021)	Baltimore, Boston, Chicago, Los Angeles, New York	People-based	MTO
48	South et al. (2018)	Philadelphia	Place-based	-
49	Timmermans et al. (2020)	Amsterdam	Place-based	Dutch District Approach
50	Van den Bogerd et al. (2021)	Teats Hill, Plymouth	Place-based	-

Table 1 (continued)

ID	Reference	Region	Intervention	Program Name
51	Walthery et al. (2015)	England	Place-based	New Deal for Communities
52	Webb et al. (2017)	Charlotte, North Carolina	People-based	HOPE VI
53	Westaway (2006)	Soweto, Johannesburg	People-based	-
54	White et al. (2017)	Caerphilly County, UK	Place-based	Community First

HOPE: The Housing Opportunities for People Everywhere; MTO: Moving to Opportunity

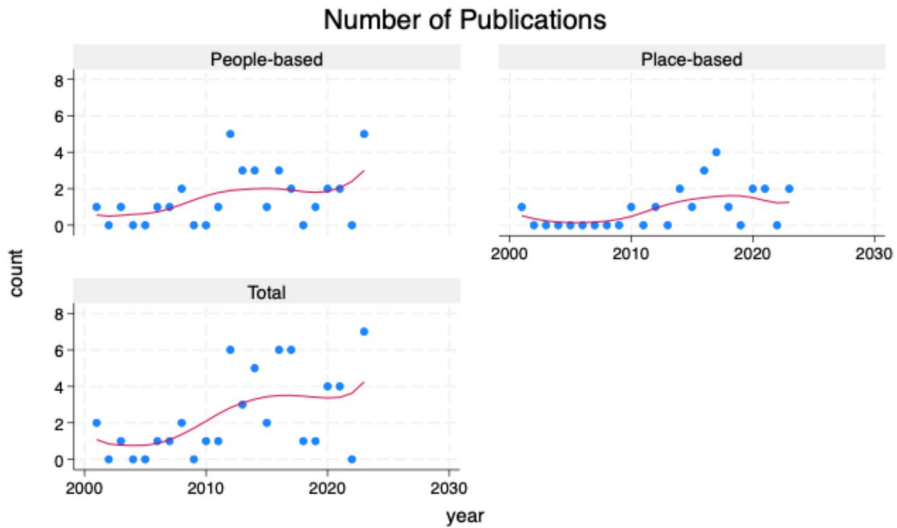


Fig. 2 Number of publications over year

(Foverskov et al., 2023), and the Moving to Opportunity (MTO) programme. Among the 34 evaluations in this category, 25 focus on the MTO programme. Administered by U.S. Department of Housing and Urban Development (HUD), MTO is a large-scale residential mobility policy experiment launched in 1994 in Baltimore, Boston, Chicago, Los Angeles, and New York. Low-income households living in public or assisted housing in improvised neighbourhoods could apply to move to private housing in low-poverty areas. Families who successfully applied were randomly assigned to either the treatment group or the control group. Families in the experimental group received assistance from non-profit organisations to find new housing units, and were given vouchers to pay for rental housing from private landlords, but only in low-poverty neighbourhoods (Katz et al., 2001).

While the allocation of social housing is not new, subsidised residential mobility is considered a policy innovation in the housing sector (Owens, 2017). In the context of urban poverty, which is often compounded by residential segregation in the US, one of the objectives of MTO is to break spatial isolation (Curley, 2005). As a result, MTO operated in a unique policy context distinct from place-based interventions. Although different in form, these people-based interventions share the common goal of addressing the idea that high levels of crime, poverty, and disorder can negatively influence people's behaviours, particularly children's, as well as mental health and wellbeing (Curley, 2005; Kearns et al., 2021).

Based on this summary of findings, two knowledge gaps are identified. First, there is a lack of evaluations in developing countries, possibly due to lack of data or public financial resources to fund these programmes. Second, though the prominence of the two approaches, there is no systematic evaluation examining their relative effectiveness. Based on the identified studies, we will address the second knowledge gap using meta-regressions.

Mental Wellbeing

Neighbourhood effects have been studied extensively, but the focus has typically been on economic outcomes. This study contributes to the literature by examining a less explored outcome: mental wellbeing. Mental wellbeing can be defined in both negative and positive terms (Lyubomirsky et al., 2005). The negative aspect is often associated with emotional disorders like anxiety and depression, while the positive aspect is commonly operationalised as life satisfaction and happiness (Diener, 1984). In this study, we group mental wellbeing outcomes from the identified studies into three categories, which are then used in our meta-analysis. We summarise various measures and the corresponding psychological instruments based on these studies, with the results presented Table 2. Some key trends are highlighted below.

Among the sampled studies, majority of studies focus only on negative wellbeing. Most studies look at psychological distress and depressive symptoms. Possibly because many psychological scales for mental disorders exist, negative wellbeing outcomes are often assessed using validated psychological scales.

In contrast, relatively few studies examine positive wellbeing in their evaluations. Outcomes and measures of positive subjective wellbeing are also less standardised. The most popular outcomes are life satisfaction (5 studies) and happiness (3 studies). For both outcomes, they are measured by a single question, which asks respondents how satisfied or happy they were with their life in general. Although some validated instruments exist—for example, the Warwick-Edinburgh Mental Wellbeing Scale (Tennant et al., 2007) and the 5-item World Health Organization Well-Being Index (Bech, 2004)—only three studies employ them in their analyses.

Finally, quite some studies adopt a hybrid approach and apply psychological scales featuring both positive and negative outcomes. For example, Graif et al. (2016), Kling et al. (2007), and Ludwig et al. (2013) used a composite index, which combines K6 (Kessler Scale; Kessler et al., 2002), CIDI-index (Kessler & Üstün, 2004) on Generalised Anxiety Disorder (GAD), plus a question on sleeping and another question on feeling calm and peace to measure the absence of mental health problems. The excessive focus on distress and anxiety symptoms makes this index leaning towards the negative side of the wellbeing spectrum. Three other popular measures that strike a stronger balance between positive and negative outcomes on the spectrum are the General Health Questionnaire (GHQ-12) (Goldberg & Blackwell, 1970), the Mental Health Inventory (MHI-5) (Berwick et al., 1991), and the Mental Component Summary (MCS) of the 12-item Short-Form Health Survey (SF-12) (Ware et al., 1996). In our meta-analysis, we label the first type which focuses more on the negative aspects as hybrid measure for mental health and the second type which have a more balanced perspective as hybrid measure for mental wellbeing.

Due to our interest on neighbourhood effects and our lack of expertise in the psychometric properties of these instruments, we will not discuss or analyse them further. Our goal here is to provide a list of options for researchers planning to study the mental health impact of neighbourhoods. Based on this list, other researchers may identify unaddressed dimensions to explore in future studies. One major finding based on this literature survey is that relatively fewer studies examine positive

Table 2 Measures and indicators of wellbeing in included studies

Wellbeing	Scale / Indicator	Study ID
<i>Positive</i>		
Feeling calm and peace	1 item	11, 25, 30, 33
Happiness	1 item	6, 29, 30
Life satisfaction	1 item	23, 32, 50, 51, 53
General wellbeing	WEMWS	21, 39
	WHO-5	50
<i>Hybrid</i>		
General wellbeing	MCS-12	9, 21, 22
	MHI-5	8, 13, 19, 43, 51, 54
General mental health	12 items	16, 25, 30
	GHQ-12	31, 32, 39
<i>Negative</i>		
General mental health	4 items	1
	5 items	1
	15 items	25, 30
	Strengths and Difficulties Questionnaire	12
Psychological distress	K6	3, 5, 14, 15, 16, 18, 25, 27, 28, 29, 30, 33, 34, 35, 36, 37, 38, 40, 44, 45, 46, 47, 48
Mood disorders	CIDI-SF	41
	Diagnosed	11
	Medication	11
Anxiety	1 item	33
	4 items	25
	CIDI	24
	CIDI-SF	44
	Diagnosed	11
	HADS-A	49
	Medication	11
	Unclear	33
Depression	1 item	48
	5 items	25
	C-DISC	4
	CES-D-10	52
	CES-D-20	7, 17, 49
	CIDI	24
	CIDI-SF	16, 20, 25, 38, 42, 44
	Depressive Mood Inventory	26
	Unclear	33
Anxiety and depression	13 items	10
PTSD	CIDI-SF	44
Psychiatric disorders	Diagnosed;	11

Table 2 (continued)

Wellbeing	Scale / Indicator	Study ID
	Medication	2, 11

C-DISC: Columbia DISC Depression Scale; CES-D: Center for Epidemiologic Studies Depression Scale; CIDI-SF: Composite International Diagnostic Interview–Short Form; GHQ: General Health Questionnaire; MCS-12: 12-item Mental Component Summary; HADS-A: Hospital Anxiety and Depression Scale – Anxiety; K6: Kessler-6; MHI-5: Mental Health Inventory-5; PTSD: Post-traumatic stress disorder; WEMWS: Warwick-Edinburgh Mental Wellbeing Scale; WHO-5: 5-item World Health Organization Well-Being Index

wellbeing using a validated scale to measure positive mental wellbeing. This represents a major gap in the literature, suggesting a promising avenue for future research.

Meta-Analysis: Model and Variables

To determine whether people-based or place-based interventions are more effective and whether neighbourhood effects depend on whether mental wellbeing is conceptualized positively or negatively, we conduct a meta-regression analysis. A standard meta-regression requires standardising estimated effect sizes for meaning comparison. This involves homogenising the scale of effect sizes, considering the model used to obtain the estimates, and whether a linear or non-linear model was applied (Baek et al., 2023). Unfortunately, in the identified studies, mental wellbeing variables are measured on diverse scales. They may be binary, ordinal, or continuous, with continuous measures expressed as z-scores, sum, or averages of sub-components. Consequently, meaningful comparison of effect sizes is challenging without additional information (e.g., the standard deviation of the dependent variable), which is often not reported. Further complications arise when results are converted (e.g., into odds ratios) or presented graphically. In cases where only p-values or confidence intervals are reported, rounding errors can lead to imprecise estimates, especially when the coefficient-to-standard-error ratio is large. Due of these challenges, we follow Card et al. (2010) by categorising findings into three classes: statistically significant detrimental effects, statistically non-significant effects, and statistically significant beneficial effects, with the significance level set at 5%.

The final data set comprises 535 estimates. Given the ordered nature of the dependent variable, we employ ordered logistic models. To account for the similarity of subgroups findings within the same study, we cluster the standard errors at the study level. As a robustness check, we also estimate a multilevel ordered logit model to address potential within-study correlations (Van den Noortgate et al., 2015).

Our meta-regression analysis incorporates several moderators (independent variables). These include three moderators related to the types of interventions and the measurement of wellbeing outcomes, as discussed in the previous section. Additionally, four moderators address the scope of the findings: population subgroups, geographical scale, time, and deprived neighbourhood. The remaining three moderators pertain to the methodological design of the evaluations. After a

pooled analysis, we perform separate analyses for people-based and place-based evaluations. In these subgroup-level analyses, our focus shifts to different neighbourhood characteristics and environments. The moderators specific to these analyses are explained below. To address issues of multicollinearity and ensure estimable standard errors, we re-group certain moderators, as indicated by the variable labels in the regression tables.

Moderators

Type of Intervention As discussed in the previous section, interventions are categorized into two types, people-based and place-based. In our analysis, people-based interventions serve as the baseline category.

Wellbeing Outcomes Our analysis begins by categorising wellbeing outcomes into three groups: positive, negative and hybrid. Positive wellbeing includes cognitive (e.g., life satisfaction), emotional (e.g., happiness), self-evaluative (e.g., feeling confident), and social aspects (e.g., feeling close to others). Negative mental health is a more diverse category encompassing symptoms of psychological distress and mental disorders such as anxiety, depression, mood disorders, and post-traumatic stress disorder (PTSD). Some studies use psychological scales that include questions related to both positive and negative aspects of mental health or wellbeing. These are categorised as hybrid. As we found interesting patterns related to positive wellbeing, to explore this pattern, we further decompose these outcomes into seven outcomes: (1) negative mental health, which include symptoms of psychological distress, anxiety, depression, mood, and PTSD; (2) mental health (hybrid), which is similar to the first category, but includes one or two questions related to positive mental wellbeing; (3) mental wellbeing (hybrid), which has a balanced mix (approximately 50–50) of questions addressing both positive and negative mental conditions; (4) feeling calm and peace; (5) happiness; (6) life satisfaction; and (7) positive wellbeing, which goes beyond a single-item response and covers other aspects of the concept, often using validated psychological scales. As the primary focus is on positive outcomes, negative mental health serves as the reference group in the analysis.

Psychological Scale Studies that measure mental wellbeing using validated psychological instruments are coded as 1. Conversely, studies that rely on a single item or develop their own measures by combining scales with single-item questions are coded as 0.

Population Subgroups Seven subgroups are identified: adolescents, adults, older people, men, women, boys and girls. These groups are not mutually exclusive, as their categorisation depends on how a study defines its sample. For instance, adults may include older people, women and men, while adolescents include both boys and girls. Each subgroup is represented as a binary variable, with adolescents serving as the reference group.

Geographical Scale People-based interventions often involve relocating individuals across an entire country, whereas place-based interventions typically targets specific neighbourhoods. To account for this geographical heterogeneity, we include a variable that captures these differences. However, incorporating location fixed effects is not feasible, as they fully overlap with the study level clustering of standard errors, rendering them non-estimable. Instead, we include country fixed effects to control for broader geographical differences.

Time Effects The variables capture the timing of follow-up interviews conducted after an intervention. Since interventions usually take years from inception to completion, we categorise studies into five groups: 1–2 years, 3–5 years, 6–10 years, 11–15 years, and a mixed category. The mixed category includes studies that pools all individuals who received a treatment at different points of time into one sample. This approach accounts for interventions implemented on a rolling-basis or studies where the evaluation period is not explicitly reported.

Deprived Neighbourhoods Most interventions targeted deprived neighbourhoods or people living in there. Findings from these interventions take value 1 and 0 otherwise.

Control Group We also control for the methodological design employed in each study. Three types of design have been identified. Two of these designs have a control group: randomised control trials (RCTs) and non-randomised comparisons. RCTs assign participants to treatment or control groups randomly, providing the most robust design for causal inference. Non-randomised design compares residents from similar regions or with comparable characteristics to establish counterfactuals. The third type is a before-after design (i.e. single difference), which evaluate changes over time without a control group. Among these, RCT offers the strongest methodological rigor, enabling researchers to interpret findings as causal effects.

Panel Data Not all studies in our analysis use longitudinal data. Studies that rely on repeated cross-sectional data are unable to controlled for individual-level unobserved heterogeneities (e.g. genetic factors). Because these factors can affect mental wellbeing over time, study using repeated cross-sectional data are unable to account for unobserved individual differences and are considered weaker.

Regression Some estimates are based on mean-comparison without adjusted for the effects of covariates. Estimates from mean comparison serve as the baseline category.

Sects. "[People-Based Interventions](#)" examines people-based interventions. We are particularly interested in the types of neighbourhood characteristics that are related to specific findings. We include the following covariates in this part of the analysis.

Neighbourhood Environments Many studies evaluate the impact the Moving to Opportunity programme in the US. Based on the baseline covariates used in this

group of studies, we code them according to whether the following neighbourhood characteristics are controlled for: **social relations** (e.g. whether participants had friends or family members living in the same neighbourhoods prior to relocation), **neighbourhood safety** (e.g. crime victimization and perceived safety), **exposure** (whether participants had lived in the neighbourhood for five or more years before relocation), and **neighbourhood poverty** levels.

Research Groups Two major research groups have published several papers on the same topic: Glymour-Schmidt-Osypuk group (SID: 15, 34, 36, 37, 38, 45, 46, 47) and the Katz-Kessler-Kling-Ludwig (KKKL) group (SID: 14, 20, 24, 25, 28, 29, 30, 44). Study 35 in Table 1 is excluded because the study employs a regression tree model and does not produce any effect size. The KKKL group is more like a research network as they did not co-author in all publications. Studies not in these two groups are in the reference group.

Sect. "Place-Based Interventions" investigates place-based interventions. Place-based interventions usually involve changes to the physical environment (e.g. demolishing old buildings, traffic calming measures, landscaping). However, some renewal programmes extend beyond physical changes and target the **internal housing environment** (e.g. constructing new units, renovating kitchen and bathroom). Additionally, many place-based interventions address the **social environment** by fostering social cohesion through recreational and cultural activities or enhancing security. **Economic environments** are also targeted in some cases, with initiatives such as creating new business opportunities or offering employability training. Finally, some programmes adopted a co-creation approach, which involves public-partnership or is initiated by residents themselves. To capture these community-driven approach, we introduce a variable to identify these **community-based** programmes.

Effectiveness of Place-Based and People-Based Interventions

Table 3 shows the distributions of the two main variables of the analysis. More than half of the estimates are statistically insignificant at the 5% level. Although in total only 19 estimates reveal a harmful impact, 157 (about 30%) estimates show a beneficial effect. If we examine the effects by wellbeing outcomes (panel A), a beneficial neighbourhood effect is more likely for positive wellbeing outcomes (29%) than a negative one (0%). Regarding programme type (panel B), place-based interventions are more likely to be beneficial. Almost all harmful impacts are reported by evaluations on people-based interventions.

The meta-regression results are reported in Table 8. in the Appendix. Models 1 to 3 summarise results based on pooled wellbeing measures (positive, negative and hybrid), while Model 4 provides results for more granular wellbeing outcomes. For clarity and ease of interpretation, Tables 4 and 5 report the marginal effects of moderators on programme effects based on ordered logistic regressions with country fixed effects (i.e. Models 2 and 4 in Table 8.). We present results based on the

Table 3 Distribution of programme estimates, by measures and programme types

	Beneficial and significant	Not statistically significant	Harmful and significant
All	157 (29.3%)	359 (67.1%)	19 (3.6%)
(A) By measure			
<i>Positive wellbeing</i>	32 (29%)	78 (71%)	0 (0%)
<i>Hybrid measures</i>	47 (31%)	104 (69%)	0 (0%)
<i>Negative mental health and wellbeing</i>	78 (28%)	177 (65%)	19 (7%)
(B) By programme Type			
Place-based	71 (35%)	131 (64.5%)	1 (0.5%)
People-based	86 (26%)	228 (69%)	18 (5%)

non-multilevel specification, as the log-likelihoods of the multilevel models show little improvement.

Place-based programmes often show a beneficial effect compared to people-based interventions. In terms of wellbeing measures, studies focusing on positive wellbeing outcomes are less likely to report a beneficial effect ($p < 0.10$) when compared to those using hybrid measures. Additionally, there are no significant effects observed for negative mental health outcomes.

Focusing on the population subgroups, beneficial effects are more commonly observed among adults and girls, while boys are more likely to experience a harmful effect. Do these effects endure over time? There is a clear distinction between short-term and long-term impacts. Since the estimates are relative to the reference group (1–2 years), the findings suggest that the benefits of interventions tend to dissipate over time. Additionally, the rigor of the study design plays a crucial role. Studies based on RCTs are more likely to report significant effects compared to those with weaker designs.

We also explore the heterogeneous findings based on different wellbeing measures (Model 4 in Table 8.). The marginal effects of the moderators are summarised in Table 5. The results that place-based interventions are more likely to have a positive impact persists. However, these interventions appear to have a detrimental effect on peaceful mindsets, life satisfaction, and happiness. The analysis based on validated measures seems to suggest otherwise (i.e. positive wellbeing), although this finding is less certain ($p < 0.10$). Specifically, only 3 out of 54 studies used validated instruments to measure positive wellbeing, indicating the need for further research in this area.

People-Based Interventions

In total, 332 estimates from 34 studies are included in this part of analysis. Since many estimates come from the same studies and intervention (i.e. MTO), we also conduct a multilevel level analysis to account for the hierarchical nature of our data as a robustness check. However, given that the log likelihood improvement

Table 4 Marginal effects of moderators on findings

	Beneficial	No	Detrimental
<i>Programme type: baseline = people-based:</i>			
Place-based	0.355** (0.137)	-0.236*** (0.054)	-0.119 (0.097)
<i>Wellbeing: baseline = Hybrid</i>			
Negative wellbeing	0.077 (0.075)	-0.063 (0.061)	-0.014 (0.015)
Positive wellbeing	-0.098 + (0.055)	0.072 + (0.040)	0.026 (0.016)
Use validated scale (baseline = no)	-0.157 + (0.089)	0.133 + (0.079)	0.024 + (0.012)
<i>Group: baseline = Adolescents</i>			
Adults	0.253*** (0.053)	-0.245*** (0.053)	-0.008 (0.007)
Boys	-0.126* (0.050)	-0.174* (0.088)	0.300** (0.091)
Girls	0.212** (0.066)	-0.205** (0.066)	-0.007 (0.007)
Men	0.556*** (0.116)	-0.547*** (0.117)	-0.009 (0.009)
Older people	0.741*** (0.116)	-0.732*** (0.115)	-0.010 (0.009)
Women	0.169 (0.203)	-0.163 (0.197)	-0.006 (0.008)
<i>Geographical scale: baseline = city</i>			
Country	0.068 (0.067)	-0.048 (0.045)	-0.020 (0.026)
Large region	-0.163*** (0.040)	0.085 (0.065)	0.078 (0.075)
Multiple cities	0.301*** (0.060)	-0.199*** (0.043)	-0.102*** (0.025)
Neighbourhood	-0.060 (0.122)	0.044 (0.086)	0.016 (0.038)
<i>Time effects: baseline = 1 to 2 years</i>			
11 to 15 years	-0.619*** (0.087)	0.553*** (0.079)	0.066** (0.025)
3 to 5 years	-0.283* (0.127)	0.276* (0.119)	0.007 (0.009)
6 to 10 years	-0.566*** (0.089)	0.520*** (0.082)	0.046* (0.020)
Varied	-0.274 + (0.150)	0.267 + (0.141)	0.007 (0.011)
<i>Control group: baseline = no (before-after)</i>			

Table 4 (continued)

	Beneficial	No	Detrimental
Non-random	0.004 (0.087)	−0.004 (0.083)	0.000 (0.004)
Random	−0.308** (0.098)	0.271** (0.089)	0.037* (0.017)
Longitudinal (baseline = repeated cross-sections)	−0.095 (0.134)	0.081 (0.118)	0.014 (0.017)
Regression-based (baseline = no)	−0.006 (0.048)	0.005 (0.039)	0.001 (0.008)
Deprived neighbourhoods (baseline = no)	−0.275 (0.545)	0.246 (0.513)	0.029 (0.034)

Robust standard errors, clustered by study, in parentheses. Average marginal effects based on Model 2 in Table 8. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$. Number of observations = 535. Log likelihood = −284.995

Table 5 Marginal effects of mental health and wellbeing outcomes on findings

	Beneficial	No	Detrimental
<i>Programme type: baseline = people-based:</i>			
Place-based	0.348*** (0.056)	−0.227*** (0.041)	−0.121** (0.038)
<i>Negative mental health: baseline: negative mental health</i>			
Calm and peace	−0.294*** (0.074)	0.179*** (0.049)	0.115** (0.034)
Life satisfaction	−0.326*** (0.084)	0.171*** (0.047)	0.155* (0.078)
Mental health (hybrid)	−0.234* (0.091)	0.155** (0.052)	0.079 + (0.041)
Happiness	−0.272** (0.093)	0.172* (0.053)	0.100* (0.045)
Mental wellbeing (hybrid)	0.178 (0.132)	−0.158 (0.122)	−0.020 + (0.012)
Positive wellbeing	0.206 (0.131)	−0.185 (0.122)	−0.022 + (0.011)

Robust standard errors, clustered by study, in parentheses. Average marginal effects based on Model 4 in Table 8. (with covariates). The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$. Number of observations = 535. Log likelihood = −273.182

of the multilevel model is minimal, the marginal effects presented in Table 6 are based on a standard ordered logit model.

Adults are less likely to experience a beneficial mental health and wellbeing impact, suggesting that the positive effects observed in the previous section may be linked to place-based interventions. This could be due to the stressful nature of relocation, at least in the short term (Curley, 2005). The stress may also arise from reduced social support and social capital after moving to a new environment (Curley, 2005). Our analysis lends some empirical support to this hypothesis and align with previous research that highlights the importance of neighbourhood-based social capital in influencing life satisfaction (Hoogerbrugge & Burger, 2018). Studies that controlled for social relations in neighbourhoods are more likely to report negative impacts and less likely to report positive outcomes. Furthermore, studies that accounted for exposure to the pre-relocation environment were also more likely to show mental health effects. In contrast, other neighbourhood risks factors such as poverty and safety do not seem to have a clear effect on mental health and wellbeing. In conclusion, moving away from a deprived neighbourhood can be both a stressful and liberating experience.

Another major concern is whether the neighbourhood effect on wellbeing endures. The short-term effect appears to be non-detrimental compared to the longer-term impacts. This finding is consistent with the treadmill model of happiness (Brickman & Campbell, 1971; Kahneman, 1999).

There are notable differences across demographic groups. Relocation has significantly different wellbeing impacts on girls and boys. A detrimental impact on boys is evident. For girls, place-based interventions generally do not have a negative impact. This could be related to finding about perceived safety in neighbourhoods. Recent research suggests that women are generally more fearful of crime than men (Johansson & Haandrikman, 2023). Since perceived safety and crime rates are linked to higher levels of stress and poorer wellbeing outcome (Putrik et al., 2019), our findings corroborate the growing body of research on the gendered fear of crime and help explain this result. Since many studies in our sample that report these finding are conducted by Glymour, Schmidt, Osypuk and colleagues, one may suspect that the observed pattern is influenced by a research group effect. However, the pattern persists even after explicitly controlling for this clustering effect.

Place-Based Interventions

In total, 203 estimates from 20 studies are included in this meta-analysis. To account for potential correlations between estimates from the same study, we conduct a multilevel level analysis as a robustness check. However, since the log likelihood of the multilevel model does not show any improvement, the marginal effects summarised in Table 7 are based on a standard ordered logit model.

Table 6 Marginal effects of moderators

	Beneficial	No	Detrimental
<i>Wellbeing: baseline = Hybrid</i>			
Negative wellbeing	0.060 (0.168)	-0.043 (0.118)	-0.017 (0.051)
Positive wellbeing	-0.115 + (0.069)	0.068 (0.055)	0.047* (0.019)
Use validated scale (baseline = no)	-0.100 (0.179)	0.074 (0.138)	0.026 (0.042)
Social relations (baseline = no)	-0.103* (0.046)	0.073* (0.033)	0.029* (0.014)
Neighbourhood poverty (baseline = no)	-0.077 (0.061)	0.055 (0.045)	0.022 (0.016)
Neighbourhood safety (baseline = no)	-0.063 (0.054)	0.045 (0.038)	0.018 (0.016)
Exposure (baseline = no)	0.291*** (0.077)	-0.208*** (0.057)	-0.083** (0.025)
<i>Group: baseline = Adolescents</i>			
Adults	-0.305*** (0.073)	0.305*** (0.073)	0.000 (0.164)
Boys	-0.069 + (0.040)	-0.149* (0.076)	0.218** (0.068)
Girls	0.324*** (0.076)	-0.324*** (0.076)	0.000 (0.017)
<i>Geographical scale: baseline = city</i>			
Multiple sites (cities, country, large region)	0.226** (0.076)	-0.113** (0.033)	-0.113* (0.053)
Neighbourhood	-0.053 (0.052)	0.010 (0.017)	0.043 (0.047)
<i>Time effects: baseline = 11 to 15 years</i>			
1 to 5 years	0.355 (0.218)	-0.284 (0.190)	-0.071* (0.036)
6 to 10 years	0.121 (0.105)	-0.084 (0.073)	-0.037 (0.033)
Varied	0.091 (0.230)	-0.061 (0.165)	-0.030 (0.066)
<i>Control group: baseline = no (before-after)</i>			
Non-random	0.277 + (0.147)	-0.236 + (0.131)	-0.041 (0.032)
Random	-0.014 (0.121)	0.010 (0.088)	0.004 (0.033)
Regression-based (baseline = no)	-0.189* (0.081)	0.153* (0.074)	0.036** (0.012)
Katz-Kessler-Kling-Ludwig	-0.008	0.006	0.002

Table 6 (continued)

	Beneficial	No	Detrimental
	(0.125)	(0.090)	(0.036)
Glymour-Schmidt-Osypuk	−0.244***	0.175**	0.07**
	(0.069)	(0.053)	(0.021)

Robust standard errors, clustered by study, in parentheses. Average marginal effects based on Model 1 in Table 9. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$. Number of observations = 332. Log likelihood = −173.390

The community-based approach has been central to many place-based policies (Jarvis et al., 2012). Public participation has shown to be associated with positive impacts, as it is more likely to represent stakeholders' interests, addresses local needs, and foster a greater sense of ownership (Hamdan et al., 2021). However, its broader impact on mental health outcomes through enhanced interventions remains unproven. Positive impacts seem to be primarily linked to changes in the internal housing environment. In contrast to people-based policies, changes in the social environment—such as community-based recreational or cultural activities in some neighbourhood regeneration programmes—do not appear to have a significant effect. Similarly, there is no clear evidence of impact from the business and human-capital-building elements of certain place-based interventions.

Turning to other covariates, the way wellbeing is measured does not appear to be associated with a specific finding. An interesting observation is that older adults are more likely to benefit from place-based programmes. This may be due to their greater sensitivity to the neighbourhood environment (Scharfet al., 2003), possibly because they spend more time at home or within their local communities. Regarding time effects, it seems less likely that mental health benefits persist as time passes, suggesting a potential “treadmill effect” (Brickman & Campbell, 1971). Additionally, the choice of model and research design does not seem to matter.

Limitations

Firstly, our meta-analysis does not explain effect sizes. This is because studies use various scales in their estimation and the absence of key statistics, such as standard errors or standard deviations of the dependent variables, needed for standardisation. Consequently, we are also unable to assess publication bias. However, since approximately 65% of the reported estimates are not statistically significant, concerns about p-hacking appear to be minimal.

Table 7 Marginal effects of moderators

	Beneficial	No	Detrimental
<i>Wellbeing: baseline = Hybrid</i>			
Negative wellbeing	-0.063 (0.067)	0.060 (0.065)	0.003 (0.004)
Positive wellbeing	0.023 (0.034)	-0.023 (0.033)	-0.001 (0.001)
Use validated scale (baseline = no)	-0.115 (0.184)	0.111 (0.180)	0.003 (0.005)
Community-based	-0.134 (0.127)	0.129 (0.123)	0.005 (0.007)
Housing environment	0.566*** (0.144)	-0.546*** (0.157)	-0.02 (0.017)
Social environment	0.207 (0.276)	-0.200 (0.267)	-0.007 (0.011)
Economic environment	0.100 (0.193)	-0.097 (0.186)	-0.004 (0.008)
<i>Group: baseline = Adolescents</i>			
Adults	-0.039 (0.043)	0.038 (0.043)	0.001 (0.001)
Men	-0.008 (0.063)	0.008 (0.061)	0.000 (0.002)
Older people	0.616*** (0.038)	-0.582*** (0.034)	-0.034*** (0.005)
Women	0.004 (0.073)	-0.004 (0.070)	0.000 (0.002)
<i>Geographical scale: baseline = city</i>			
Country	0.579*** (0.046)	-0.431*** (0.045)	-0.148*** (0.004)
Large region	-0.081 (0.081)	0.077 (0.079)	0.003 (0.005)
Neighbourhood	0.246+ (0.140)	-0.243+ (0.138)	-0.003 (0.005)
<i>Time effects: baseline = 1 to 2 years</i>			
11 to 15 years	-0.452*** (0.041)	0.439*** (0.048)	0.013 (0.013)
3 to 5 years	-0.429*** (0.070)	0.418*** (0.072)	0.010 (0.010)
6 to 10 years	-0.292*** (0.082)	0.289** (0.083)	0.003 (0.003)
Varied	-0.459*** (0.063)	0.446*** (0.065)	0.013 (0.015)
<i>Control group: baseline = no (before-after)</i>			
Non-random	-0.066	0.063	0.002

Table 7 (continued)

	Beneficial	No	Detrimental
	(0.051)	(0.047)	(0.004)
Random	0.069	−0.067	−0.002
	(0.107)	(0.105)	(0.002)
Longitudinal (baseline = repeated cross-sections)	−0.057	0.055	0.002
	(0.137)	(0.133)	(0.005)
Regression-based (baseline = no)	0.140*	−0.134*	−0.006
	(0.061)	(0.058)	(0.008)

Robust standard errors, clustered by study, in parentheses. Average marginal effects based on Model 2 in Table 10. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$. Number of observations = 199. Log likelihood = −87.100

Secondly, although our search is not limited to interventions in less developed countries, our sample includes only one study from a less advanced economy. Therefore, our findings should not be generalised to less developed regions. This also highlights a promising avenue for future research.

Thirdly, given the number of published studies on the topic, any systematic review faces the trade-off between breadth and methodological quality. As this study aims to assess the existence of neighbourhood effects on wellbeing, we prioritise empirical rigor and include only studies with experimental or quasi-experimental design using mainly longitudinal and, with some exceptions, repeated cross-sectional data with control groups. As a result, this study may overlook important types of interventions and wellbeing measures, suggesting potential areas for future research.

Finally, despite the existence of validated instruments for measuring positive wellbeing, only a few studies have utilised these tools. Many studies rely on a single question to assess positive wellbeing. Since we found that neighbourhood interventions are less likely to yield positive wellbeing outcomes, but based on only a small number of studies, future research with rigorous designs is necessary to confirm this finding. As a first step, national panel surveys could incorporate relevant questions to support future research in this field. Additionally, more effort should be dedicated to developing psychometrically validated indicators for life satisfaction and happiness.

Conclusions

This study begins with the debate between psychologists and urban geographers regarding the existence of neighbourhood effects on mental wellbeing. To shed light on the debate, we define six sub-questions, which we briefly answer here. Two main types of intervention are identified: place-based and people-based.

Place-based interventions include refurbishment, greening, and regeneration, with regeneration being the most comprehensive, addressing social and economic environments. The people-based approach exemplified by subsidised residential mobility is considered innovative, though more passive, as it does not focus on improving the neighbourhood environment itself.

In terms of mental wellbeing, most empirical studies define the concept negatively, focusing on various mental health problems through existing validated psychological instruments. Only a few studies adopt a positive approach and measure subjective wellbeing positively in terms of happiness and life satisfaction. While validated scales for positive wellbeing exist, they have not been sufficiently exploited in research.

Empirically, based on results from ordered logit regressions, we find that place-based programmes are more likely to have a beneficial effect on mental wellbeing. The overall effect of these programmes is largely positive. Sub-group analysis reveals that boys, particularly in the Moving to Opportunity (MTO) programme, are more likely to experience harmful effects. In contrast, girls are the main beneficiaries, with a positive effect observed in most studies.

To address the question of why there is a divergence in findings between psychology and urban studies, we find substantial variations based on gender, age, and the time between intervention and evaluation. This supports the hypothesis that individual factors play a significant role in explaining wellbeing variations. However, studies employing a longitudinal design confirm that neighbourhood effects exist. Among the various environmental factors, the social environment seems to have a more significant influence than the economic environment.

Place-based policies have garnered significant attentions from researchers and policymakers. These policies usually focus on growth and development (Duranton & Venables, 2021), business activities (Givord et al., 2013), innovation (Morisson & Doussineau, 2019), employment (Kline & Moretti, 2013), and crime (Lazzati & Menichini, 2016), as they are economically efficient due to spillovers between neighbourhoods (Neumark & Simpson, 2015). Our findings suggest that the potential impact on wellbeing from place-based interventions is stronger than that of people-based interventions.

However, these results should not be read as a disapproval of people-based policies. Our analysis indicates that subjective wellbeing is largely influenced by individual-level factors and the social environment. Future policy refinements could focus on enhancing social support to help individuals who relocate to become more socially embedded in their new neighbourhoods. Moreover, while subjective wellbeing is a crucial policy outcome, if it is a policy target, policy effectiveness may be fragile in the long term, as individuals tend to adapt to their new environments over time. Our results imply that greater priority could be placed on improving the social environment of neighbourhoods. The question of how to achieve this is beyond the scope of the current study and should be an area for future, evidence-based policy research.

Appendix

Table 8 Ordered logit models for sign and significance of the general wellbeing effects

	DV: Ordered outcome for sign and significance			
	(1)	(2)	(3)	(4)
<i>Programme type: baseline = people-based:</i>				
Place-based	-0.290 (0.894)	-3.845 (3.960)	-3.217 (2.324)	-4.429* (1.920)
<i>Group: baseline = Adolescents</i>				
Adults	-1.533** (0.510)	-1.690*** (0.509)	-1.660** (0.514)	-2.009*** (0.531)
Boys	4.768*** (1.340)	5.181** (1.704)	5.121** (1.774)	5.693** (2.166)
Girls	-1.359** (0.480)	-1.480** (0.489)	-1.751*** (0.476)	-1.902*** (0.534)
Men	-0.666 (0.939)	-3.240*** (0.842)	-3.372*** (0.877)	-3.808*** (0.976)
Older people	-2.012 (1.737)	-4.747** (1.542)	-5.219** (1.747)	-6.156*** (1.778)
Women	-0.445 (1.013)	-1.243 (1.201)	-1.258 (1.256)	-1.559 (1.352)
<i>Geographical scale: baseline = city</i>				
Country	1.318** (0.459)	-0.790 (0.805)	-1.159 (1.160)	-0.831 (0.841)
Large region	1.973* (0.950)	2.420** (0.902)	1.241 (2.010)	0.486 (0.635)
Multiple cities	-4.109*** (1.223)	-3.293* (1.360)	-2.943* (1.418)	-4.495* (1.796)
Neighbourhood	-0.093 (0.588)	0.716 (1.435)	0.787 (1.309)	1.061 (2.079)
<i>Time effects: baseline = 1 to 2 years</i>				
11 to 15 years	3.830** (1.180)	5.442** (1.806)	5.012*** (1.487)	7.235*** (1.987)
3 to 5 years	0.827 (0.811)	2.848+ (1.458)	2.709* (1.182)	3.876*** (1.104)
6 to 10 years	3.272** (1.091)	4.950** (1.758)	4.715** (1.483)	6.854*** (1.965)
Varied	-0.965 (0.759)	2.780+ (1.652)	3.679+ (1.916)	4.862** (1.758)
<i>Control group: baseline = no (before-after)</i>				
Non-random	0.573 (0.448)	-0.028 (0.623)	0.102 (0.678)	-0.016 (0.663)
Random	1.993* (0.817)	2.188* (0.868)	1.978* (0.857)	2.281*** (0.613)

Table 8 (continued)

	DV: Ordered outcome for sign and significance			
	(1)	(2)	(3)	(4)
Longitudinal (baseline = repeated cross-sections)	0.704 (0.669)	0.600 (0.848)	0.317 (0.801)	-0.633 (0.567)
Regression-based (baseline = no)	-0.277 (0.355)	0.038 (0.315)	0.042 (0.316)	0.157 (0.357)
Deprived neighbourhoods (baseline = no)	0.453 (1.141)	1.739 (3.813)	1.208 (2.058)	1.017 (1.526)
Use validated scale (baseline = no)	1.086 (0.672)	1.049+ (0.624)	0.863 (0.558)	3.164+ (1.641)
<i>Wellbeing: baseline = Hybrid</i>	-0.574	-0.500	-0.555	
Negative wellbeing	(0.726)	(0.516)	(0.519)	
Positive wellbeing	0.574 (0.361)	0.737+ (0.431)	0.566 (0.345)	
<i>Wellbeing: baseline = Negative mental health</i>				
Calm and peace				3.586* (1.525)
Life satisfaction				4.666* (2.324)
Mental health (hybrid)				2.467 (1.556)
Happiness				3.094+ (1.787)
Mental wellbeing (hybrid)				-1.347 (1.031)
Positive wellbeing				-1.571 (1.043)
Random effects			0.370 (0.579)	
Country FE	No	Yes	Yes	Yes
Observations	535	535	535	535
Log likelihood	-303.244	-286.381	-284.995	-273.182

Robust standard errors, clustered by study, in parentheses. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. Estimated cut-points, 2 for each model, are not reported in the Table. Random effects at the study level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Table 9 Moderation analysis, people-based interventions

	DV: Ordered outcome for sign and significance	
	(1)	(2)
<i>Group: baseline = Adolescents</i>		
Adults	-2.341*** (0.661)	-2.334*** (0.678)
Boys	15.967*** (0.545)	20.282*** (3.102)
Girls	-2.433*** (0.464)	-2.525*** (0.431)
<i>Geographical scale: baseline = city</i>		
Multiple sites (cities, country, large region)	-2.294 + (1.220)	-2.430 + (1.330)
Neighbourhood	1.409 (1.439)	1.365 (1.505)
<i>Time effects: baseline = 11 to 15 years</i>		
1 to 5 years	-2.629 (1.906)	-2.786 (2.026)
6 to 10 years	-0.911 (0.813)	-0.851 (0.843)
Varied	-0.703 (1.706)	-0.730 (1.762)
<i>Control group: baseline = no (before-after)</i>		
Non-random	-1.955 (1.219)	-1.998 (1.277)
Random	0.100 (0.876)	-0.032 (0.946)
Regression-based (baseline = no)	1.301* (0.614)	1.409* (0.587)
Use validated scale (baseline = no)	0.742 (1.361)	0.670 (1.104)
<i>Wellbeing: baseline = Hybrid</i>		
Negative wellbeing	-0.421 (1.231)	-0.461 (1.116)
Positive wellbeing	0.960* (0.415)	0.827 (0.528)
Social relations (baseline = no)	0.746* (0.337)	0.903 + (0.509)
Neighbourhood poverty (baseline = no)	0.561 (0.452)	0.701 (0.597)
Neighbourhood safety (baseline = no)	0.457 (0.387)	0.554 (0.421)
Exposure (baseline = no)	-2.114***	-2.442**

Table 9 (continued)

	DV: Ordered outcome for sign and significance	
	(1)	(2)
	(0.635)	(0.781)
Katz-Kessler-Kling-Ludwig	0.057 (0.908)	0.037 (0.900)
Glymour-Schmidt-Osypuk	1.773*** (0.530)	1.957** (0.637)
Random effects		0.162 (0.310)
Observations	332	332
Log likelihood	-175.390	-174.846

Robust standard errors, clustered by study, in parentheses. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. Estimated cut-points, 2 for each model, are not reported in the Table. Random effects at the study level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Table 10 Moderation analysis, place-based interventions

	DV: Ordered outcome for sign and significance		
	(1)	(2)	(3)
<i>Group: baseline = Adolescents</i>			
Adults	1.201 (1.372)	0.282 (0.320)	0.282 (0.320)
Men	2.581 (2.158)	0.059 (0.454)	0.059 (0.454)
Older people	-0.801 (1.874)	-19.327*** (1.689)	-21.713*** (1.689)
Women	1.566 (1.896)	-0.032 (0.522)	-0.032 (0.522)
<i>Geographical scale: baseline = city</i>			
Country	1.371 (1.196)	-18.402*** (1.735)	-20.789*** (1.735)
Large region	1.175 (1.483)	0.672 (0.655)	0.672 (0.655)
Neighbourhood	-2.876 (2.038)	-2.289 (1.725)	-2.288 (1.725)
<i>Time effects: baseline = 1 to 2 years</i>			
11 to 15 years	2.378+ (1.399)	4.242*** (1.106)	4.242*** (1.106)
3 to 5 years	1.574 (1.398)	4.043** (1.281)	4.043** (1.281)
6 to 10 years	1.856 (1.565)	2.830* (1.324)	2.830* (1.324)
Varied	-0.017 (1.104)	4.309** (1.431)	4.309** (1.431)
<i>Control group: baseline = no (before-after)</i>			
Non-random	0.276 (0.519)	0.478 (0.347)	0.478 (0.347)
Random	0.107 (1.887)	-0.501 (0.811)	-0.501 (0.812)
Longitudinal (baseline = repeated cross-sections)	0.119 (1.005)	0.413 (1.006)	0.413 (1.007)
Regression-based (baseline = no)	-0.443+ (0.226)	-1.059* (0.513)	-1.059* (0.513)
Use validated scale (baseline = no)	1.358 (1.043)	0.833 (1.366)	0.833 (1.366)
<i>Wellbeing: baseline = Hybrid</i>			
Negative wellbeing	1.777 (1.578)	0.462 (0.508)	0.462 (0.508)
Positive wellbeing	0.314 (0.552)	-0.166 (0.244)	-0.166 (0.244)

Table 10 (continued)

	DV: Ordered outcome for sign and significance		
	(1)	(2)	(3)
Community-based	0.744 (0.916)	0.977 (0.935)	0.977 (0.935)
Housing environment	-2.217 (1.348)	-4.123*** (1.180)	-4.123*** (1.180)
Social environment	2.762 (2.697)	-1.506 (2.040)	-1.506 (2.040)
Economic environment	-0.171 (1.237)	-0.732 (1.405)	-0.732 (1.405)
Country FE	No	Yes	Yes
Random effects			0.000 (0.000)
Observations	199	199	199
Log likelihood	-98.889	-87.100	-87.100

Robust standard errors, clustered by study, in parentheses. The dependent variable is an ordered outcome: 1 = significant beneficial effect, 2 = no statistically significant effect, 3 = significant detrimental effect. Estimated cut-points, 2 for each model, are not reported in the Table. Random effects at the study level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

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Declaration

Conflict of Interest The authors declare that they have no conflict of interest.

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