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The ambiguity of 'balanced neighbourhoods': how Rotterdam's housing policy undermines urban social resilience

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Cities worldwide increasingly adopt social resilience strategies, yet their implementation often obscures real drivers of urban renovation with ambiguous indicators. This study examines Rotterdam's 'balanced neighbourhoods' policy, based on property values, and its claimed contribution to urban social resilience. Using empirical data and structural equation modelling, we investigate how housing value mix affects social cohesion and informal support in 'balanced neighbourhood' configurations. Only 2.1% of possible configurations fit Rotterdam's urban policy claims, and even those yield counterproductive associations. We argue that the ambiguous definition of 'balanced neighbourhoods' obscures policy goals, allowing areas in Rotterdam North to meet 'balance' criteria without reflecting the municipality's long-term composition targets, while the South—dominated by social housing—faces demolition. Our study highlights the need for more nuanced measures of resilience and calls for shifting from interventions that alter the physical composition of neighbourhoods to enhancing social cohesion as a key factor promoting resilient actions.

Resilience strategies offer a system view for linking community capacities with social concerns and urban interventions, addressing uncertainties that threaten the future functionality of cities and the well-being of their inhabitants[1]. Notably, urban social resilience emphasises the strength and quality of social connections that foster collective action and solidarity across diverse social segments while also considering the unique characteristics of urbanisation, such as housing, urban sprawl, and specific urban infrastructure, that influence a community's ability to anticipate and respond to various shocks, stresses, and changes[2]. Diversity, redundancies and connections between people build capabilities to absorb disturbances and reorganise in the face of changing circumstances[3]. Hence, social cohesion, at the basis of urban social resilience, provides a social fabric supporting collective action against threats, dispositions for caring and, eventually, positive social transformation[4]. Urban experiments such as the 100 Resilience Cities (100RC) showcase this systemic view of urban social resilience in the framework of cross-sectoral collaboration[5], where social cohesion is one component of the overall assessment of city health[6], linking capacities of 'marginal' communities to urban intervention and policies for addressing inequality and building strong economies[7].

While this system view can leverage innovative interconnections between community capabilities and urban interventions, it is simultaneously constrained by the existing approaches to urban policy that may obscure crucial issues such as vulnerability, sustainability, disaster risk, adaptation, and poverty while neglecting the importance of power, justice, and equity in solutions[8]. This dual nature allows for creating new potentials but also provides room for reinforcing ongoing controversial policies that may contain inconsistencies and tensions, thereby limiting positive adaptation and transformative change of the urban social resilience paradigm[9]. Integrating this approach is crucial to achieving the Sustainable Development Goals, particularly target 11.b, which emphasises adopting policies to enhance resilience to disasters in cities and human settlements. Our work illustrates this issue by researching the implications of integrating the existing housing policy in the 2016 Rotterdam Resilience Strategy (RRS), as an instance of 'balance neighbourhood' approach[10].

The 'balanced neighbourhood' concept is grounded on the premise that mixing class, racial, ethnic or religious backgrounds at the neighbourhood level can provide disadvantaged individuals with a 'window to the world'[11], counteracting segregation, lack of liveability and other social dysfunctionalities[12,13]. In particular, interventions through the specific housing mix are among the most widely employed because of their ability to diversify households that reside next to each other[14]. The right combination of bonds between similar people and bridges between heterogeneous groups

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is expected to foster collective efficacy and inclusiveness, characterising resilient cities[15]. Controversy stems from evidence that heterogeneous groups living side-by-side do not interact meaningfully or gain the alleged benefits of social mixing[16]. Furthermore, social mixing policies turn spatial inequality irrelevant under the guise of liveability[17], limit housing options for disadvantaged groups[12], and conceal economic, commercial and political drivers for withdrawal from public housing[18].

The inherent controversies related to social mixing policies are introduced in the RRS under the broader goal of a 'balanced society', which links urban social resilience to the 2016 housing vision (*Woonvisie* in Dutch). The Woonvisie aims at mixing housing for 'improving socioeconomic balance [and] attracting households with middle or higher incomes, social climbers, and young potentials'[19](p. 13), demolishing 13,500 homes (10,900 of the Social housing price segment) and enabling Middle, Higher, and Top price segments increase by 46,600 new housing units[20]. These segments are classified based on the property's tax valuation (*WOZ-value*), a metric central to Rotterdam's definition of 'balance' (see 'Methods').

This paper highlights 'ambiguity' as a special characteristic of the Rotterdam case, setting it apart from other international approaches to social mixing and urban resilience. Ambiguity arises in the conditions that establish 'balanced' housing configurations, as they comprise a set of scenarios and mathematical inequalities with a range of possible values rather than a single value[21](p. 14).

Previous research has shown that the municipality has effectively 'balanced' the city, attracting highly educated and middle-income households[22], and problematising social housing and 'migrant low-skilled population' as a source of public disorder and socioeconomic risk[23,24]. Remarkably, the United Nations filed a series of reports denouncing Rotterdam's housing policies as potentially discriminatory[25,26]. These urban renewal policies have been concentrated in the southern part of the city[27], raising concerns about uneven spatial impacts as the indices used to evaluate these policies overlooked critical spatial factors like spatial autocorrelations or multicollinearities[24]. The literature, however, has not examined the implications of the ambiguous definition of 'balanced neighbourhood' concerning social resilience ambitions in cities. Hence, there is a lack of empirical evidence of the relationship between property value distribution, ambiguously defined as 'balanced', and the levels of social cohesion increasing the willingness to provide informal support to neighbours or friends who need help; the latter considered the core mechanism of urban social resilience[28].

We use empirical data from a survey conducted by the municipality of Rotterdam and a cross-sectional confirmatory approach based on Partial Least Squares—Structural Equation Modelling (PLS-SEM), K-means clustering, and Local Indicators of Spatial Association (LISA) to examine how does *mixing property value across different 'balanced neighbourhood' configurations in Rotterdam's urban policy affect informal support through social cohesion?* In particular, this research proposes a research model that reflects the RRS assumption that *the more balanced property values composition in an area positively impacts the perception of social cohesion and willingness to offer informal support*[10](p. 65)[19], (p. 17), according to four hypotheses:

- H1: Social cohesion positively affects informal support at the neighbourhood level.
- H2: Neighbourhood balance positively affects social cohesion.
- H3: Neighbourhood balance positively affects informal support.
- H4: The relationship between Neighbourhood balance and Informal support is mediated by Social cohesion.

To test the research model, the study first defines the range of possible values for the ambiguous operationalisation of a 'balanced neighbourhood'. Next, it identifies the subset of solutions that fit the research model and clusters them into representative sets. Finally, the research selects the solutions that best fit the research model for each cluster, explores the spatial autocorrelation of 'balanced neighbourhood' across the city, and tests the hypotheses H1, H2, H3 and H4.

Results

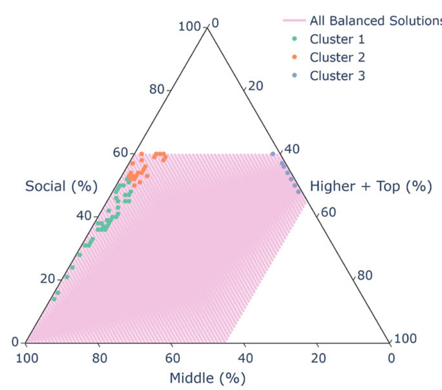
Identifying and grouping solutions with a good fit

Our analysis starts with the estimation of the complete solution space that satisfies Rotterdam municipality's criteria for a *balanced neighbourhood*[21]. Rotterdam's municipal definition of a balanced neighbourhood is not a single target value but rather a set of mathematical inequalities (Fig. 1a) that specify acceptable ranges for the proportion of Social, Middle, and Higher +Top housing. Any integer solution that meets these criteria is officially considered 'balanced'. Thus, the large, shaded region in Fig. 1b depicts all acceptable solutions—i.e., every allowable combination of the three segments that satisfies these municipal inequalities. This means an entire continuum of housing distributions qualifies as 'balanced', not just a single, fixed ratio.

There is no unique distribution but a whole space comprising 3162 possible integer solutions as displayed in a ternary plot Fig. 1b. Ternary plots provide a compact way to visualize three-part compositional data, in this

$$
\begin{cases}
0\% \le Social \le 60\% \\
45\% \le Social + Middle \le 100\% \\
40\% \le Middle + Higher + Top \le 100\% \\
0\% \le Middle \le 100\% \\
0\% \le Higher \le 100\% \\
0\% \le Top \le 100\% \\
Social + Middle + Higher + Top = 100\%
\end{cases}
$$

a



b

Fig. 1 | House stock value distributions within the 'balanced neighbourhood' definition in Rotterdam. Segments were categorised according to the value of a property for tax purposes in the Netherlands (WOZ-value)[36](p. 10): (i) Social, less than €220,000; (ii) Middle, ranging from €220,000 to €265,000; (iii) Higher, ranging from €265,000 and €400,000; and (iv) Top, exceeding €400,000. Any combination within the solution space is an acceptable solution, and thus, the municipality will consider the neighbourhood to be balanced. Even though the municipality distinguishes Higher and Top as two different brackets, they do not specify a difference in their definition of balance; thus, they can be merged (see 'Methods'). **a** Conditions that define when a neighbourhood has a 'balanced' housing stock. Each bracket (Social, Middle, Higher, and Top) is specified by its WOZ-value range; they sum to 100 percent[21](p. 14). **b** Ternary plot of all 3162 solutions meeting the municipality's 'balanced' criteria (shaded region). Each axis runs from 0 percent (edge opposite a corner) to 100 percent (the corner), reflecting the proportion of that housing segment. The coloured points (≈ 2.1 percent of all solutions) denote those distributions that achieve SRMR < 0.08 in our research model, clustered by K-Means.

case the proportions of Social, Middle, and Higher+Top housing. Each corner of the triangular figure represents 100 percent of the corresponding housing segment. A point placed within the triangle indicates the specific combination (in percent) of all three segments, always summing to 100 percent. For example, a point near the 'Social' corner has a higher percentage of Social housing, whereas one near the 'Middle' corner indicates a larger share of Middle housing. Moving across the triangle necessarily shifts the proportion of each segment because the total remains fixed at 100 percent. Note that the corresponding values must be searched along each of the axes.

To assess how each feasible solution aligns with our research model, we used Partial Least Squares Structural Equation Modelling (PLS-SEM) to calculate the Standardised Root Mean Squared Residual (SRMR). The model centres on four mutually exclusive hypotheses (H1, H2, H3, and H4), meaning that no single distribution can fulfil more than one hypothesis. For clarity on the definitions and testing procedures for each hypothesis, we refer readers to the Methods section. The SRMR measures how closely the empirical correlation matrix matches the model-implied correlation matrix[29]. A value of 0 indicates a perfect fit, while 0.08 is widely accepted as a practical cut-off[30]. We therefore considered only those solutions whose SRMR values were below 0.08 and also satisfied the 95% confidence interval (CI) quantile criteria.

Only 66 (≈2.1%) solutions had an acceptable goodness-of-fit represented with coloured points in Fig. 1b. This suggests that most configurations deemed 'balanced' do not align with the research model underneath Rotterdam's urban policy that claims that social mixing in cities has relevance for promoting urban social resilience.

The solutions with an acceptable goodness-of-fit were clustered using the K-Means algorithm into three different clusters within the overall solution space (Fig. 1b). Transitioning from the ternary plot to a parallel coordinates plot enables the visualization of individual observations, revealing the specific compositional details within each cluster (Fig. 2). Clusters 1 and 2 exhibit concave shapes. The structure of the 'balanced neighbourhood' from Cluster 1 is close to a normal distribution with a strong middle segment, while Cluster 2 resembles a concave structure with a bias to the Social segment. In contrast, Cluster 3 presents a convex shape with a polarised structure and a virtually inexistent middle segment.

From each cluster, we selected the solution with the best fit to test the hypotheses, which lead to the evaluation of the research model for three selected solutions resulting in three Selected Models for further investigation (Fig. 2). Thus, Selected Model 1, Model 2 and Model 3, each evaluate the research model defined by H1, H2, H3 and H4 using their pertaining *objective distribution* in Fig. 2 to calculate the value of *Neighbourhood balance* of every neighbourhood (see Methods).

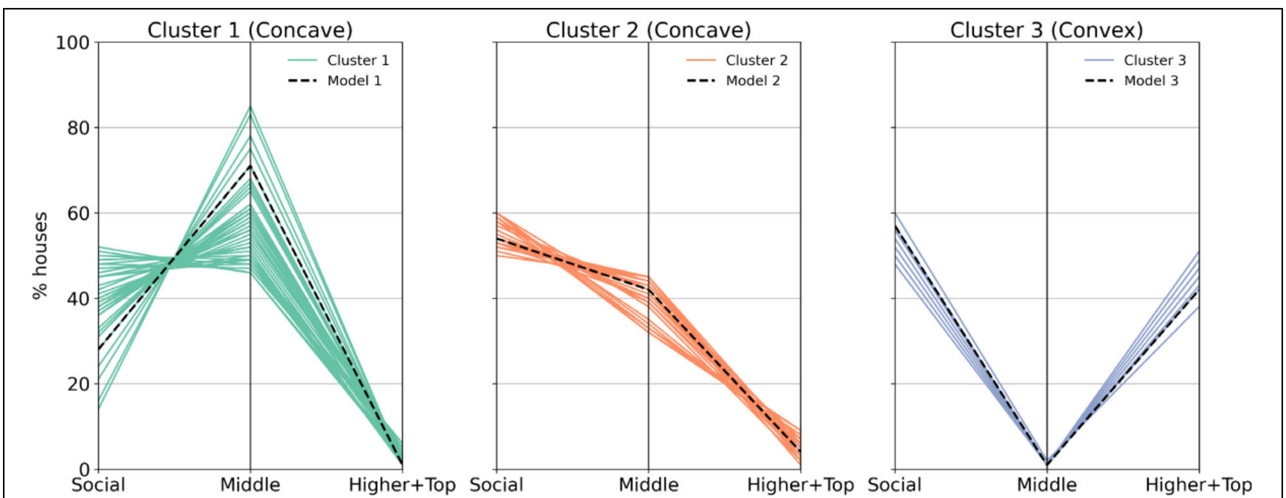
Exploring neighbourhood balance in different models

To better understand the broader spatial implications of policy decisions, we assess the distribution of the measurement of Neighbourhood balance across the city's neighbourhoods for the different selected models (Fig. 3). In Selected Models 1 and 2, there is a smaller concentration of neighbourhoods with high balance in the North of Rotterdam compared to Selected Solution 3. Conversely, in Selected Models 1 and 2, there are non-significant effects towards the South, but again, when we consider the convex distribution of Model 3, we can then see significant results that indicate a lower balance towards the South.

This result is linked to the difference between convex versus concave shapes of the objective distributions of each model (Fig. 2): Models 1 and 2 aimed for a higher percentage of Middle housing rather than Higher and Top, whereas Model 3 minimises the number of Middle housing price segments. As a result, the North exhibits a bias toward a high level of balance in Model 3 even though it is characterised by polarised housing distributions, skewed towards the Higher segments, whereas Models 1 and 2 that emphasise a greater proportion of Middle housing do not suggest such high balance in the North.

Assessing fit of selected models

We used PLS-SEM to test the hypotheses H1, H2, H3 and H4, following the methodology of Hair et al.[31]. We first examine the model fit tests to ensure



Concave distributions		Convex distribution
Custer 1 Best fit: Selected Model 1 Social: 28% Middle: 71% Higher + Top: 1%	Cluster 2 Best fit: Selected Model 2 Social: 54% Middle: 42% Higher + Top: 4%	Cluster 3 Best fit: Selected Model 3 Social: 57% Middle: 1% Higher + Top: 42%

Fig. 2 | Clusters of the house stock distributions within the 'balanced neighbourhood' definition in Rotterdam that show an acceptable goodness-of-fit. We differentiate between concave and convex clusters based on the shape of the distributions within the cluster. Best-fitting models for each cluster are shown in dashed lines, and their values are shown below.

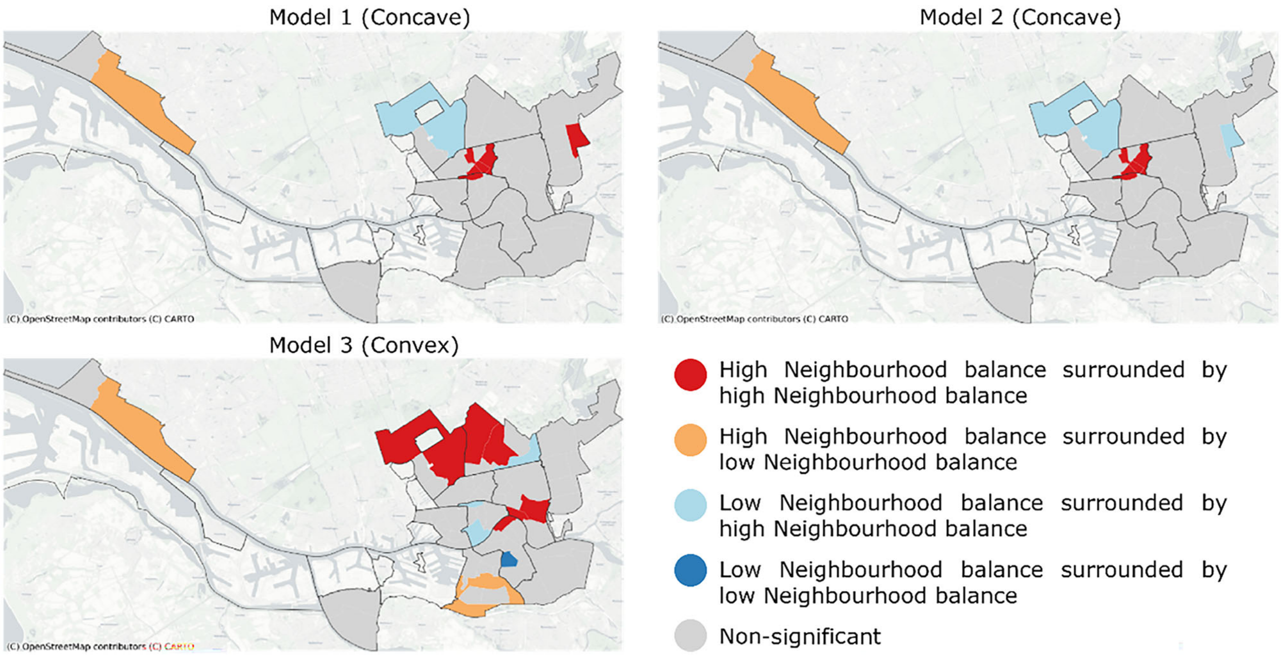


Fig. 3 | LISA choropleth of Neighbourhood balance. The LISA identify spatial clusters of similar or dissimilar values of Neighbourhood balance across the neighbourhoods for each Selected Model, helping to pinpoint areas where balance has been achieved. LISA clusters significant to a 95% confidence interval.

Table 1 | Goodness-of-fit of selected models

	Selected Model 1		Selected Model 2		Selected Model 3	
	Value	95%CI	Value	95%CI	Value	95%CI
dG	0.044	0.057	0.040	0.056	0.050	0.055
SRMR	0.042	0.067	0.043	0.069	0.050	0.060
dL	0.049	0.125	0.053	0.132	0.069	0.102
dML	0.218	0.278	0.202	0.272	0.247	0.267

Summary of non-parametric model fit tests and SRMR indices for the three selected models, including their respective 95% confidence intervals.

the robustness of our analysis. Once the goodness-of-fit is confirmed, we evaluate the measurement models to identify the items that best represent the model constructs. We begin by assessing the reflective measurement models and then proceed to the formative measurement models. Finally, we assess the reliability and validity of the inner structural model and present the relationships between the constructs.

The adequacy of the three selected models was assessed using non-parametric model fit tests (dG, dM, and dML) and a model fit index (SRMR), with the results presented in Table 1. A lower value of the non-parametric model fitness indicates a better model fit[32]. Additionally, the selected models were found to have scores below the commonly accepted threshold of 0.08[30], indicating an acceptable fit. Moreover, all goodness-of-fit measures met the 95% confidence interval (CI) quantile criteria.

Formative measurement model

After confirming model fit, we evaluated how well different indicators captured complex constructs such as Social cohesion in the formative measurement model. This evaluation ensured accurate construct measurement and meaningful contributions to the overall model. In order to establish the reliability and validity of Social cohesion modelled as an emergent construct, we first examined the goodness-of-fit of the model, which was deemed satisfactory with an SRMR value below 0.08 within the 95% confidence interval[33]. Next, we analysed the statistical significance and size of the weights for each indicator. However, the Social cohesion construct presented issues with multicollinearity among its items. The PLS-SEM analysis reduced the Social cohesion construct to either the percentage of residents who reported that local residents share their views (SC3) or the percentage of residents who reported feeling at home with local residents (SC5), depending on the specific model used. The distinct specifications of Social cohesion in Selected Models 1 and 2, compared to Model 3, can not only influence the direction of the relationships in the research model but also render them incomparable.

Consequently, we test the correlation between the percentage of residents who say local residents share each other's views (SC3; Models 1 and 2) and the percentage of residents who say they feel at home with local residents (SC5; Model 3). After examination, we found that SC3 and SC5 were positively related and highly collinear ($r2 = 0.8$, $VIF > 3$). Therefore, such different specifications in the measurement model will not explain differences across selected models. As a result, for Selected Models 1 and 2, Social cohesion is specified as SC3 (Weight = 1, 95% CI = [1.00, 1.00]), and for Model 3 is specified as SC5 (Weight = 1, 95% CI = [1.00, 1.00]) (Table 2).

Structural model and evaluation of hypotheses

In the final step, we analysed the structural model to test our hypotheses, examining how Neighbourhood balance, Social cohesion, and Informal support interact within the overall framework. We first considered multicollinearity between the constructs, using the reflective construct Informal support as the dependent variable and calculating the VIF[31]. VIF values between the constructs were below 2, indicating no multicollinearity issues. Then, we proceed to assess the adjusted coefficient of determination, R^2, which measures the variation in the endogenous constructs, and Cohen's effect size, f^2, which indicates the change in R^2 when a specified exogenous construct is removed from the model[34].

Social cohesion and Informal support had a positive relationship in Selected Models 1 and 2, supporting H1, while the relationship was non-significant in Model 3 (Table 3). For Model 1 the direct effect of Social cohesion on Informal support was $\beta = 0.352$ (95% CI = [0.021; 0.637]; $f^2 = 0.108$); for Model 2 was $\beta = 0.351$ (95% CI = [0.064; 0.617]; $f^2 = 0.114$); and for Model 3 was $\beta = 0.325$ (95% CI = [−0.012; 0.601]; $f^2 = 0.107$). The association between Neighbourhood balance and Informal support yielded a non-significant result for the three models, providing no support to H3 in all cases. On the other hand, Models 1 and 2 (concave models) showed different results compared to Model 3 (convex model) concerning the

Table 2 | Assessment of formative constructs across selected models

		Models 1 and 2 (Concave)		Model 3 (Convex)	
Variable	Item	Weight	95%CI	Weight	95%CI
Social cohesion	SC1: % of residents who say that local residents know each other	NA[a]	NA[a]	NA[a]	NA[a]
	SC2: % of residents who say that local residents spend a lot of time with each other	NA[b]	NA[b]	NA[b]	NA[b]
	SC3: % of residents who say that local residents share each other's views	1.00	[1.00, 1.00]	NA[b]	NA[b]
	SC4: % of residents who say that local residents help each other	NA[b]	NA[b]	NA[b]	NA[b]
	SC5: % of residents who say they feel at home with local residents	NA[b]	NA[b]	1.00	[1.00, 1.00]
Neighbourhood balance	NB: Negative of the Kullback-Leibler divergence of the WOZ-value distribution in a neighbourhood with respect to the objective balance distribution	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]

Weights and 95% confidence intervals (CI) for each item associated with the constructs of Social cohesion and Neighbourhood balance. Items marked as 'NA' were excluded from analysis due to high multicollinearity or non-significant weight[31].
[a]Item dropped due to high multicollinearity.
[b]Item dropped due to insignificant weight.

association between Neighbourhood balance and Social cohesion (H2). This association was found significant for Models 1 and 2, but contrary to the initial hypothesis, it was negative instead of positive. For Model 1, the direct effect of Neighbourhood balance on Social cohesion was $\beta = -0.467$ (95% CI = [−0.671; −0.048]; $f^2 = 0.279$); and for Model 2 was $\beta = -0.412$ (95% CI = [−0.621; −0.055]; $f^2 = 0.204$). Conversely, in Model 3, the relationship between Neighbourhood balance and Social cohesion was non-significant. Consequently, we found that Social cohesion fully mediated the relationship between Neighbourhood balance and Informal support for Models 1 and 2 but in the contrary direction of the initial hypothesis H4. This full mediation effect is non-existent in Model 3.

The difference in results between Selected Models 1 and 2 and Selected Model 3 can be attributed not to the different specifications of Social cohesion measures (SC3 and SC5), which are highly collinear (r^2=0.8, VIF > 3), but to the different specification of balance for each model. The strong negative correlation ($r = -0.9$) between the different balance specifications highlights how varying definitions and measures can lead to significantly different policy implications and outcomes.

The findings from our structural model analysis reveal significant variations in the relationships between Neighbourhood balance, Social cohesion, and Informal support across the selected models. Particularly, Selected Models 1 and 2 (concave) demonstrated a negative association between Neighbourhood balance and Social cohesion, which, contrary to our initial hypotheses, led to full mediation in the relationship with Informal support. In contrast, Model 3 (convex) showed non-significant effects in these relationships, underscoring the role that the specification of balance plays in shaping social dynamics. We ran a stress test for all 66 distributions with acceptable goodness-of-fit across the three clusters of possible balanced distributions to assess whether there was a change in the significance and direction of direct and indirect effects. The results were robust, so the three selected models are representative of their corresponding clusters.

Discussion

Our contribution highlights how pre-existing social mixing frameworks to design the social fabric can lead to obscure and contradictory outcomes against the core principle of social resilience, grounded on social cohesion.

While urban resilience opens an opportunity to explore the positive interplay between social cohesion and housing renovation[1], its transformative potential is limited by inconsistencies in controversial mixing policies. In Rotterdam, these inconsistencies arise from retrieving a housing policy based on an ambiguous definition of 'balanced neighbourhood'. A 'balanced neighbourhood' is defined dichotomously; it is either in balance or not, based on the conditions set on the property value (i.e., WOZ-value in the Netherlands). At first glance, this binary approach based on property value offers simplicity and clarity in political discourse[35]. However, the calculations across all possible configurations created 3,162 possible solutions, hindering comparison across neighbourhoods while providing no insight into the complex social dynamics of urban communities.

Ambiguity obscures policy goals by keeping what is meant by a 'balanced neighbourhood' undetermined. A neighbourhood with no Social housing could still be considered balanced if the Middle, Higher, and Top segments are within the specified ranges. Simultaneously, a polarised neighbourhood with only Social and Higher + Top segments can be classified as 'balanced' as much as a neighbourhood with only the Middle segment. However, the concept of 'balanced' merges the Higher and Top segments into a single category. Consequently, the municipality's long-term goal of a balanced composition of 20% Social, 30% Middle, 30% Higher and 20% Top segments[36] cannot be inferred from their current measure of balance. Ambiguity not only prevents a clear assessment of the impact of social mixing policies on social cohesion but also provides a fertile ground for cherry-picking, where 'objective' indicators can obscure the true drivers for urban renovation[24,37].

More importantly, evidence on social mixing in Rotterdam is contrary to the intention to shape a cohesive society as stated by the RRS. Our study reveals that only 2.1% of the possible configurations fit the research model underneath the RRS policy. In other words, many configurations considered balanced do not support the municipality's causal claims on social cohesion and informal support, suggesting that social mixing in cities for social resilience is generally irrelevant. More importantly, within this very small subset fitting the model, associations are contrary to the RRS intention.

While the expectation is that a housing value distribution with a strong middle segment leads to higher social cohesion and informal support (e.g., Model 1 and 2), our results indicate a negative relationship between balance and social cohesion. Additionally, neighbourhoods with a more polarised value distribution do not show a significant association with the willingness to care for neighbours and friends (e.g., Model 3). Hence, in the few scenarios where social mixing in cities matters for urban social resilience, it does so in a counterproductive manner.

Our findings align with the existing literature suggesting that mixed-income neighbourhoods do not necessarily foster social integration[38,39], but often result in social distance and conflict due to differing lifestyles and expectations[40]. Interventions fostering social mixing in cities through housing renovation do not overcome the root causes of social polarisation but instead reproduce it in such a way that segregated sub-communities live close to each other with minimal interaction, further weakening the social fabric essential for resilience[15]. For instance, the federal program HOPE VI aimed to revitalize distressed public housing in the U.S. by demolishing high-rise projects and replacing them with mixed-income communities like the Woonvisie. However, the program led to widespread displacement, as many low-income residents could not afford to return to redeveloped sites, resulting in a net loss of affordable housing and contributing to gentrification rather than equitable urban renewal[41]. The 'balanced ideal' risks exacerbating existing inequalities

Table 3 | Results of the structural model across the selected models

a. Structural Model Assessment

		Model 1 (Concave)						Model 2 (Concave)						Model 3 (Convex)					
Dependent variable	Independent variable	β	SD	95% CI	f^2	R^2	Hypothesis testing (direct effects)	β	SD	95% CI	f^2	R^2	Hypothesis testing (direct effects)	β	SD	95% CI	f^2	R^2	Hypothesis testing (direct effects)
Social cohesion						0.21						0.16						0.09	
	Neighbourhood balance	**−0.467*****	0.146	**[−0.671; −0.048]**	0.279		H1: Significant but contrary	**−0.412*****	0.143	**[−0.621; −0.055]**	0.204		H1: Significant but contrary	0.321	0.179	[−0.015; 0.649]	0.115		H1: Not supported
Informal support						0.07						0.08						0.09	
	Social cohesion	**0.352****	0.155	**[0.021; 0.637]**	0.108		H2: Supported	**0.351****	0.146	**[0.064; 0.617]**	0.114		H2: Supported	0.325	0.162	[−0.012; 0.601]	0.107		H2: Not Supported
	Neighbourhood balance	0.097	0.121	[−0.160; 0.310]	0.008		H3: Not supported	0.108	0.111	[-0.102; 0.317]	0.011		H3: Not supported	0.037	0.114	[−0.174; 0.272]	0.001		H3: Not supported

b. Direct, indirect and total effects

		Model 1 (Concave)						Model 2 (Concave)						Model 3 (Convex)					
		Direct		Indirect		Total		Direct		Indirect		Total		Direct		Indirect		Total	
Dependent variable	Independent variable	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Informal support																			
	Social cohesion	**0.352****	**[0.021; 0.637]**			**0.352****	**[0.021; 0.637]**	**0.351****	**[0.064; 0.617]**			**0.351****	**[0.064; 0.617]**	0.325	[−0.012; 0.601]			0.325	[−0.012; 0.601]
	Neighbourhood balance	0.097	[−0.160; 0.310]	−0.164	[−0.345; 0.010]	−0.067	[−0.307; 0.222]	0.108	[−0.102; 0.317]	−0.145	[−0.330; -0.003]	−0.037	[−0.238; 0.269]	0.037	[−0.174; 0.272]	0.104	[−0.028; 0.304]	0.141	[−0.047; 0.382]

No significant effects (β) are those in which: (1) values are outside of the confidence interval (CI) or (2) the confidence interval (CI) includes zero. Significance levels: *$p < 0.001$; **$p < 0.01$; ***$p < 0.05$.

All reported confidence intervals (CIs) are based on a 95% confidence level. The bold values represent statistically significant effects from the PLS-SEM model. These effects are considered significant when the 95% confidence intervals do not include zero.

The table outlines the relationships between the key variables Social cohesion, Neighbourhood balance, and Informal support. For each selected model, it provides the path coefficients (β), standard deviations (SD), 95% confidence intervals (CI), effect sizes (f^2), and R^2 values, as well as the outcomes of hypothesis testing. In Selected Models 1 and 2, Neighbourhood balance significantly negatively affects Social cohesion, contrary to expectations, while the relationship between Social cohesion and Informal support is supported. Selected Model 3, however, shows that these effects are not significant. The table also includes an analysis of direct, indirect, and total effects, illustrating the overall impact of the variables, where non-significant effects are indicated when confidence intervals include zero.

and undermining the potential for positive social transformation that urban resilience strategies aim to achieve[4].

In Rotterdam, this issue is exemplified by interventions designed to balance the Social housing price segment, which have paradoxically increased socioeconomic polarisation, as evidenced by rising housing prices[22,42]. Our spatial analysis shows an additional dimension of the spatial divide, revealing a clear pattern of polarised housing distribution in the North that, despite formally meeting balance conditions, deviates from the long-term city-wide municipality goals of 20% Social, 30% Middle, 30% Higher and 20% Top segments[36]. In other words, it seems that there are enough Higher and Top segments in the Northern area despite the existing Social housing stock. Conversely, the municipality typically problematises the Rotterdam South area due to its Social housing stock, being the South an implicit target area for the renovation/demolition plans within the Woonvisie[27]. In this ambiguous context, inhabitants and policymakers in Rotterdam take as common knowledge the stark polarisation between the two sides of the river[19,20].

In light of the counterproductive and, at best, irrelevant role of social mixing policies grounded in an ideal of 'balanced' defined by property value, one should pay greater attention to the practical consequences experienced by inhabitants. Particularly, policies aimed at increasing the number of expensive housing units for low-income in Rotterdam South disrupt established social networks and undermine social cohesion among original residents[25]. Urban redevelopment plans in the Netherlands and the United States have resulted in a loss of cheap housing, further limiting housing options[12]. By contrast, other strategies that are not based on urban redevelopment have obtained contrasting results. Inclusionary zoning policies in England and Australia that promote housing diversity through affordability mandates have avoided the displacement of low-income households[43]. Conversely, Singapore's Ethnic Integration Policy, which enforces ethnic quotas in public housing estates to encourage racial integration and prevent ethnic enclaves, has led to a negative correlation between ethnic and socioeconomic segregation in most public housing subzones[44]. These divergent results have fuelled scepticism about the effectiveness of social mix policies, with some arguing that they represent a misallocation of public funds and resources, potentially exacerbating structural inequalities rather than addressing them[13,45].

Unlike many international approaches, Rotterdam's reliance on a physical indicator such as property value reveals a fundamental tension between policy ideals and the complex realities of localised urban dynamics. The polarisation between Rotterdam North and South exemplifies how such policies, grounded in ambiguous metrics, can unintentionally reinforce existing divides rather than bridge them. By focusing on this single case, the study provides critical insights into the interplay between social mixing, social cohesion, and resilience within a specific urban context, highlighting the unintended and often counterproductive outcomes of such strategies. Our mediation analysis underlines that social cohesion—rooted in trust, reciprocity, and participation—is not only a key factor explaining the relationship between neighbourhood balance and informal support, but also a more effective driver of resilient actions than a physical indicator like property value. Rotterdam's experience thus emphasises the need for policies that move beyond ambiguous definitions of balance to adopt locally adaptive, community-driven policies better equipped to build resilience.

While our study contributes to the literature by employing property values as a proxy for income mix, it also acknowledges its limitations and calls for more nuanced and accurate measurement tools to assess social resilience. First and foremost, cross-sectional data restricts our ability to infer causality or capture the evolving effects of housing balance over time. Second, the low fit of the data in the research model might indicate its excessive simplicity, akin to data richness. Increasing the number of parameters can enhance the model's fit but may also obscure theoretical clarity and generalisability[46,47]. Third, our results take social cohesion as a single-indicator construct, while the multidimensional nature of social cohesion cannot be reduced to a single-indicator[48], likely because the use of aggregate data can obscure individual variations and interactions within the population, leading to incorrect inferences about individual behaviours or characteristics based on group-level data in what is known as the ecological fallacy[49]. Methodological developments in multilevel structural equation modelling could in the future open the possibility to perform mediation in multilevel modelling using microdata for individual responses to social cohesion and willingness to help neighbours, while using neighbourhood level indicators for the measurement of balance. Finally, informal support measured by respondents' willingness to help may not reflect real behaviour. During the COVID-19 pandemic, shown support exceeded the stated willingness[50], indicating true informal support levels can only be measured after a stressor.

The exclusion of other influential factors, such as ethnic diversity or urban design, and reliance on self-reported measures of social cohesion also suggest avenues for future research. For example, our findings align with prior research, revealing a lower willingness to help in areas with higher percentages of non-Dutch residents towards Rotterdam South, emphasising the importance of considering social positions in the resilience literature[51]. Moderation analysis was conducted for the PLS-SEM model using a measurement of ethnic mix, showing no moderation effects, but showing direct association with social cohesion. Even if Rotterdam's policy explicitly focuses on property value mix, future research should fully articulate the role of ethnic mix and other types of mixing in the model. In spite of that, previous research also showed that the scale from the Dutch government could be reduced to two indicators using microdata, putting into question the validity of the indicators collected by the Dutch administration[52]. Future research should also explore the effects of spatial autocorrelation and the structure of citizen interactions across neighbourhoods. Understanding these dynamics is crucial for developing policies that enhance urban social resilience and address the unique needs of each community.

Methods

High-level overview

Rotterdam's urban resilience and housing policy are structured at a neighbourhood level (*buurt* in Dutch). Hence, we assess our research model on urban social resilience across the possible ways of operationalising a 'balanced neighbourhood' following the 'Atlas Development Housing Stock'[21](p. 14). The research model overview is depicted in the different Steps of Fig. 4.

The definition of a balanced neighbourhood is not singular, but instead encompasses a range of possibilities, reflecting the multiple combinations of property values across different housing categories that satisfy a set of specified inequalities (Fig. 1a). Specifically, the proportion of Social housing must range between 0% and 60%; the combined share of Social and Middle housing must constitute between 45% and 100% of the total housing stock; and the combined proportion of Middle, Higher, and Top housing must range from 40% to 100%. These thresholds underline the fact that the conditions for defining a balanced neighbourhood are not fixed but depend on the diverse ways in which the inequalities can be met, allowing for a total of 3162 distinct integer combinations that meet the specified balance criteria (Fig. 4, Step 1). For example, a neighbourhood consisting of 60% Social, 9% Middle, and 31% Higher+Top would be in balance, as well as a neighbourhood with a distribution of 1% Social, 98% Middle, and 1% Higher+Top.

Each neighbourhood in Rotterdam is defined by its unique distribution of housing values. For example, the neighbourhood of Zuiderpark en Zuidrand has a composition of 79% Social, 2% Middle and 19% HIgher + Top. To evaluate the degree of alignment between these observed distributions and the distinct integer combinations that meet the specified balance criteria outlined in the Atlas Development Housing Stock, we calculated the negative of the Kullback-Leibler (KL) divergence[53]. For example, the KL divergence of Zuiderpark en Zuidrand for the previous example of 60% Social, 9% Middle, and 31% Higher + Top would yield a Neighbourhood balance of NB = −0.08 nats. Instead, the possible objective distribution of 1% Social, 98% Middle, and 1% Higher+Top would yield a Neighbourhood balance for Zuiderpark en Zuidrand in 2019 with NB = −3.76 nats (Fig. 4,

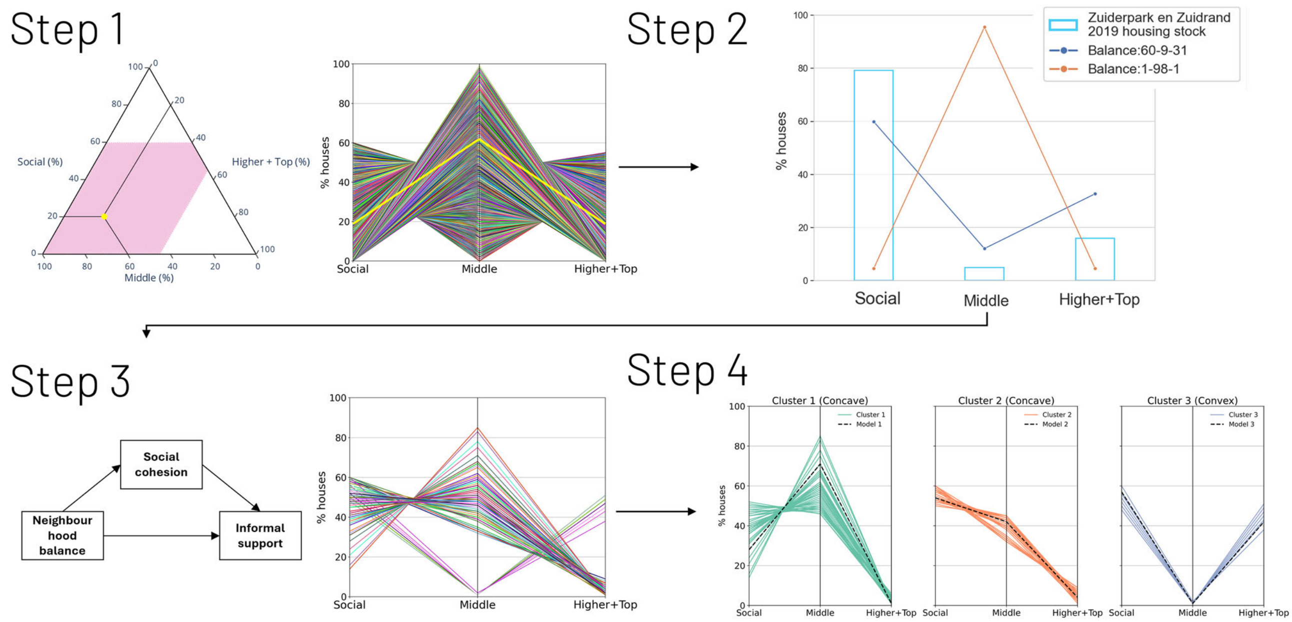


Fig. 4 | Research methodology explained in numbered steps. Step 1 consisted in identifying all the distinct integer combinations that meet the specified balance criteria according to the municipality. This can be seen in the pink shaded area, or equivalently in all the different lines that compose the right figure in Step 1. As an example, the yellow dot in the ternary plot corresponds to the yellow line in the parallel coordinates plot. Step 2 shows the housing stock composition of the neighbourhood of Zuiderpark en Zuidrand and provides two examples of possible objective distributions of that would be considered balanced. For each of those distributions, the level of Neighbourhood balance was calculated using the KL divergence. Once Neighbourhood balance has been calculated for all the possibilities shown in Step 1 for every neighbourhood, then the PLS-SEM model is run to evaluate the model performance. Only solutions that provide an acceptable goodness-of-fit are considered and are shown in the right figure of Step 3. Finally, the solutions that fit the model are clustered, and the three best-fitting solutions are used for the evaluation of the hypotheses, as shown in Step 4.

Step 2). A less negative Neighbourhood balance reflects a smaller difference between the observed distribution of housing values in the neighbourhood and the hypothetical balanced distribution, suggesting that the neighbourhood is more balanced according to the first example. For every of the 3162 integer combinations that the definition of balance from the Atlas can yield, we calculated the Neighbourhood balance of each Rotterdam neighbourhood.

A Partial Least Squares Structural Equation Model (PLS-SEM) was then constructed to examine the relationships between three constructs: Neighbourhood balance, Social cohesion, and Informal support. The 'Neighbourhood balance' construct was iteratively defined using each of the 3162 possible values derived from the KL divergence calculations. For each iteration, the PLS-SEM was run to evaluate model performance. Statistical inference relied on percentile bootstrap confidence intervals based on 4999 bootstrap runs[54]. Only the models which reported an acceptable standardised root mean squared residual (SRMR) measure were considered. This step enabled us to identify for which set of all possible 'balanced neighbourhood' distributions deduced from the Atlas where one could allege a significant effect of the policy intervention (Fig. 4, Step 3).

Next, we clustered the models that fit using the K-Means algorithm for unravelling underlying groups and the structure of relations[55]. We selected the model with the best fit for each cluster to assess our hypotheses, accounting for the direct and indirect effects between Neighbourhood balance, Social cohesion, and Informal support (Fig. 4, Step 4). Finally, we employed Local Indicators of Spatial Association (LISA) maps to identify localised regions on a map that display either balanced or imbalanced housing across different measures of neighbourhood balance[56].

Data

We used data in the Wijkprofiel (Neighbourhood profile) collected by the Research and Business Intelligence (OBI) department in Rotterdam to measure Social cohesion and Informal support[57]. The Wijkprofiel uses the methodology defined by the Dutch Office of Social and Cultural Planning for surveying perceptions of social cohesion[58], as well as the willingness to help friends or neighbours who need help. For the analysis, the data from the year 2019 was chosen because it was the most recent year for which Wijkprofiel survey data were available prior to the onset of the COVID-19 outbreak (which also enables us to control the effect of the pandemic).

We also used Addresses and Buildings Key Registry (BAG) containing data on WOZ-values per neighbourhood provided for assessing the level of balance in neighbourhoods. The WOZ-value, or the 'Waardering Onroerende Zaken' value, is the assessed value of a property for tax purposes in the Netherlands[59]. In the context of Rotterdam, housing price segments were categorised as follows in the Woonvisie addendum[36](p. 10): (i) Social, WOZ-value of less than €220,000; (ii) Middle, WOZ-values ranging from €220,000 to €265,000; (iii) Higher, WOZ-values falling between €265,000 and €400,000; and (iv) Top, WOZ-value exceeding €400,000. The WOZ-values for these segments may require annual adjustments in accordance with the National Mortgage Guarantee limit[36](p. 2). As neighbourhoods comprise both rental and owner-occupied housing, the ideal approach would involve categorizing properties based on rental prices for rental units and housing values for owner-occupied units. However, due to data limitations, our analysis relied solely on housing values. Since official documentation aligns rental prices and housing values within the same categorical framework, using housing value for all properties provides a reasonable approximation for this study.

For this study, neighbourhoods had to be adapted to take into consideration changes in the administrative boundaries of the Wijkprofiel survey. Firstly, neighbourhoods not included in the survey were excluded from the subsequent research. Secondly, combined neighbourhoods in the survey had their shapefiles and data values merged accordingly. Lastly, the neighbourhood of Groot IJsselmonde was divided into North and South in the survey. Since housing data is collected based on the official administrative boundaries, the Wijkprofiel values for Groot IJsselmonde North and South were aggregated using a weighted average, with the number of Wijkprofiel respondents in each area serving as the weights.

As a result, the analysis included a total of $N = 70$ neighbourhoods or data points. This follows the accepted assumption that the sample size for PLS-SEM should be greater than 10 times the number of model links pointing at any latent variable in the model[60].

Neighbourhood balance

In the definition of a 'balanced neighbourhood' provided by the municipality of Rotterdam[21], balance is expressed as a dichotomous variable where a neighbourhood is either in balance or not based on the conditions in Fig. 1a. The municipality considers any combination of variables within this parameter space as an acceptable solution and, consequently, designates the neighbourhood as balanced. In our study, we undertook a comprehensive decomposition of the solution space defined by Fig. 1a, examining all feasible integer combinations that adhere to the stipulated conditions. Our primary focus lies in identifying and comparing the extent to which each neighbourhood approaches the prescribed balance for each unique combination.

The level of balance of a neighbourhood, *Neighbourhood balance* (NB), is therefore measured as the negative Kullback-Leibler (KL) divergence between the WOZ-value distribution of a neighbourhood, P, and one of the possible distributions that satisfy the conditions of balance, Q[61]. The resulting measurement is defined as:

$$NB = -D_{KL}(P \parallel Q) = -\sum_{x \in X} P(x)\, ln\left(\frac{P(x)}{Q(x)}\right). \qquad (1)$$

The Q distributions define the standard against which balance is measured. A more negative NB indicates a greater divergence between the actual WOZ-value distribution and the assumed balanced distribution.

Social cohesion

In accordance with the definition provided by the Dutch Office for Social and Cultural Planning, social cohesion can be characterized as the degree to which individuals, both in their actions and perceptions, exhibit shared norms and values, engage in social interactions, possess a sense of public familiarity, and maintain mutual trust as members of a community and as citizens[58]. Therefore, *Social cohesion* is modelled as an emergent variable out of the following indicators at the neighbourhood level collected in the Wijkprofiel survey:

- (SC1) Percentage of residents who say that locals know each other
- (SC2) Percentage of residents who say that locals spend a lot of time with each other
- (SC3) Percentage of residents who say that locals share each other's views
- (SC4) Percentage of residents who say that locals help each other
- (SC5) Percentage of residents who say they feel at home with locals

Informal support

Mutual aid serves as the key mechanism for achieving social resilience[62]. Therefore, the willingness to help friends or neighbours who need help was used to measure the informal support of a neighbourhood. As a result, *Informal support* is modelled with a single indicator in the Wijkprofiel survey:

- Percentage of residents who say they are willing to care for neighbours and friends

K-means clustering

To identify representative balance distributions and uncover underlying patterns, we apply unsupervised clustering. By grouping the 3162 possible balanced neighbourhood configurations into distinct sets, we can extract a set of representative configurations that serve as the foundation for assessing the relationship between Neighbourhood balance, Social cohesion, and Informal support. This structured approach enables a more targeted evaluation of how different balance distributions influence social resilience.

In this study, we used the k-means clustering algorithm because it is simpler, faster and has fewer parameters to set than other algorithms like DBSCAN or Expectation–Maximization[55]. In k-means, an initial number, k, of clusters is specified, and then, the algorithm places k centroids at random. Then, it calculates the Euclidean distance from each point in the dataset to the centroids. With this, it assigns each data point to the closest centroid using the distance in the previous step. The new centroids are calculated by taking the averages of the distances in each cluster, and the algorithm is rerun until the centroids do not change or for a specified number of iterations[55].

Partial least squares structural equation modelling (PLS-SEM)

Structural Equation Modelling (SEM) is widely recognized as a powerful statistical technique in social sciences[63]. It allows for the simultaneous examination of observed variables and constructs, facilitating comprehensive analyses of relationships among variables. One notable capability of SEM is mediation analysis, which explores how one variable mediates the relationship between two others. For instance, in our study, it allowed us to understand the role of Social cohesion in mediating the relationship between Neighbourhood balance and Informal support. Unlike direct effects, mediation analysis elucidates the mechanisms through which changes in independent variables influence dependent variables via intervening variables[33].

Partial Least Squares Structural Equation Modelling (PLS-SEM) is an iterative estimation approach that handles both reflective (Mode A) and formative (Mode B) constructs[64]. Here, mode BNNLS was used to estimate social cohesion, given the presence of multicollinearity between the indicators. Mode BNNLS uses the best fitting proper indices (BFPI) algorithm, which restricts the signs of the weights of each observable variable to guarantee that it contributes to its own construct in a predefined way[65].

Path coefficients in PLS-SEM quantify the relationships between the constructs, capturing the strength and direction of dependencies. PLS-SEM is preferred in research contexts involving complex theoretical frameworks, formatively measured constructs, and data with non-normal distributions, offering advantages such as robustness against multicollinearity and suitability for small sample sizes[31,64]. For further insights into SEM methodologies, including comparisons with Covariance-based SEM (CB-SEM), readers are referred to comprehensive reviews by experts in the field[33,63,64].

Local indicators of spatial association (LISA)

Local Indicators of Spatial Association (LISA) are tools for measuring spatial autocorrelation that focus on the relationships between each observation and its surrounding observations to gain insights into the spatial structure of the data. LISA categorizes observations into four groups: high values surrounded by high values (HH), low values surrounded by low values (LL), high values surrounded by low values (HL), and low values surrounded by high values (LH). The main goal is to identify patterns where an observation's value and the average of its neighbours are either more similar (HH, LL) or more dissimilar (HL, LH) than would be expected by chance[66]. For this research, neighbours are defined using the Moore neighbourhood of an observation.

Data availability

Data and code can be found here: https://github.com/willygpv/balanced_neighbourhood.

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Author contributions

G.P.V. worked on the data curation, formal analysis and visualisations. M.S. worked on visualisations. C.B.A. supervised the project. All authors wrote the manuscript and conceptualized the research goal and methodology.

Competing interests

The authors declare no competing interests.

Additional information

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