The Ambiguity of 'Balanced Neighbourhoods': How Rotterdam's Housing Policy Undermines Urban Social Resilience

Abstract

Over the past decade, cities worldwide have increasingly adopted urban social resilience strategies, implementing systemic approaches to foster collective action and solidarity while considering the nuances of urbanisation. Their implementation, however, not only often prevents a clear assessment of the impact on resilience but also provides a fertile ground for cherry-picking, where ambiguous indicators can obscure the true drivers for urban renovation. This study examines the relationship between the "balanced neighbourhood" concept based on property value as defined by Rotterdam's municipal policy and its contribution to urban social resilience. We use empirical data and structural equation modelling to investigate the relationship between property value distribution, social cohesion, and informal support in "balanced neighbourhood" configurations. Our findings reveal that only 2.1% of the possible property value configurations fit the research model underneath Rotterdam's urban policy claims on social cohesion and informal support, and even in these cases, the associations are counterproductive. We argue that the ambiguous definition of "balanced neighbourhoods" obscures policy goals with certain areas, particularly in the North, paradoxically meeting policy conditions without showing the municipality's long-term target composition, whereas the South, with a higher concentration of social housing, is targeted for renovation/demolition plans. Our study highlights the need for more nuanced and accurate measurement tools to assess social resilience and calls for a shift in focus from interventions that alter the physical composition of neighbourhoods to focusing on enhancing social cohesion as a key factor promoting resilient actions.

Introduction

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 (Woodruff et al., 2022). Particularly, 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 (Doff, 2017). Diversity, redundancies and connections between people build capabilities to absorb disturbances and reorganise in the face of changing circumstances (Elmqvist et al., 2019). 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 (Quigley et al., 2018). Urban experiments such as the 100 Resilience Cities (100RC) showcase this systemic view of urban social resilience in the framework of cross-sectorial collaboration, (Beevers et al., 2022), where social cohesion is one component of the overall assessment of city health (Fastiggi et al., 2020), linking capacities of “marginal” communities to urban intervention and policies for addressing inequality and building strong economies (Shi, 2021).

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 (Fitzgibbons & Mitchell, 2021). 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 (Creutzig et al., 2024). 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) (Gemeente Rotterdam, 2016a), noting that the housing policy is not only controversially based on the idea of social mixing in cities but is also ambiguously operationalised under the concept of a “balanced neighbourhood”.

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” (Tunstall & Lupton, 2010), counteracting segregation, lack of liveability and other social dysfunctionalities (Bolt et al., 2010; Colomb, 2011). 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 (Hananel et al., 2022). The right combination of bonds between similar people and bridges between heterogeneous groups is expected to foster collective efficacy and inclusiveness, characterising resilient cities (Feinberg et al., 2020). Controversy stems from evidence that heterogeneous groups living side-by-side do not interact meaningfully or gain the alleged benefits of social mixing. (Levin et al., 2022). Furthermore, social mixing policies turn spatial inequality irrelevant under the guise of liveability (Meij et al., 2021), limit housing options for disadvantaged groups (Bolt et al., 2010), and conceal economic, commercial and political drivers for withdrawal from public housing (Capp et al., 2022).

The inherent controversies related to social mixing policies are introduced in the RRS under the wider goal of a “balanced society”, which links urban social resilience to the 2016 housing vision

(*Woonvisie* in Dutch). The Woonvisie aims at housing mixing for "balancing population demographic [and] attract highly educated people to the city" (Gemeente Rotterdam, 2016b), demolishing 13,500 homes (10,900 of the Social housing segment) and enabling Middle, Higher, and Top price segments increase by 46,600 new housing units (Gemeente Rotterdam, 2019a).[1] Nonetheless, 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 (Gemeente Rotterdam, 2020, p.14).

Previous research has shown that the municipality has effectively "balanced" the city, attracting highly educated and middle-income households (Custers, 2021) and problematising social housing and "migrant low-skilled population" as a source of public disorder and socioeconomic risk (Scholten et al., 2019; Uitermark et al., 2017). Remarkably, the United Nations filed a series of reports denouncing Rotterdam's housing policies as potentially discriminatory (UN-OHCHR, 2021, 2024). These urban renewal policies have been concentrated in the southern part of the city (Custers & Willems, 2024), raising concerns about uneven spatial impacts as the indices used to evaluate these policies overlooked critical spatial factors like spatial autocorrelations or multicollinearities (Uitermark et al., 2017). 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 (Adger et al., 2020).

This paper uses 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 *mixing property value across different "balanced neighbourhood" configurations from Rotterdam's urban policy affects informal support through social cohesion?* In particular, this research proposes a research model that reflects the RRS assumption "*the more balanced property values composition in an area positively impacts the perception of social cohesion and willingness to offer informal support*", 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 research first establishes the range of possible values that the ambiguous operationalisation of a "balanced neighbourhood". It then defines 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**.

[1] The municipality uses the value of a property for tax purposes (WOZ-value—Valuation of Immovable Property Act value) to classify dwellings into Social, Middle, Higher, and Top hierarchical segments in a specific area (see Methods).

Results

Identifying and grouping solutions with good fit

Our analysis starts with the estimation of the complete solution space that satisfies Rotterdam municipality's criteria for a *balanced neighbourhood* (Figure 1a) (Gemeente Rotterdam, 2020). Remarkably, there is no unique distribution but a whole space comprising 3,162 possible integer solutions (Figure 1b). Each solution represents a different combination of housing stock values that meet the municipality's definition of balance.

To understand the implications of these solutions on our research model — which is based on hypotheses H1, H2, H3, and H4 — we evaluated the **Standardised Root Mean Squared Residual (SRMR)** for each solution using **Partial Least Squares Structural Equation Modelling (PLS-SEM).** The SRMR is a goodness-of-fit measure that quantifies how strongly the empirical correlation matrix differs from the model-implied correlation matrix (Benitez et al., 2020). A value of 0 for the SRMR would indicate a perfect fit, and the generally accepted threshold is 0.08, established by Hu & Bentler (1999). We consider only the models with an SRMR below this threshold that meet the 95% confidence interval (CI) quantile criteria.

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

Figure 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) (Gemeente Rotterdam, 2019b, 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).

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

Figure 1a. Conditions defining when a neighbourhood has a balanced housing stock according to the WOZ. Source: Gemeente Rotterdam, 2020, p.14

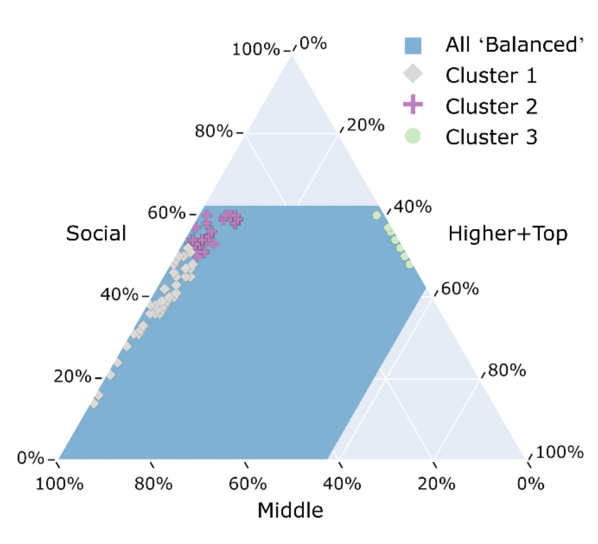
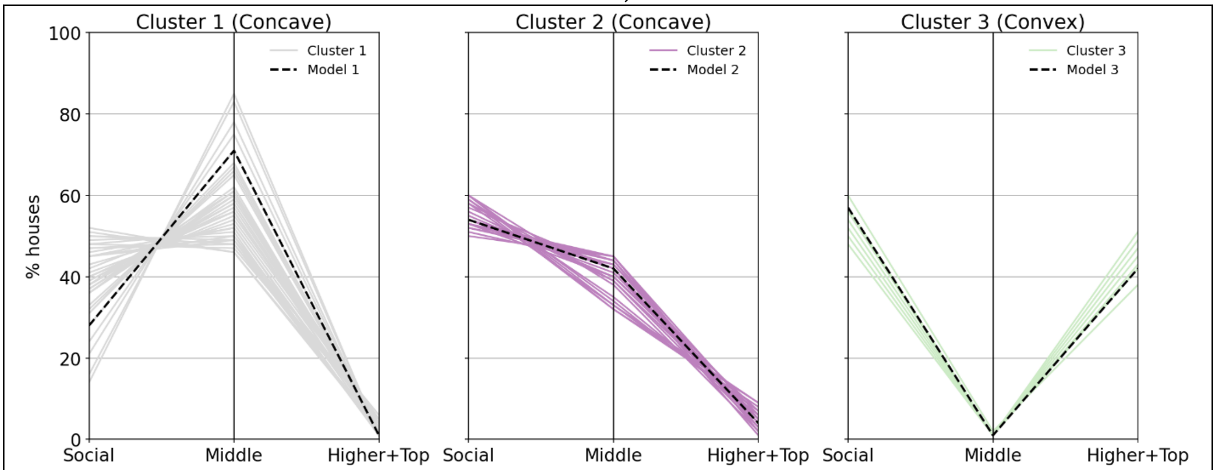


Figure 1b. Blue shade shows the full solution space of the "balanced neighbourhood" distribution according to Rotterdam's definition (3,162 solutions). The points are all solutions yielding an acceptable goodness-of-fit (≈ 2.1%) for the research model defined by H1, H2, H3 and H4. The points are divided into the three identified clusters.

The solutions with an acceptable goodness-of-fit were clustered using the K-Means algorithm into three different clusters within the overall solution space (Figure 1b). Transitioning to the distribution curves enables a more granular analysis, revealing the specific compositional details within each cluster (Figure 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, leading to the evaluation of the research model for three selected solutions leading to three Selected Models for further investigation (Figure 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 Figure 2 to calculate the value of *Neighbourhood balance* of every neighbourhood (see Methods).

Figure 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.



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%

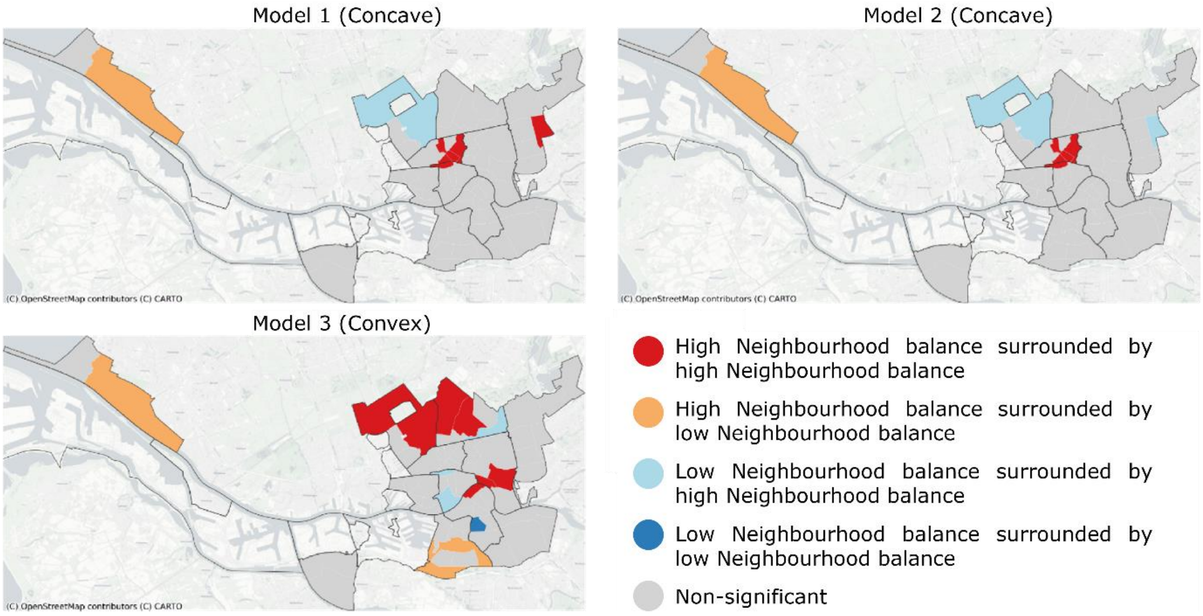
Exploring Neighbourhood balance in different models

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 (Figure 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: 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 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.

Figure 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.



Evaluating hypotheses using selected models

To test the hypotheses **H1, H2, H3** and **H4** using PLS-SEM, the research followed the steps laid out by J. Hair et al. (2019). We first examine the model fit tests to ensure 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.

Assessing model fit of selected models

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 (Rademaker & Schuberth, 2020). Additionally, the selected models were found to have scores below the commonly accepted threshold of 0.08 established by Hu & Bentler (1999), indicating an acceptable fit. Moreover, all goodness-of-fit measures met the 95% confidence interval (CI) quantile criteria.

Table 1: Goodness-of-fit of selected models. Summary of non-parametric model fit tests and SRMR indices for the three selected models, including their respective 95% confidence intervals.

	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

Formative measurement model

In the next step we focus on the formative measurement model, which is essential for determining how well different indicators represent complex constructs like social cohesion, ensuring that these constructs are accurately captured and contribute meaningfully 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 as proposed by Henseler (2020) (**¡Error! No se encuentra el origen de la referencia.**). 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, as 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 that 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, we conclude that such different specifications in the measurement model will not explain differences across different 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).

Table 2: Assessment of formative constructs across selected models. 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 as established by J. Hair et al. (2019).

		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]
a: Item dropped due to high multicollinearity; b: Item dropped due to insignificant weight.					

Structural model

The structural model analysis is the final step in our process, where we examine the relationships between the key constructs identified in the measurement models to test our hypotheses and understand how these constructs interact with each other in the overall framework. We first considered multicollinearity between the constructs, using the reflective construct Informal support as the dependent variable and calculating the VIF following Hair et al. (2019). 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 (Cohen, 1988).

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 β = 0.352 (95% CI = [0.021; 0.637]; f2 = 0.108); for Model 2 was β = 0.351 (95% CI = [0.064; 0.617]; f2 = 0.114); and for Model 3 was β = 0.325 (95% CI = [-0.012; 0.601]; f2 = 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 another hand, Models 1 and 2 (concave models) showed different results compared to Model 3 (convex model) concerning the 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 β = -0.467 (95% CI = [-0.671; -0.048]; f2 = 0.279); and for Model 2 was β = -0.412 (95% CI = [-0.621; -0.055]; f2 = 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.

Table 3: Results of the structural model across the selected models. 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 has a significant negative effect on Social cohesion, but 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.

a. Structural Model Assessment

		Model 1 (Concave)						Model 2 (Concave)						Model 3 (Convex)					
Dependent variable	Independent variable	β	SD	95% CI	f²	R2	Hypothesis testing (direct effects)	β	SD	95% CI	f²	R2	Hypothesis testing (direct effects)	β	SD	95% CI	f²	R2	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

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.

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]**
	Neighbour. 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.

Discussion

While urban resilience opens an opportunity to explore the positive interplay between social cohesion and housing renovation (Woodruff et al., 2022), 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 (de Bruijn, 2019). However, the calculations across all possible configures created 3,162 possible solutions across, 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 (Gemeente Rotterdam, 2019b), 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 (Schinkel & van den Berg, 2011; Uitermark et al., 2017).

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 (Coffé & Geys, 2006; Wang & Kemeny, 2023) but often results in social distance and conflict due to differing lifestyles and expectations (D. King & MacGregor, 2000). 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 (Feinberg et al., 2020). The “balanced ideal” applied uniformly across diverse neighbourhoods does not account for the unique characteristics and needs of each community. Instead, the one-size-fits-all approach risks exacerbating existing inequalities and undermining the potential for positive social transformation that urban resilience strategies aim to achieve (Quigley et al., 2018).

In Rotterdam, this issue is exemplified by interventions designed to balance the Social housing segment, which have paradoxically increased socioeconomic polarisation, as evidenced by rising housing prices (Custers, 2021; Kenyon et al., 2024). Our spatial analysis shows an additional dimension of the spatial divide, noting a clear pattern of polarised housing distribution in the North that, paradoxically and given the ambiguous definition of balanced neighbourhood, formally meets social mixing policy conditions, even though it deviates from the long-term city-wide municipality goals of 20% Social, 30% Middle, 30% Higher and 20% Top segments (Gemeente Rotterdam, 2019b). 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 (Custers & Willems, 2024). In this ambiguous context, inhabitants and policymakers in Rotterdam take as common knowledge the stark polarisation between the two sides of the river (Gemeente Rotterdam, 2016b, 2019a). In light of the counterproductive and, at best, irrelevant role of social mixing policies grounded in an ideal of "balanced" defined by value property, one should pay higher attention to the practical consequences experienced by inhabitants. In particular, policies aimed at increasing expensive housing units for low-income in Rotterdam South disrupt established social networks and undermine social cohesion among original residents (UN-OHCHR, 2021).

Shall the municipality continue its housing policy based on the idea of a "balanced neighbourhood", it must target specific distributions that demonstrably contribute to the intended social and resilience benefits. Otherwise, the risk of perpetuating social inequities and weakening community support structures remains high, calling into question the validity and effectiveness of the current policy framework. The results of our mediation analysis further highlight that social cohesion is the key factor explaining the relationship between neighbourhood balance and informal support. Therefore, aspects of social cohesion—such as trust, reciprocity, and participation—should be considered more relevant factors for promoting resilient actions instead of neighbourhood balance as measured by the WOZ value.

While our study contributes to the literature by employing house market 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 (Schwab & Held, 2020; Shih & Chai, 2016). 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 (Tolsma et al., 2009), 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 (G. King, 2013). Additionally, informal support measured by respondents' willingness to help may not reflect real behaviour. During the COVID-19 pandemic, shown support exceeded the stated willingness (Veldacademie, 2021), 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 (Copeland et al., 2020). However, we do not fully articulate the role of racialisation in urban policy and social cohesion. 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

Urban resilience and housing policy in Rotterdam are structured at a neighbourhood level (*buurt* in Dutch). Hence, we assess our research model on urban social resilience across the possible ways of operationalizing a "balanced neighbourhood" in Rotterdam following the "Atlas Development Housing Stock" (Gemeente Rotterdam, 2020, p.14). For every possible distribution that the definition of balance from the Atlas can yield, we calculated the Neighbourhood balance of each Rotterdam neighbourhood using the Kullback-Leibler (KL) divergence (Kullback, 1997).

The measurements of "Neighbourhood balance" were then fed into the PLS-SEM model one at a time to identify the subset with a good fit. Statistical inference relied on percentile bootstrap confidence intervals based on 4999 bootstrap runs (Aguirre-Urreta and Rönkkö, 2018)[2]. 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. Then, we clustered the models that fit using the k-means algorithm (Pedregosa et al., 2011) for unravelling underlying groups and the structure of relations. Finally, we select for each cluster the model with the best fit to assess our hypotheses, accounting for the direct and indirect effects between Neighbourhood balance, Social cohesion, and Informal support. Finally, we employed Local Indicators of Spatial Association (LISA) maps to identify localized regions on a map that display either balanced or imbalanced housing across different measures of neighbourhood balance.(Anselin, 1995).

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 (Gemeente Rotterdam, 2022). The Wijkprofiel uses the methodology defined by the Dutch Office of Social and Cultural Planning for surveying perceptions of social cohesion (Schnabel et al., 2008), as well as the willingness to help friends or neighbours who need help. For the analysis, the data from the year 2019 was chosen due to it being the most recent year for which Wijkprofiel survey data was 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 (Dutch Ministry of Housing and Spatial Planning, n.d.). In the context of Rotterdam, housing segments were categorized as follows in the Woonvisie addendum (Gemeente

[2] 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 (Dijkstra & Henseler, 2011).

Rotterdam, 2019b, 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 (Gemeente Rotterdam, 2019b, p.2).

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 (J. F. Hair et al., 2011).

Analytical framework

Neighbourhood balance

In the definition of a "balanced neighbourhood" provided by the municipality of Rotterdam (Gemeente Rotterdam, 2020, p.14), balance is expressed as a dichotomous variable where a neighbourhood is either in balance or not based on the conditions in Figure 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 Figure 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 (Kullback & Leibler, 1951, p. 81). The resulting measurement is defined as:

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

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 (Schnabel et al., 2008). 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 view
- (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

In line with Aldrich (2017) we argue that the end mechanism through which social resilience is achieved is mutual aid, therefore, the willingness to help friends or neighbours who need help was used to measure the informal support of a neighbourhood. Therefore, *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 find relevant insights into the results that different balance distributions may yield, it is relevant that we select instances which are representative of the possible situations. To this end, unsupervised clustering allows us to group the possible distributions that define balance into several representative sets.

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 (Pedregosa et al., 2011). 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 (Pedregosa et al., 2011).

Partial Least Squares Structural Equation Modelling (PLS-SEM)

Structural Equation Modelling (SEM) is widely recognized as a powerful statistical technique in social sciences (J. Hair et al., 2016). 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 (Henseler, 2020).

Partial Least Squares Structural Equation Modelling (PLS-SEM) is an iterative estimation approach that handles both reflective (Mode A) and formative (Mode B) constructs (Lauro et al., 2018). 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 (J. Hair et al., 2019; Lauro et al., 2018). 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 (J. Hair et al., 2016; Henseler, 2020; Lauro et al., 2018).

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 (Arribas-Bel, 2015). For the purposes of this research, neighbours are defined using the Moore neighbourhood of an observation.

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Supplementary materials

Model predictive power

The predictive relevance (Q^2) of construct items was calculated to evaluate the model's predictive power (J. Hair et al., 2019). Q^2 values above 0, 0.25, and 0.50 indicate small, medium, and large predictive relevance, respectively. Values below 0 suggest a lack of predictive accuracy. Table 4 shows that Models 1 and 2 have small to medium predictive power for Social cohesion, while Model 3 has lower accuracy. All models lack predictive power for Informal support.

The final assessment involves calculating prediction errors: the difference between mean absolute error (ΔMAE) and the difference between the root mean squared error (ΔRMSE). If Q^2 shows predictive power, these metrics compare predictions to a naïve benchmark (linear regression model). Higher RMSE or MAE compared to the benchmark indicates low predictive accuracy (positive ΔRMSE and ΔMAE). Table 4 indicates that Model 1 has higher predicted errors for Social cohesion, suggesting low predictive power, whereas Models 2 and 3 show negative values, indicating higher predictive power.

Overall, the selected models showed acceptable explanatory power, but low predictive accuracy. Selected Model 1 had the best overall goodness-of-fit, but Model 3 captured the relationship between Social cohesion and Informal support with better explanatory power.

Table 4: Structural model predictive power. This table summarizes the ΔMAE, ΔRMSE, and Q^2 metrics for the three structural models. Higher ΔMAE and ΔRMSE values suggest lower predictive accuracy, while Q^2 values indicate the level of predictive relevance. The selected models showed acceptable explanatory power, but low predictive accuracy, with some constructs dropped due to multicollinearity or insignificant weights.

		Model 1 (Concave)			**Model 2 (Concave)**			**Model 3 (Convex)**		
	Item	ΔMAE	ΔRMSE	Q^2	ΔMAE	ΔRMSE	Q^2	ΔMAE	ΔRMSE	Q^2
Social cohesion	SC1: % of residents who say that local residents know each other	NA[a]	NA[a]	NA[a]	NA[a]	NA[a]	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]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]
	SC3: % of residents who say that local residents share each other's views	0.001	0.001	0.184	-0.013	-0.022	0.139	NA[b]	NA[b]	NA[b]
	SC4: % of residents who say that local residents help each other	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]
	SC5: % of residents who say they feel at home with local residents	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	NA[b]	-0.114	-0.126	0.008
Neighbourhood balance	NB: Negative of the Kullback-Leibler divergence of the WOZ-value distribution in a neighbourhood with respect to the objective balance distribution	-0.046	-0.069	-0.032	-0.099	-0.152	-0.043	-0.117	-0.145	-0.020

a: Item dropped due to high multicollinearity; b: Item dropped due to insignificant weight. What is RMSE an MAE?, check the reference.