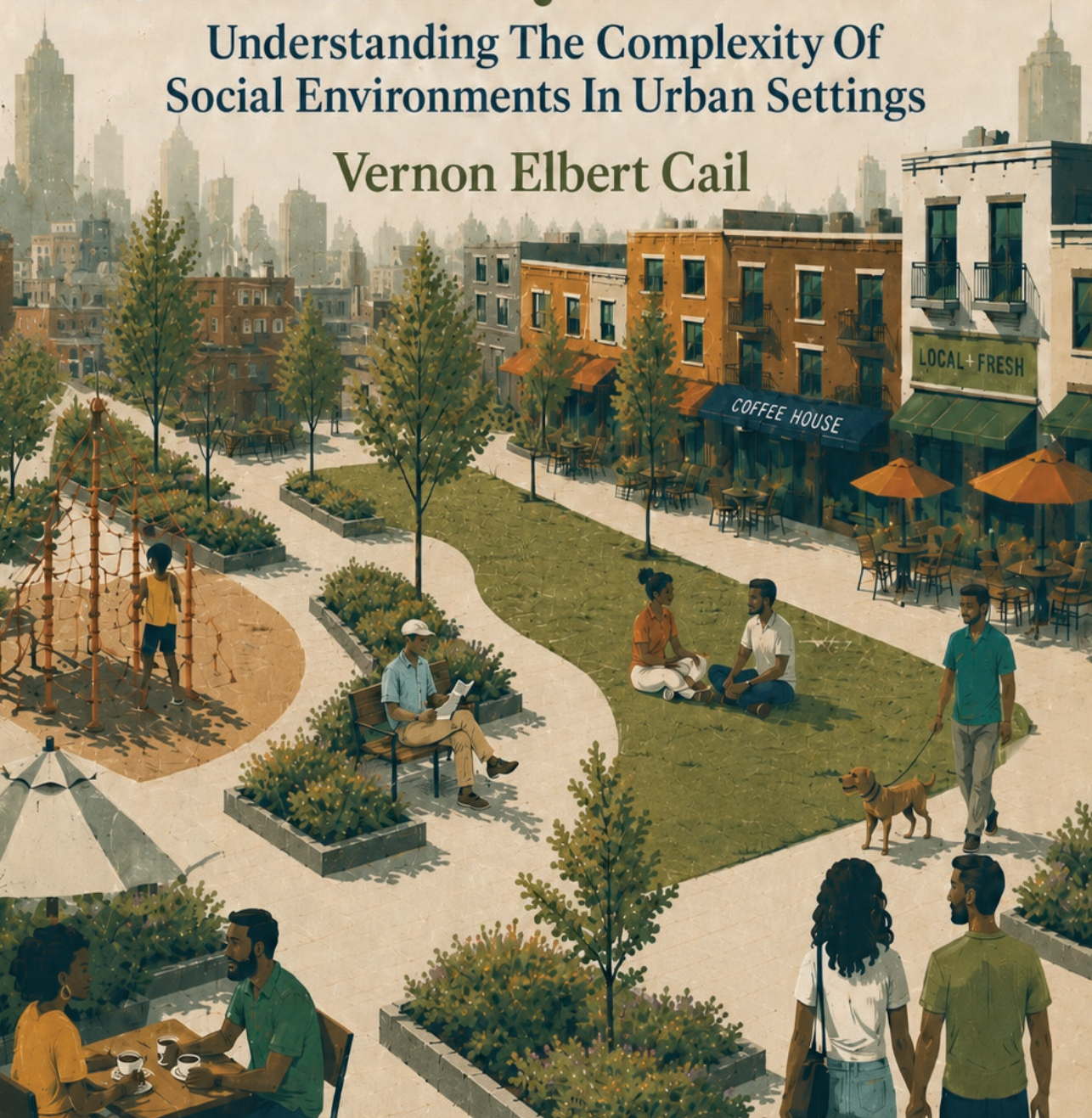
The Social Fabric Of Urban Health

Understanding The Complexity Of Social Environments In Urban Settings

Vernon Elbert Cail



Propositions belonging to the thesis

The Social Fabric of Urban Health: Understanding the Complexity of Social Environments in Urban Settings

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1. Neighborhood social cohesion plays an important role in health, but the relationship is complex and nuanced. [This thesis]
2. The shift towards digital communication does not replace the critical health impact of in-person social interaction for mental health and well-being. [This thesis]
3. Understanding urban health inequities requires examining the urban environment as a whole, where the social environment plays an integral role. [This thesis]
4. Differences in health outcomes across neighborhoods emerge from the interplay of neighborhood-level factors and the dynamics of residential segregation, creating and reinforcing inequalities over time. [This thesis]
5. Integrating complex systems approaches and traditional epidemiological methods offers a comprehensive understanding for complex public health problems, as both approaches enhance one another. [This thesis]
6. As wealth inequalities continue to widen in European cities, declining trust within communities will become an increasingly important determinant of population health.
7. Because health and social inequities arise from the way societies are organized, addressing them will require reforming the systems that produce them.
8. Effective health policies recognize that lived experiences differ across individuals and groups.
9. Including people from marginalized communities in decision-making empowers them to control their own future.
10. Understanding complex problems begins with the willingness to question simple explanations.
11. Everyone needs a helping hand whether they realize it or not.

The Social Fabric of Urban Health: Understanding the Complexity of Social Environments in Urban Settings

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The Social Fabric of Urban Health: Understanding the complexity of social environments in urban settings

Het sociale weefsel van stedelijke gezondheid: inzicht in de complexiteit van sociale omgevingen in stedelijke gebieden

Thesis

to obtain the degree of Doctor from
Erasmus University Rotterdam
by command of the
rector magnificus

Prof.dr.ir. A.J. Schuit

and in accordance with the decision of the Doctorate Board.
The public defence shall be held on

Monday 7 September 2026, at 15.30 hrs
by

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Chapter 1: Introduction

Over half of the world's population currently resides in urban areas [1]. By 2050, some estimates project that urban populations will exceed two-thirds of the world's population, or approximately 6.68 billion people [1]. The growth of urban populations is occurring in regions across the world. In Europe, approximately 75% of the population lives in urban areas, making it one of the most urbanized regions globally [1]. These estimates are based on classifications of geographic areas defined by international organizations, which facilitate international comparisons [2]. There are three broad categories of geographic areas: cities, towns, and rural areas [2]. Urban areas refer to cities and surrounding towns [2], and this definition is adopted in this thesis. Defining features of urban areas include high population density and diverse populations. These features shape the living experience within urban areas. High-density areas can create vibrant living environments, by facilitating access to services and economic opportunities, as well as supporting efficient public transportation systems and new housing developments [3]. In addition, European urban areas, particularly large cities, are international hubs for innovation and cultural exchanges due to having a diverse population from a wide range of ethnic and socioeconomic backgrounds. These features, however, do not always result in vibrant living conditions. Many urban areas also contain deprived neighborhoods with limited access to public services, less economic opportunities, and overcrowded living conditions. Because urban environments shape all aspects of life, the migration shift to urban areas has major consequences on the social structure, economy, and the natural environment [1].

Urbanization and health

Urbanization has significant implications for public health, as it influences both the opportunities for improved well-being and the increased risks associated with urban living. Research has shown that urbanization can promote a variety of health benefits, which has been referred to as the urban health advantage [4]. Compared to rural areas, urban environments tend to have a stronger labor market and more opportunities for economic prosperity [4, 5]. Furthermore, walkable infrastructures and access to public spaces in urban environments can strengthen social networks and social cohesion [3, 4, 6]. Urban environments also offer more access to essential goods and services such as nutritious food, housing, education, and healthcare [4, 7, 8]. Finally, the density and diversity of urban populations increase possibilities for political mobilization and social movements that enables communities to advocate for better living conditions, housing standards, and public health infrastructure [4, 9]. Collectively, these mechanisms show how urbanization can play a positive role in shaping health outcomes.

Rapid urbanization can also pose significant health risks, which has been referred to as the urban health penalty [10]. Expanding urban populations can put a strain on infrastructure, resulting in overcrowded housing conditions, inadequate sanitation, and increase exposure to environmental pollution, all of which contribute to poor health outcomes [10]. These burdens are often concentrated in deprived neighborhoods, leaving those residing in these areas exposed to higher rates of infectious disease, mental illness, chronic conditions, and mortality [11-13]. Given the continued growth of urban populations, improving health in urban environments has become a central public health priority,

resulting in a growing body of research on urban health. Understanding the underlying determinants of health within urban environments is essential for developing effective and equitable interventions.

Physical and social environmental determinants of urban health

Empirical research indicates that the physical and social environment are two fundamental features of urban living that jointly influence urban health [12]. Aspects of the physical environment include both environmental exposures such as air pollution, noise, and climate conditions, and elements of the man-made built environment such as urban design, public spaces, and access to resources [12]. The social environment refers to "the groups to which we belong, the neighborhoods in which we live and the policies we create to order our lives" [14]. Key aspects of the social environment include neighborhood social cohesion, the presence of social norms, levels of safety and violence, and various forms of social organization of places [12].

Empirical evidence about the relation between the physical environment and health is extensive and demonstrates a wide range of health outcomes [15]. For example, greater exposure to air pollution, noise, and heat has been linked to adverse physical and mental health [16-18], whereas access to green space is positively associated with several aspects of human health and well-being [19].

While research on the physical environment and health is well-established, studies on the social environment's impact on health are rapidly advancing for at least two reasons. First, urbanization is occurring at an unprecedented pace, making urban areas denser and more diverse than ever before. These changes not only affect the composition of urban areas, which includes a wide range of cultural, ethnic, and socioeconomic backgrounds, but also shape how inhabitants form new relationships and interact with one another. Second, advances in digital technology have significantly altered the social fabric of modern society. With greater access to the internet and communication devices, more people now rely on technology to build and maintain social relationships [20, 21]. As social environments continue to evolve, further research is needed to understand the role of modern social environments in shaping population health.

Overview of social environment research

Much of the public health research on the social environment is informed by earlier sociological work. In the late nineteenth century, Émile Durkheim, one of the earliest and most influential scholars in sociology, demonstrated that variations in suicide rates across regions were patterned by broader social forces, such as collective norms and the level of social integration within a group [22]. His work laid the foundation for the idea that social context can influence health outcomes beyond individual characteristics [22]. In the 1920s and 1930s, scholars from the Chicago School of Sociology analyzed cities as social ecosystems, and introduced concepts such as social disorganization and social control to explain how urban growth shapes social behavior [14]. Social disorganization occurs when poverty, residential instability, and ethnic heterogeneity lead to the breakdown of social structures and community bonds. Communities displaying signs of social disorganization tended to have higher rates of crime and delinquent behaviors [14]. Social control refers to a set of rules, social norms, and mechanisms that can regulate individual and group behavior and maintain social order [23]. Research on

social control shows that it can mitigate the detrimental effects of living in disadvantaged communities [24]. This body of evidence played a significant role in shaping research on a key aspect of the social environment: social capital.

An extensive body of literature has defined social capital from various perspectives [25], but public health research primarily adopts two interpretations: the social networks approach and the social cohesion approach [26]. The social network approach stems from the work of the French sociologist Pierre Bourdieu, who defined social capital as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition —or in other words, to membership in a group" [27]. Along with economic and cultural capital, Bourdieu described social capital as a form of capital that shaped social class structures with the dominant elite class holding most of the forms of capital [27]. Bourdieu's work emphasized social capital at the individual level and explained how goods and resources are distributed in a society.

The cohesion approach was largely influenced by the works of James Coleman and Robert Putnam [28, 29]. Coleman viewed social capital as "a variety of entities that consist of some aspect of social structure and facilitate certain actions among individuals within that social structure" [30], while Putnam defined social capital as "features of the social organizations such as trust, norms, and networks that can improve the efficiency of society by facilitating coordinated actions" [31]. Both scholars argued that social capital was facilitated by trusting relationships, reciprocity, and norms, but Coleman focused on its functional role at the individual level within small-scale social structures like families and schools, while Putnam argued that the wider community benefits from social capital through civic engagement [25, 28, 32].

In public health research, the network approach typically examines social resources and networks, while highlighting inequalities in access to social resources, whereas the cohesion approach tends to examine perceptions of trust in others, perceptions of social belonging and integration, and levels of civic or social participation [26]. Their findings indicate that both types of social capital are protective against risk like all-cause mortality, cardiovascular diseases, and certain cancers, as well as promote mental health [33-35]. By providing access to resources and various forms of support, social networks help mitigate the effects of stress and social isolation [22]. Moreover, more cohesive communities promote health through mechanisms such as collective efficacy, informal social control, and reciprocity [24, 36]. These findings highlight the potential of the social environment to improve urban health outcomes and reduce health inequities [37].

Urbanization and within-city health inequities

Another critical concern associated with the growing urban populations is the widening urban health inequities, which refer to systematic differences in health outcomes among population groups living within the same urban area [38-40]. The focus of this thesis is health inequities that are spatially patterned within urban environments (i.e., within-city inequities). This focus is particularly important because within-city health inequities remain prevalent across Europe, despite ongoing efforts to address them [40, 41].

The full extent of the mechanisms underlying within-city health inequities remains unclear; however, evidence has shown that these causes are complex, involving the interplay of social, economic, and environmental factors [12, 40, 42, 43]. Specifically, this body of evidence indicates that within-city health inequities stem from the unequal distribution of material resources such as income, employment, and housing quality, as well as social resources like education, access to healthcare, and environmental conditions across urban neighborhoods [43, 44]. These factors, collectively referred to as the social determinants of health, play a critical role in shaping health outcomes [43]. People with low socioeconomic positions (SEP) typically have fewer resources and less access to amenities than affluent populations, contributing to worse health outcomes [45]. In addition, residential segregation reinforces these spatial patterns of inequities, with low SEP confined to deprived neighborhoods [44, 46, 47]. Despite this growing body of evidence, further research on how the complex interplay of these factors drives health inequities is still needed.

Understanding the complexity of urban health

While research linking social capital to health is extensive, there are areas to build upon these findings. Most existing evidence is based on cross-sectional data, which measures social capital and health outcomes at a single point in time, but this study design has two limitations. First, both social capital and health status can change over time, and cross-sectional studies cannot detect these changes. Second, while social capital can influence health outcomes, health status can also affect social capital. For example, people struggling with depression may engage less with others, limiting opportunities to build trusting relationships. This is why cross-section studies cannot determine the temporal order of a relationship. These limitations in cross-sectional studies highlight the need for using longitudinal data, which might shed light into the causal role of social capital [33].

The timeframe of the analysis also plays a crucial role in understanding the relationship between social capital and health. Social processes and health status operate at different rates. For example, social cohesion develops slowly and reflects deep-rooted community ties, while depressive symptoms may fluctuate more rapidly depending on daily circumstances or life events. Examining from both long-term and short-term perspectives can capture these different processes and provide a more comprehensive understanding of how social capital influences health outcomes.

Another important area of research is examining the interplay between social capital and other determinants in urban environments, as this research might uncover the underlying mechanisms that drive urban health and health inequities. Understanding these mechanisms requires testing whether social capital interacts with other determinants in urban environments and whether it mediates along causal pathways [33, 48]. Recent advances in causal inference methodologies now allow disentangling these causal pathways [49]. Such improvements in study design and data analysis represent significant progress in understanding the relationship between social capital and health.

Public health research recognizes that the processes shaping health are complex, multifactorial, and nonlinear [48]. That is why more researchers are turning to complex systems approaches, which aim to understand the interrelations within a system by examining it as a whole [42, 50, 51]. Many believe complex systems approaches are suitable for addressing within-city urban health inequities, because they exhibit complex features including interdependent relationships and feedback loops [42].

Moreover, complex systems approaches may provide insights that traditional epidemiologic approaches might miss [48]. Complex systems approaches supplement traditional epidemiological methods by offering a framework for capturing complex features and inspiring new hypotheses for further empirical investigations [42, 48]. Adopting both complex systems and traditional methods offer a more comprehensive perspective on tackling within-city health inequities that can advance health policy.

Research aim

The overarching aim of this thesis is to further understand how the social environment contributes to urban health and urban health inequities.

To address this aim, this thesis adopts a mixed-methods approach to examine how various aspects of the social environment shape health and contribute to inequities in urban contexts. Each empirical chapter focuses on a different aspect of the social environment and employs a different methodological approach. Collectively, these chapters offer a comprehensive understanding of how social contexts influence urban health and contribute to urban health inequities.

Outline of thesis

Chapter 2 examines the within-individual and between-individual associations between perceived neighborhood social cohesion and self-assessed health, and explores whether these relationships vary across age, socioeconomic position, and gender.

Chapter 3 investigates the extent to which neighborhood social cohesion mediates and interacts with the associations between perceived neighborhood safety and disorder, and self-assessed health.

Chapter 4 assesses the relationships between social network characteristics and both momentary depressive symptomatology and daily fluctuations in depressive symptoms among older adults.

Chapter 5 uses a systems-thinking approach to develop a causal loop diagram (CLD), which illustrates how the dynamic interplay of neighborhood factors contributes to the development and persistence of urban health inequities in cities in high-income European countries.

Chapter 6 presents a summary of the main findings. It goes on to address overarching methodological considerations and reflect on the interpretation of main findings. The chapter concludes with implications for policy and directions for future research.

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Chapter 2: Changes in perceived neighborhood social cohesion and self-assessed health: 17-year follow-up of the Dutch GLOBE study

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European Journal of Public Health. 2024; 34 (6): 1079-1085

Abstract

Background: Prior research has indicated that residents who perceive their neighborhood as more cohesive have better mental and physical health than those with lower perceived neighborhood social cohesion. However, because most studies are based on cross-sectional data, it remains unclear whether improving the perceptions of social cohesion leads to better health over time. **Methods:** This study applied random effects within-between models to examine the within-individual and between-individual associations of perceived neighborhood social cohesion and poor self-assessed health (SAH) in a cohort of Dutch adults with 17 years follow-up. We also tested whether such associations varied by age, educational levels, and gender. **Results:** The results of pooled analyses indicated that higher perceived neighborhood social cohesion was associated with better SAH (OR: 0.72 95%CI 0.65, 0.80), but did not find conclusive evidence that within-individual changes in perceived neighborhood social cohesion were associated with SAH (OR: 0.96 95%CI 0.89, 1.04). We also did not observe any moderating effects for age, educational level, or gender. **Conclusions:** This study provides some evidence that improving social cohesion in neighborhoods may be a beneficial health promotion strategy.

Keywords

social cohesion, self-assessed health, longitudinal analysis, random effects within-between models, health promotion

Introduction

Public health officials and policymakers face persistent challenges when addressing neighborhood inequalities in health (1). In order to advance the development of interventions designed to improve health in neighborhoods, it is important to know how residents' perceptions of their neighborhood impacts their health (2). One determinant that is widely examined in this context is perceived neighborhood social cohesion (3, 4). Within the field of public health, social cohesion is often considered a group-level construct that refers to the "extent of connectedness and solidarity among groups in a society" (5). It is believed that higher perceptions of neighborhood cohesion are beneficial to individual health through various mechanisms (6). The first of these is collective efficacy, which refers to residents' perceived ability to undertake collectively desired actions (7). Collective efficacy has been shown to protect communities against neighborhood violence, which is associated with adverse health outcomes (2). The second mechanism, informal social control, characterizes the neighborhood's ability to enforce and maintain social norms, which can inhibit deviant health behaviors such as underage drinking and smoking (3). Finally, reciprocity among neighborhood residents involves residents helping each other with the expectation that the favor will be returned (3). This mechanism helps ensure that health-promoting resources are distributed throughout the community. Despite its potential for improving health, social cohesion also have the potential to harm groups of people (8). For example, tightly knit communities have the ability to exclude minorities or restrict individual freedoms (8).

There is a burgeoning body of empirical research examining the effects of neighborhood social cohesion on a wide range of health outcomes, especially self-assessed health (SAH) (4). SAH is a widely used measure of individual health, because it can be easily administrated and has been shown to be a strong predictor of mortality (9-11) and objective health outcomes (12). A 2019 review of the literature found considerable evidence supporting the association between social cohesion and SAH (4). It should be noted, however, that most of these findings were largely based on cross-sectional data. Therefore, they lack the ability to draw causal conclusions and to determine the temporal direction, leaving doubt as to whether improving the perceptions of social cohesion will actually lead to better health.

In response to these limitations, there is a call to use longitudinal study designs and advanced statistical methods for approaching causal relationships (4). One method that is proliferating in epidemiologic research is fixed effects models (13). When applied to longitudinal data, fixed effects models can estimate associations between changes in exposures and outcomes within individuals. The primary appeal to using these models is that individuals act as their own control by comparing measures at different time points, thereby removing confounding from unobserved time-invariant factors (13). The drawback to fixed-effects models is that the effects of time-invariant covariates (e.g., gender) cannot be estimated (13). An even more flexible model is the Random Effects Within Between (REWB) model, which has the ability to estimate both within-individual and between-individual associations simultaneously (14, 15).

Previous research also suggests that the relationship between the social environment and health may vary by certain sociodemographic factors (16-18). Older adults, especially those with limited mobility, rely more on their own social network (19), spend more time in their neighborhood, and stay longer in the same living environment than younger adults (20). Consequently, the local community might be more important for the health of older individuals than younger adults. Differences across socioeconomic positions (SEP) may also modify the relationship between neighborhood social cohesion

and health. The level of educational attainment, a common SEP indicator, is a strong predictor of where individuals will reside and who they interact with. Less-educated individuals generally have less access to resources and more exposure to neighborhood disorder compared to more educated individuals (21). Some research suggest that improvements in social cohesion could buffer adverse exposures for people with low SEP (17). Therefore, people with less education may have a greater benefit in health from improvements in social cohesion than more-educated people (17). Finally, while several studies investigated gender differences in the strength of the association between neighborhood factors and health, evidence is contradictory. For example, a stronger association has been reported between perceptions of neighborhood social cohesion and mental health in men than in women (22). Yet, stronger associations between related environmental factors (such as trust) and SAH for women compared to men have been found as well (16). While this illustrates the importance of more research, it leaves us agnostic about the direction of the gender differences.

To fill these important knowledge and methodological gaps, the current study aims to examine the within-individual and between-individual associations of perceived neighborhood social cohesion and SAH. We hypothesize that 1) higher perceived social cohesion is positively associated with better SAH (between-individual association), and 2) changes in perceived neighborhood social cohesion are positively associated with changes in SAH (within-individual association). The second aim of this analysis is to determine whether the relationship between perceived neighborhood social cohesion and health varies across age, socioeconomic position, and gender. We hypothesize that the between-individual and within-individual association of higher perceived social cohesion with better SAH will be larger among older adults compared to young adults, and individuals with less education compared to individual with more education. Given the contradictory evidence for gender, we do not hypothesize a direction for this analysis.

Methods

Data

This study used data from the GLOBE study, a prospective cohort study aimed at understanding the socioeconomic inequalities in health in the Netherlands. Baseline measurements were taken in 1991 on a representative sample of 27,070 adults from the city of Eindhoven and surrounding villages (23). A smaller subset was followed up in subsequent waves via postal surveys and oral interviews (23). More details about the GLOBE study are available elsewhere (23). The use of personal data in the GLOBE study is in compliance with the Dutch Personal Data Protection Act and the Municipal Database Act, and has been registered with the Dutch Data Protection Authority (number 1248943).

This analysis included data from the follow-up surveys in 2004, 2011, 2014, and 2021. We were primarily interested in examining participants who remained in the same neighborhood during the entire observation period. By excluding participants who moved, we would yield an association that is easier to conclude that changes in perceived neighborhood cohesion led to changes in SAH and not due to factors associated with moving. Therefore, we included only participants with at least two waves of data who remained in the same neighborhood throughout the observation period. A total of 8,963 participants had data across the four waves. We excluded 2,694 participants with missing postal codes, 789

participants who changed neighborhoods, and 2,882 participants with less than two observations, resulting in a final sample of 2,598 participants (see Figure 1).

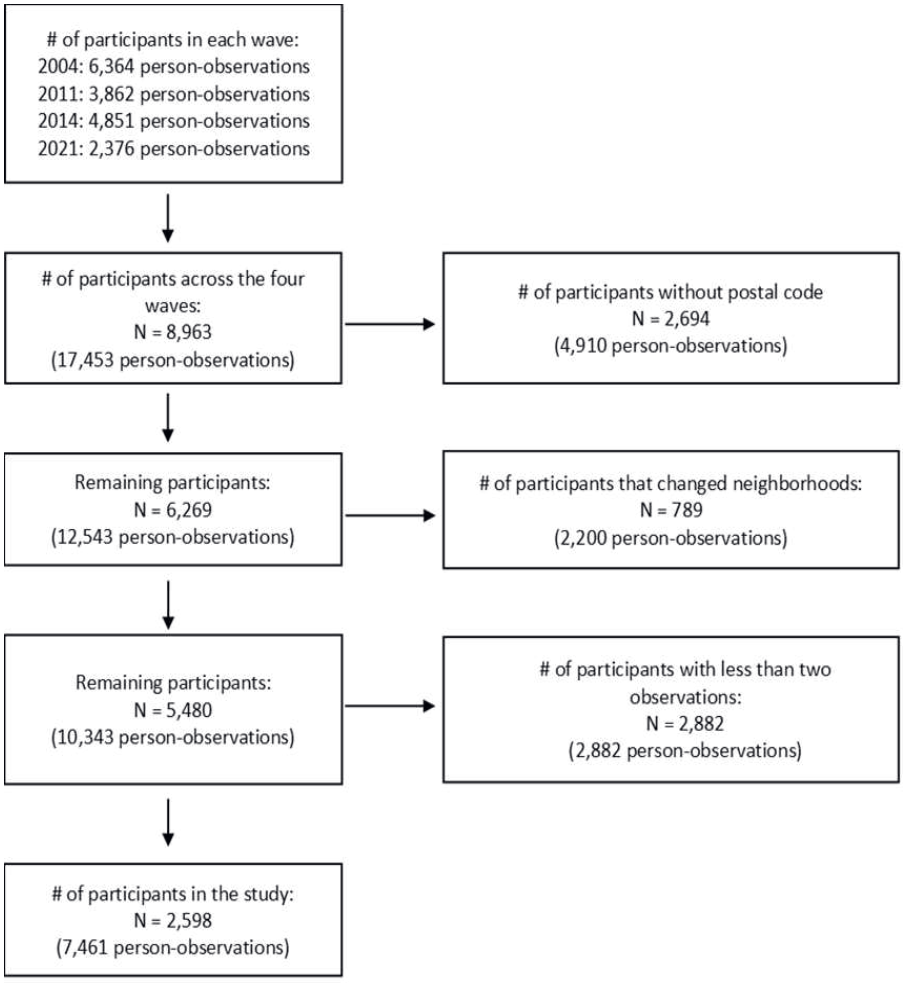


Figure 1. Flow chart of the participants in the study

Perceived neighborhood social cohesion

We assess perceived neighborhood social cohesion with a four-item scale based on two widely used instruments (7, 24, 25). Respondents were asked to what extent they agree or disagree with the following questions about their neighborhood: (a) People in this neighborhood get along with each other pleasantly, (b) People in this neighborhood are willing to help each other (c) I often feel alone in this neighborhood, and (d) I would move out of this neighborhood if I get the chance. The first two items capture perceived collective efficacy, whereas the last two items measure a sense of belonging (25). Response categories were 'strongly agree', 'agree', 'neither agree nor disagree', 'don't agree', and 'strongly don't agree', ranging from one to five. Responses were coded so that higher values indicate a higher perceived neighborhood social cohesion. The individual scores were summed into a new scale with a possible range from 4 to 20. The scale had acceptable internal consistency with Cronbach's alphas ranging from 0.68 - 0.74 across the four waves.

Self-assessed health

The outcome variable is SAH, which was assessed by asking the participants the single-question item: How would you rate your health in general? The five response categories ranged from poor, fair, good, very good, to excellent. For the main analysis, the variable was dichotomized into poor health (poor and fair) and good health (good, very good, and excellent), which is consistent with majority of previous research (4).

Covariates and moderators

We controlled for time-varying and time invariant variables that could affect the relationship between perceived neighborhood social cohesion and SAH. Age, living arrangement (living with a partner, living without a partner), monthly household income (<€1200, €1200–1800, €1800–2600, >€2600), employment status (employed, unemployed, retired), financial difficulties in the past year (yes, no), the number of people in the household, years of residence in the neighborhood, and home ownership status (home owner or renter) were included as time-varying covariates. Time-invariant covariates (measured in 2004) were gender (male, female), place of birth (the Netherlands, elsewhere), and highest attained educational level according to International Standard Classification of Education (low = ISCED 0 – 2, middle = ISCED 3 – 4, high = ISCED 5 – 7). Age, educational level, and gender were also used as moderators.

Statistical Analyses

Missing variables (ranging from home ownership at 0.5% to household income at 12.4%) were assumed to be missing at random and were handled by using the multivariate imputation by chained equations (MICE) package in R (26). Five imputed datasets were generated and pooled together to report the estimates, expressed in odds ratios (OR), and their 95% confidence interval. All analyses were conducted in R 4.2.2 (27).

Descriptive statistics of the study population were calculated for the 2004 wave of the study. A two-level multilevel logistic Random Effects Within Between (REWB) model was used to assess the between-individual and within-individual associations of perceived neighborhood social cohesion with poor SAH. Perceived neighborhood social cohesion and the time-varying covariates were decomposed into their individual-specific means (between-individual estimates) and deviations from those individual-specific means (within-individual estimates). Between-individual estimates were calculated as the average individual's mean value of the variable across all time points, whereas within-individual estimates were calculated as a deviation score of the difference in time point specific values of each wave and the person-specific mean. The REWB models were adjusted for the time-varying and time-invariant covariates listed above. Moderation by age, educational level, and gender was assessed by including interaction terms between the between-individual and within-individual estimates of perceived neighborhood social cohesion and the respective moderating variables. For the moderation analysis age was dichotomized to adults aged sixty and older and younger adults, which is close to the median age of the study population (57) and the current average retirement age (i.e., 65) in the Netherlands.

Four sensitivity analyses were conducted. First, we examined the associations of perceived neighborhood social cohesion with poor SAH among all participants including those who changed neighborhoods during the observation period, which provides a more comprehensive perspective of the relationship between neighborhood social cohesion and SAH. Second, to detect all within-individual changes in SAH that occurred in our sample, we treated SAH as a continuous variable and estimated the relationship between perceived neighborhood social cohesion with SAH with REWB linear models. Third, we examined the association between perceived neighborhood social cohesion and lagged poor SAH, where health was lagged by one wave. Fourth, we examined the association between SAH and lagged perceived neighborhood social cohesion. The final two analyses assessed potential reverse causality.

Results

Descriptive statistics

Table 1 presents a description of the study population in the 2004 wave of the GLOBE study. The study population in 2004 consisted of 2,584 respondents, of which 55% were female. The average age was 53.8 years (SD: 13.6). Most respondents had a low educational level (43%) followed by high (29%) and middle (22%). Approximately 14% of the study population reported either fair or poor health. The average perceived neighborhood social cohesion score was 16.0 (SD: 2.4).

Table 1. Description of the study population in the 2004 wave of the GLOBE study.

Variables	N (%) or Mean (SD)	Range (min, max)
Total Participants	2,584	
Outcome		
Self-assessed health		
Good health	2,168 (83.9)	
Poor health	356 (13.8)	
Missing (%)	60 (2.3)	
Exposure		
Perceived social cohesion	16.0 (2.4)	(5, 20)
Missing (%)	145 (5.6)	
Time-invariant variables		
Gender (%)		
Male	1,149 (44.5)	
Female	1,435 (55.5)	
Birthplace (%)		
The Netherlands	2,360 (91.3)	
Elsewhere	168 (6.5)	
Missing	56 (2.2)	
Educational levels (%)		
Low	1,111 (43.0)	
Middle	590 (22.8)	
High	755 (29.2)	
Missing	128 (5.0)	
Time-varying variables		
Age	54.3 (12.4)	(25, 85)
Living arrangement, (%)		
Living with a partner	2,086 (80.7)	
Living without a partner	422 (16.3)	
Missing	76 (2.9)	
Employment status, (%)		
Employed	1,195 (46.3)	
Retired	649 (25.1)	
Unemployed	579 (22.4)	
Missing	321 (12.4)	
Household income, (%)		
<€1200	265 (10.3)	
€1200–€1800	572 (22.1)	
€1800–€2600	658 (25.5)	
>€2600	768 (29.7)	
Missing	321 (12.4)	
Financial strain, (%)		
No	1,808 (69.9)	
Yes	736 (28.5)	

Missing	40 (1.5)	
Years of residence	18.3 (13.0)	(0, 77)
Missing (%)	139 (5.4)	
Home ownership, %		
Home owner	1,744 (67.5)	
Renter	827 (32.0)	
Missing	13 (0.5)	
Household size (no. of persons)	2.5 (1.3)	(0, 30)
Missing (%)	13 (0.5)	

Table 2. Between-individual and within-individual associations of perceived neighborhood social cohesion and poor SAH from a two-level multilevel logistic REWB model, and moderation by age, educational level, and gender from participants who remained in the same neighborhood and with at least two waves of data

	Unadjusted model	Adjusted model [c]	Moderation models [c]		
			Age	Educational level	Gender
	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)
Between-individual estimates					
Social cohesion	0.63 (0.55, 0.71)	0.72 (0.65, 0.80)	0.77 (0.66, 0.89)	0.73 (0.63, 0.84)	0.73 (0.63, 0.84)
Old age					
< 60			Ref		
>= 60			18.96 (0.57, 620.15)		
Educational level					
Low		Ref	Ref	Ref	Ref
Middle		0.65 (0.37, 1.15)	0.57 (0.36, 0.89)	0.34 (0.01, 7.86)	0.58 (0.35, 0.97)
High		0.71 (0.41, 1.22)	0.59 (0.35, 1.01)	1.49 (0.04, 54.86)	0.63 (0.36, 1.09)
Gender					
Male		Ref	Ref	Ref	Ref
Female		0.86 (0.57, 1.31)	0.85 (0.54, 1.34)	0.85 (0.57, 1.27)	1.45 (0.07, 27.73)
Interaction terms					
Age x Social cohesion					
< 60			Ref		
>= 60			0.88 (0.72, 1.09)		
Educational level x Social cohesion					
Low				Ref	
Middle				1.04 (0.85, 1.26)	
High				0.95 (0.75, 1.19)	

Gender x Social cohesion					
Male					Ref
Female					0.96 (0.80, 1.16)
Within-individual estimates					
Social cohesion	0.95 (0.89, 1.02)	0.96 (0.89, 1.04)	0.93 (0.82, 1.05)	0.94 (0.88, 1.01)	0.93 (0.85, 1.02)
Age		1.08 (1.01, 1.16)		1.09 (1.02, 1.17)	1.11 (1.03, 1.19)
Old age					
< 60			Ref		
>= 60			0.96 (0.61, 1.49)		
Interaction terms					
Age x Social cohesion					
< 60			Ref		
>= 60			1.03 (0.87, 1.24)		
Educational level x Social cohesion					
Low				Ref	
Middle				1.07 (0.91, 1.25)	
High				0.98 (0.84, 1.14)	
Gender x Social cohesion					
Male					Ref
Female					1.04 (0.92, 1.18)
AIC [a]	5448	5152	5170	5163	5153
BIC [b]	5497	5380	5413	5419	5395

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets,

[c] adjusted for age, educational status, gender, birthplace, living arrangement, employment status, household income, financial strain, years of residence, home ownership, household size

Main analysis

Table 2 shows an unadjusted between-individual association, between more perceived neighborhood social cohesion and a lower odds of poor SAH (OR: 0.63 95%CI 0.55, 0.71). This relationship was slightly attenuated after adjusting for sociodemographic factors (OR: 0.72 95%CI 0.65, 0.80). Within-individual changes in perceived neighborhood social cohesion were not associated with changes in SAH, in both the unadjusted (OR: 0.95 95%CI 0.89, 1.02) and adjusted model (OR: 0.96 95%CI 0.89, 1.04).

Moderation analysis

The results from the moderation analysis indicate that age (OR: 0.88 95%CI 0.72, 1.09), educational level (Ref vs Middle: OR: 1.04 95%CI 0.85, 1.26, Ref vs High: OR: 0.95 95%CI 0.75, 1.19), and gender (OR: 0.96 95%CI 0.80, 1.16) did not moderate the between-individual association of perceived neighborhood social cohesion and SAH. We also did not find evidence for moderation by age (OR: 1.03 95%CI 0.87, 1.24), educational level (Ref vs Middle: OR: 1.07 95%CI 0.91, 1.25, Ref vs High: OR: 0.98 95%CI 0.84, 1.14) or gender (OR: 1.04 95%CI 0.92, 1.18) for the within-individual associations.

Sensitivity analysis

When examining all participants including those who changed neighborhood, we found that perceived neighborhood social cohesion was associated with a lower odds of poor SAH across individuals (OR: 0.74 95%CI 0.67, 0.81) after adjusting for sociodemographic factors, which is in line with the main analysis. The within-individual association between perceived social cohesion and poor SAH was in the same direction as the main analysis, but reached significance (OR: 0.93 95%CI 0.88, 0.98) after adjusting for sociodemographic factors.

When treating SAH as continuous variable, we found that that higher perceived neighborhood social cohesion across individuals was associated with better SAH after adjusting for sociodemographic factors ($\beta = 0.07$, 95%CI: 0.06; 0.08), which is consistent with the main analysis. Within-individual changes in perceived neighborhood social cohesion were positively associated with changes in SAH when accounting for sociodemographic factors ($\beta = 0.01$, 95%CI: 0.00; 0.02).

Similar to the finding from the main analysis, we observed that higher perceived neighborhood social cohesion was associated with a lower odds of poor health in the subsequent wave across individuals (OR: 0.71 95%CI 0.55, 0.93). We did not observe within-individual associations between perceived neighborhood social cohesion and the lagged SAH (OR: 0.99 95%CI 0.89, 1.11), which is consistent with main analysis.

The results from the final sensitivity analysis indicate that poor SAH was associated with lower perceptions of neighborhood social cohesion in the subsequent wave (β: -0.99 95%CI -1.26, -0.71). We did not observe within-individual associations of SAH and perceived neighborhood social cohesion in the subsequent wave (β: -0.04 95%CI -0.29, 0.21).

Discussion

The present study used REWB models to assess the between-individual and within-individual associations of perceived neighborhood social cohesion and poor SAH. Our findings suggest that higher perceptions of neighborhood social cohesion are associated with a lower odds of poor SAH. However, we did not find conclusive evidence that increases in perceived neighborhood social cohesion are associated with better SAH within individuals. This analysis also did not find evidence that either of these associations varied by age, educational level, or gender.

Our findings that higher perceptions of neighborhood social cohesion were associated with better SAH across individuals are in line with previous research that examined between-individual associations of perceived neighborhood social cohesion and SAH (4, 28-30) and was confirmed by the two sensitivity analyses that examined all participants and treated SAH as a continuous variable respectively.

Our findings for the within-individual associations of perceived neighborhood social cohesion and health were not as straightforward. The results from the main analysis, using the dichotomized SAH-variable among participants that did not relocate, revealed no clear within-individual association. However, when examining all participants or when using the numeric SAH variable, the results did suggest an association between changes in perceived neighborhood social cohesion and changes in SAH. The lack of association for the main analysis might be attributed to a lack of variation (i.e., a lack of change in binary SAH) in the outcome variable, which is a common limitation of fixed effects models (31). Using a dichotomous measure in a within model will only detect large changes or changes at the cut-off point (i.e., between good and fair), but not any changes that occur within the dichotomized categories such as from good to very good. This approach results in excluding a substantial amount of the available variation and a proportion of the sample, which is why the sensitivity analysis was performed. Furthermore, it should be noted that the magnitude of the within-individual associations were minimal and were much smaller than the between-individual associations. On the one hand, this may suggest that the impact of social cohesion on SAH is relatively limited, but on the other hand, this may imply that only drawing on within-individual changes may underestimate the total impact of social cohesion on health. Therefore, future research should leverage different study designs to help establish the true effect of social cohesion on health.

The findings from the lagged analyses were mixed. The between-individual associations showed that perceived neighborhood social cohesion was related to lagged SAH, which is in line with the main findings. However, we observed no within-individual associations in the lagged models. The lengths of the lags varied up to seven years, which may have been longer than the time it takes for changes in perceived neighborhood social cohesion to impact changes in SAH. In the final sensitivity analysis, we observed no relationships for within-individual associations of SAH and the lagged perceived neighborhood social cohesion. These findings provide some evidence against reverse causality and some validation for the direction of our hypothesis. Due to the lack of robustness of our within-individual associations, we cannot confidently state that these findings support our hypothesis that within-individual changes in perceived neighborhood social cohesion were associated with changes in SAH.

While investigating potential modifiers, we observed no variations in the association between perceived neighborhood social cohesion and health by age, educational level, or gender. Therefore, we cannot confirm that increasing perceptions of neighborhood cohesion is more beneficial for a particular subpopulation. We hypothesized that older adults would benefit more than younger adults since they

are more dependent on the social support in the community. However, since aging adults also face physical mobility issues, other neighborhood attributes like quality of the built environment and neighborhood disorder may play a more important role for the health of older adults than perceptions of the neighborhood social environment (32). The lack of studies that investigates the moderating effect of age on the association between the social environment and health indicates a knowledge gap for future research to address.

The moderating effect of SEP on social cohesion and health is still unclear. Some research support the buffering effects hypothesis, which posits that people from disadvantaged populations will have greater health benefits of social cohesion compared to people from non-disadvantaged populations (17). However, social cohesion and social capital are broad constructs and encompass numerous dimensions (28). Our study operationalized collective efficacy and sense of belonging as an index of the social environment. Therefore, it is possible that other dimensions of social cohesion could capture the moderating effect of SEP. Future research could distinguish between the different dimensions of social cohesion and consider their particular relationship with health (28).

Our study observed no differences between men and women. Although gender differences in the association of social cohesion or related social capital variables and health have been observed in prior research (16, 22, 33), it remains unclear which group have more favorable outcomes. Some research suggest that women may benefit more than men from higher levels of social cohesion (16) or area social capital (33) due to differences in the perceptions of the neighborhood, differences in the exposures within the neighborhood, and differences in vulnerabilities to certain aspects of the neighborhood. These findings underscore the interplay of factors explaining why men and women interact with their living environments differently. A plausible explanation for our results is that gender differences could be context-specific, and thus cultural differences in gender norms could influence whether men or women benefit more from changes in the social environment. As a leading country in gender egalitarianism, differences in gender norms might not be prominent in Dutch societies.

We acknowledge that our study also has some limitations. First, the measurements were based on self-reported survey data from the same data source making our results vulnerable to recall and same source biases. It would be methodological advantageous to use objective measurements from different data sources. Second, dichotomizing SAH resulted in a loss of information and given the limited sample size, the models might suffer from a substantial reduction of statistical power (31). Similarly, it is also plausible that our models lacked sufficient statistical power to detect the interaction effects.

Conclusion

Understanding how perceptions of the neighborhood influence health is a top public health priority. This study contributes to the literature by simultaneously examining the between-individual and within-individual associations of perceived neighborhood social cohesion and SAH. Our main findings provides further evidence for the relationship between perceived neighborhood social cohesion and SAH, and provides some evidence that increasing perceived neighborhood social cohesion may impact residents' health over time. With these new insights, policymakers can design interventions that improve health and reduce health disparities.

Conflict of interest

The authors declare no conflicts of interest

Funding

The study was supported by a grant from the European Commission HORIZON 2020 research as a part of the Marie Skłodowska-Curie Actions Innovative Training Networks [grant number 956780]; Erasmus Initiative 'Smarter Choices for Better Health'[no grant number]; and the Netherlands Organization for Scientific Research (NWO/ZonMw) [grant number 09150161810158 / VI.Veni.194.041]. The funders had no role in the study design or the analysis and interpretation of the data. All authors and their institutions reserve intellectual freedom from the funders.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

Key points

- Higher perceived neighborhood social cohesion is associated with better self-assessed health.
- The association between within-individual changes in perceived neighborhood social cohesion and within-individual changes in health is inconclusive.
- The association between perceived neighborhood social cohesion and self-assessed health does not vary by age, educational level, or gender.

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Appendix

Supplementary Table 1. Between-individual and within-individual associations of perceived neighborhood social cohesion and poor SAH with covariate coefficients from a two-level multilevel logistic REWB model, and moderation by age, gender and educational level from all participants

	Unadjusted model	Adjusted model	Moderation models		
	OR (95%CI)	OR (95%CI)	Age OR (95%CI)	Educational level OR (95%CI)	Gender OR (95%CI)
Between-individual estimates					
Social cohesion	0.79 (0.74, 0.84)	0.74 (0.67, 0.81)	0.85 (0.77, 0.94)	0.84 (0.65, 1.09)	0.80 (0.67, 0.95)
Age		1.07 (1.04, 1.10)		1.05 (1.00, 1.11)	1.07 (1.04, 1.09)
Old age					
< 60			Ref		
>= 60			60.00 (0.37, 9616)		
Educational level					
Low		Ref	Ref	Ref	Ref
Middle		0.63 (0.30, 1.30)	0.53 (0.18, 1.56)	6.95 (0.43, 112.29)	0.51 (0.20, 1.30)
High		0.51 (0.22, 1.15)	0.45 (0.17, 1.14)	2.26 (0.05, 101.50)	0.44 (0.23, 0.86)
Gender					
Male		Ref	Ref	Ref	Ref
Female		0.88 (0.47, 1.65)	0.73 (0.35, 1.52)	0.93 (0.37, 2.31)	2.18 (0.30, 15.67)
Birthplace					
Elsewhere		Ref	Ref	Ref	Ref
Netherlands		0.57 (0.27, 1.18)	0.56 (0.31, 1.01)	0.54 (0.23, 1.23)	0.46 (0.28, 0.76)
Living arrangements					
Without a partner		Ref	Ref	Ref	Ref
With a partner		1.10 (0.48, 2.49)	1.23 (0.57, 2.68)	0.88 (0.35, 2.19)	0.91 (0.55, 1.50)

Employment				
Employed	Ref	Ref	Ref	Ref
Retired	1.35 (0.49, 3.70)	4.12 (1.49, 11.35)	1.90 (0.50, 7.21)	1.36 (0.32, 5.75)
Unemployed	6.04 (2.18, 16.69)	10.20 (5.35 19.44)	6.26 (1.44, 27.12)	5.78 (2.78, 12.00)
Household income				
<€1200	Ref	Ref	Ref	Ref
€1200–€1800	0.19 (0.06, 0.59)	0.28 (0.04, 1.92)	0.36 (0.05, 2.42)	0.42 (0.05, 3.15)
€1800–€2600	0.18 (0.03, 0.85)	0.27 (0.04, 1.56)	0.28 (0.08, 1.01)	0.31 (0.09, 1.06)
>€2600	0.12 (0.01, 0.86)	0.14 (0.02, 0.91)	0.21 (0.04, 1.13)	0.24 (0.05, 1.06)
Financial strain				
No	Ref	Ref	Ref	Ref
Yes	4.63 (1.83, 11.68)	4.08 (2.16, 7.72)	4.06 (2.39, 6.90)	4.56 (2.09, 9.96)
Years of residence	0.97 (0.95, 1.00)	0.98 (0.97, 1.00)	0.98 (0.95, 1.00)	0.97 (0.94, 1.01)
Home ownership				
Renter	Ref	Ref	Ref	Ref
Home owner	0.52 (0.28, 0.98)	0.55 (0.30, 0.98)	0.54 (0.23, 1.30)	0.55 (0.33, 0.93)
Household size	0.89 (0.79, 1.00)	0.87 (0.71, 1.06)	0.92 (0.83, 1.02)	0.89 (0.80, 0.99)
Interaction terms				
Age x Social cohesion				
< 60		Ref		
>= 60		0.81 (0.59, 1.10)		
Educational level x Social cohesion				
Low			Ref	
Middle			0.86 (0.71, 1.04)	
High			0.91 (0.71, 1.16)	
Gender x Social cohesion				
Male				Ref
Female				0.94 (0.83, 1.07)

Within-individual estimates					
Social cohesion	0.92 (0.86, 1.00)	0.93 (0.88, 0.98)	0.90 (0.70, 1.15)	0.91 (0.84, 0.99)	0.91 (0.75, 1.12)
Age		1.12 (1.07, 1.17)		1.10 (1.02, 1.19)	1.11 (1.04, 1.18)
Older age					
< 60			Ref		
>= 60			0.76 (0.43, 1.35)		
Living arrangements					
Without a partner		Ref	Ref	Ref	Ref
With a partner		0.94 (0.34, 2.53)	0.75 (0.43, 1.28)	0.93 (0.50, 1.76)	0.83 (0.34, 2.02)
Employment					
Employed		Ref	Ref	Ref	Ref
Retired		0.92 (0.52, 1.60)	1.22 (0.45, 3.32)	1.13 (0.38, 3.37)	1.00 (0.45, 2.18)
Unemployed		2.55 (1.53, 4.23)	3.46 (1.04, 11.45)	2.58 (1.19, 5.56)	2.31 (0.55, 9.69)
Household income					
<€1200		Ref	Ref	Ref	Ref
€1200–€1800		0.93 (0.57, 1.53)	0.89 (0.47, 1.66)	1.15 (0.55, 2.40)	1.35 (0.86, 2.14)
€1800–€2600		0.97 (0.53, 1.77)	0.93 (0.36, 2.39)	1.14 (0.36, 3.55)	1.55 (0.58, 4.16)
>€2600		0.94 (0.45, 1.94)	0.90 (0.21, 3.81)	1.08 (0.19, 5.91)	1.49 (0.50, 4.41)
Financial strain					
No		Ref	Ref	Ref	Ref
Yes		1.85 (1.16, 2.94)	1.57 (0.84, 2.93)	1.62 (0.81, 3.22)	1.73 (0.91, 3.31)
Years of residence		0.99 (0.97, 1.01)	0.99 (0.96, 1.02)	0.99 (0.96, 1.01)	0.99 (0.98, 1.01)
Home ownership					
Renter		Ref	Ref	Ref	Ref
Home owner		0.59 (0.16, 2.21)	0.59 (0.06, 5.52)	0.71 (0.21, 2.40)	0.56 (0.28, 1.11)
Household size		0.97 (0.88, 1.06)	0.95 (0.84, 1.07)	0.96 (0.85, 1.08)	0.95 (0.87, 1.04)
Interaction terms					
Age x Social cohesion					
< 60			Ref		
>= 60			1.05 (0.72, 1.53)		

Educational level x Social cohesion					
Low				Ref	
Middle				1.09 (0.94, 1.26)	
High				0.99 (0.83, 1.18)	
Gender x Social cohesion					
Male					Ref
Female					1.04 (0.80, 1.35)
AIC [a]	9301	8942	9063	9020	8985
BIC [b]	9353	9187	9324	9295	9246

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets

Supplementary Table 2. Between-individual and within-individual associations of perceived neighborhood social cohesion and SAH with covariate coefficients from a two-level multilevel linear REWB model, and moderation by age, educational level, and gender from participants who remained in the same neighborhood and with at least two waves of data

	Unadjusted model	Adjusted model	Moderation models		
	β (95%CI)	β (95%CI)	Age β (95%CI)	Educational level β (95%CI)	Gender β (95%CI)
Between-individual estimates					
Social cohesion	0.09 (0.08; 0.11)	0.07 (0.06; 0.08)	0.06 (0.04; 0.08)	0.06 (0.04; 0.08)	0.07 (0.05; 0.08)
Age		-0.01 (-0.01; -0.00)		-0.01 (-0.01; -0.00)	-0.01 (-0.01; -0.01)
Old age					
< 60			Ref		
>= 60			-0.19 (-0.66; 0.26)		
Educational level					
Low		Ref	Ref	Ref	Ref
Middle		0.10 (0.03; 0.17)	0.11 (0.05; 0.18)	0.10 (-0.36; 0.58)	0.10 (0.03; 0.17)
High		0.11 (0.04; 0.19)	0.13 (0.05; 0.20)	-0.31 (-0.80; 0.17)	0.11 (0.04; 0.19)
Gender					
Male		Ref	Ref	Ref	Ref
Female		-0.01 (-0.06; 0.04)	-0.01 (-0.06; 0.04)	-0.01 (-0.06; 0.04)	-0.08 (-0.47; 0.30)
Birthplace					
Elsewhere		Ref	Ref	Ref	Ref
Netherlands		0.07 (-0.03; 0.17)	0.07 (-0.03; 0.17)	0.07 (-0.02; 0.18)	0.07 (-0.03; 0.17)
Living arrangements					
Without a partner		Ref	Ref	Ref	Ref

With a partner	-0.06 (-0.15; 0.01)	-0.07 (-0.16; 0.01)	-0.07 (-0.15; 0.01)	-0.06 (-0.15; 0.01)
Employment				
Employed	Ref	Ref	Ref	Ref
Retired	-0.10 (-0.22; 0.00)	-0.24 (-0.38; -0.11)	-0.10 (-0.22; 0.01)	-0.10 (-0.22; 0.01)
Unemployed	-0.35 (-0.46; -0.24)	-0.41 (-0.53; -0.30)	-0.35 (-0.45; -0.24)	-0.35 (-0.46; -0.24)
Household income				
<€1200	Ref	Ref	Ref	Ref
€1200–€1800	0.12 (-0.01; 0.26)	0.13 (-0.00; 0.27)	0.12 (-0.00; 0.26)	0.12 (-0.01; 0.26)
€1800–€2600	0.12 (-0.00; 0.26)	0.13 (-0.00; 0.26)	0.13 (-0.00; 0.27)	0.12 (-0.00; 0.26)
>€2600	0.28 (0.13; 0.44)	0.29 (0.13; 0.44)	0.28 (0.13; 0.44)	0.28 (0.13; 0.43)
Financial strain				
No	Ref	Ref	Ref	Ref
Yes	-0.25 (-0.33; -0.17)	-0.25 (-0.33; -0.16)	-0.25 (-0.33; -0.17)	-0.25 (-0.33; -0.17)
Years of residence	0.00 (-0.00; 0.00)	0.00 (-0.00; 0.00)	0.00 (-0.00; 0.00)	0.00 (-0.00; 0.00)
Home ownership				
Renter	Ref	Ref	Ref	Ref
Home owner	-0.00 (-0.07; 0.06)	0.00 (-0.06; 0.06)	-0.00 (-0.07; 0.06)	-0.00 (-0.07; 0.06)
Household size	0.01 (-0.00; 0.02)	0.01 (0.00; 0.02)	0.01 (-0.00; 0.02)	0.01 (-0.00; 0.02)
Interaction terms				
Age x Social cohesion				
< 60		Ref		
>= 60		0.00 (-0.02; 0.03)		
Educational level x Social cohesion				
Low			Ref	
Middle			-0.00 (-0.02; 0.02)	
High			0.02 (-0.00; 0.05)	

Gender x Social cohesion					
Male					Ref
Female					0.00 (-0.01; 0.02)
Within-individual estimates					
Social cohesion	0.01 (0.00; 0.02)	0.01 (0.00; 0.02)	0.01 (-0.00; 0.02)	0.01 (0.00; 0.02)	0.01 (-0.00; 0.02)
Age		-0.01 (-0.02; -0.00)		-0.01 (-0.02; -0.00)	-0.01 (-0.02; -0.00)
Old age					
< 60			Ref		
>= 60			0.02 (-0.03; 0.08)		
Living arrangements					
Without a partner		Ref	Ref	Ref	Ref
With a partner		-0.02 (-0.10; 0.05)	-0.02 (-0.10; 0.05)	-0.02 (-0.10; 0.05)	-0.02 (-0.10; 0.05)
Employment					
Employed		Ref	Ref	Ref	Ref
Retired		0.01 (-0.05; 0.08)	0.00 (-0.07; 0.07)	0.01 (-0.05; 0.08)	0.01 (-0.05; 0.08)
Unemployed		-0.11 (-0.19; -0.03)	-0.12 (-0.20; -0.04)	-0.11 (-0.19; -0.03)	-0.11 (-0.19; -0.03)
Household income					
<€1200		Ref	Ref	Ref	Ref
€1200–€1800		-0.02 (-0.11; 0.05)	-0.03 (-0.11; 0.05)	-0.02 (-0.11; 0.05)	-0.02 (-0.11; 0.05)
€1800–€2600		-0.01 (-0.12; 0.09)	-0.01 (-0.12; 0.08)	-0.01 (-0.12; 0.09)	-0.01 (-0.12; 0.09)
>€2600		0.01 (-0.11; 0.13)	0.00 (-0.11; 0.12)	0.01 (-0.11; 0.13)	0.01 (-0.11; 0.13)
Financial strain					
No		Ref	Ref	Ref	Ref

Yes		-0.03 (-0.09; 0.01)	-0.03 (-0.09; 0.01)	-0.03 (-0.09; 0.01)	-0.03 (-0.09; 0.01)
Years of residence		-0.00 (-0.00; 000)	-0.00 (-0.00; 0.00)	-0.00 (-0.00; 0.00)	-0.00 (0.00; 0.00)
Home ownership					
Renter		Ref	Ref	Ref	Ref
Home owner		0.04 (-0.13; 0.21)	0.04 (-0.13; 0.21)	0.04 (-0.13; 0.21)	0.04 (-0.13; 0.21)
Household size		0.00 (-0.00; 0.01)	0.00 (-0.00; 0.01)	0.00 (-0.00; 0.01)	0.00 (-0.00; 0.01)
Interaction terms					
Age x Social cohesion					
< 60			Ref		
>= 60			0.00 (-0.01; 0.02)		
Educational level x Social cohesion					
Low				Ref	
Middle				-0.00 (-0.02; 0.02)	
High				-0.00 (-0.02; 0.01)	
Gender x Social cohesion					
Male					Ref
Female					0.00 (-0.01; 0.02)
AIC [a]	16134.96	15727.01	15768.42	15758.98	15744.50
BIC [b]	16190.30	15962.21	16017.45	16021.84	15993.53

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets

Supplementary Table 3. Between-individual and within-individual associations of perceived neighborhood social cohesion and the lagged poor SAH from a two-level multilevel logistic REWB model

	Unadjusted Model	Adjusted Model [c]
	OR (95%CI)	OR (95%CI)
Between-individual estimates		
Social cohesion	0.73 (0.64, 0.83)	0.71 (0.55, 0.93)
Within-individual estimates		
Social cohesion	1.04 (0.64, 1.15)	0.99 (0.89, 1.11)
AIC [a]	4674	4713
BIC [b]	4714	4929

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets,

[c] adjusted for age, educational status, gender, birthplace, living arrangements, employment status, household income, financial strain, years of residence, home ownership, household size

Supplementary Table 4. Between-individual and within-individual associations of SAH and lagged perceived neighborhood social cohesion from a two-level multilevel linear REWB model

	Unadjusted Model	Adjusted Model [c]
	β (95%CI)	β (95%CI)
Between-individual estimates		
Self-assessed health		
Good health	Ref	Ref
Poor health	-1.46 (-1.71, -1.20)	-0.99 (-1.26, -0.71)
Within-individual estimates		
Self-assessed health		
Good health	Ref	Ref
Poor health	-0.07 (-0.32, 0.17)	-0.04 (-0.29, 0.21)
AIC [a]	28824	4713
BIC [b]	28871	4929

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets,

[c] adjusted for age, educational status, gender, birthplace, living arrangements, employment status, household income, financial strain, years of residence, home ownership, household size

Supplementary Table 5. Between-individual and within-individual associations of perceived neighborhood social cohesion and poor SAH with covariate coefficients from a two-level multilevel logistic REWB model, and moderation by age, educational level, and gender from participants who remained in the same neighborhood and with at least two waves of data

	Unadjusted model	Adjusted model	Moderation models		
	OR (95%CI)	OR (95%CI)	Age OR (95%CI)	Educational level OR (95%CI)	Gender OR (95%CI)
Between-individual estimates					
Social cohesion	0.63 (0.55, 0.71)	0.72 (0.65, 0.80)	0.77 (0.66, 0.89)	0.73 (0.63, 0.84)	0.73 (0.63, 0.84)
Age		1.06 (1.03, 1.09)		1.05 (1.02, 1.08)	1.05 (1.02, 1.09)
Old age					
< 60			Ref		
>= 60			18.96 (0.57, 620.15)		
Educational level					
Low		Ref	Ref	Ref	Ref
Middle		0.65 (0.37, 1.15)	0.57 (0.36, 0.89)	0.34 (0.01, 7.86)	0.58 (0.35, 0.97)
High		0.71 (0.41, 1.22)	0.59 (0.35, 1.01)	1.49 (0.04, 54.86)	0.63 (0.36, 1.09)
Gender					
Male		Ref	Ref	Ref	Ref
Female		0.86 (0.57, 1.31)	0.85 (0.54, 1.34)	0.85 (0.57, 1.27)	1.45 (0.07, 27.73)
Birthplace					
Elsewhere		Ref	Ref	Ref	Ref
Netherlands		0.50 (0.26, 0.97)	0.49 (0.25, 0.95)	0.50 (0.20, 1.25)	0.49 (0.26, 0.94)
Living arrangements					
Without a partner		Ref	Ref	Ref	Ref
With a partner		1.10 (0.48, 2.49)	1.13 (0.50, 2.54)	1.17 (0.62, 2.19)	1.14 (0.57, 2.29)
Employment					
Employed		Ref	Ref	Ref	Ref

Retired		1.47 (0.56, 3.88)	2.21 (0.87, 5.58)	1.83 (0.79, 4.24)	1.55 (0.62, 3.85)
Unemployed		6.82 (3.26, 14.24)	7.93 (3.84, 16.38)	7.44 (3.69, 14.99)	7.02 (3.22, 15.32)
Household income					
<€1200		Ref	Ref	Ref	Ref
€1200–€1800		0.34 (0.15, 0.80)	0.33 (0.13, 0.81)	0.43 (0.16, 1.11)	0.35 (0.13, 0.89)
€1800–€2600		0.28 (0.12, 0.67)	0.27 (0.10, 0.70)	0.33 (0.13, 0.80)	0.27 (0.11, 0.70)
>€2600		0.12 (0.04, 0.36)	0.13 (0.04, 0.40)	0.18 (0.06, 0.49)	0.14 (0.05, 0.42)
Financial strain					
No		Ref	Ref	Ref	Ref
Yes		2.57 (1.40, 4.73)	2.60 (1.40, 4.81)	2.74 (1.60, 4.69)	2.63 (1.50, 4.62)
Years of residence		0.97 (0.95, 0.99)	0.98 (0.96, 0.99)	0.98 (0.96, 0.99)	0.98 (0.96, 0.99)
Home ownership					
Renter		Ref	Ref	Ref	Ref
Home owner		0.68 (0.42, 1.09)	0.68 (0.45, 1.02)	0.66 (0.39, 1.11)	0.67 (0.42, 1.06)
Household size		0.98 (0.86, 1.11)	0.95 (0.85, 1.06)	0.98 (0.89, 1.07)	0.99 (0.87, 1.12)
Interaction terms					
Age x Social cohesion					
< 60			Ref		
>= 60			0.88 (0.72, 1.09)		
Educational level x Social cohesion					
Low				Ref	
Middle				1.04 (0.85, 1.26)	
High				0.95 (0.75, 1.19)	
Gender x Social cohesion					
Male					Ref
Female					0.96 (0.80, 1.16)
Within-individual estimates					
Social cohesion	0.95 (0.89, 1.02)	0.96 (0.89, 1.04)	0.93 (0.82, 1.05)	0.94 (0.88, 1.01)	0.93 (0.85, 1.02)

Age	1.08 (1.01, 1.16)		1.09 (1.02, 1.17)	1.11 (1.03, 1.19)
Old age				
< 60		Ref		
>= 60		0.96 (0.61, 1.49)		
Living arrangements				
Without a partner	Ref	Ref	Ref	Ref
With a partner	1.10 (0.59, 2.05)	0.91 (0.46, 1.79)	0.96 (0.49, 1.87)	1.11 (0.61, 2.01)
Employment				
Employed	Ref	Ref	Ref	Ref
Retired	1.03 (0.58, 1.85)	1.09 (0.56, 2.10)	0.98 (0.61, 1.60)	1.05 (0.61, 1.78)
Unemployed	2.18 (1.31, 3.62)	2.37 (1.22, 4.59)	1.98 (1.17, 3.36)	2.17 (1.25, 3.75)
Household income				
<€1200	Ref	Ref	Ref	Ref
€1200–€1800	1.11 (0.64, 1.94)	1.27 (0.64, 2.52)	1.07 (0.62, 1.83)	1.25 (0.71, 2.20)
€1800–€2600	1.07 (0.54, 2.10)	1.22 (0.66, 2.23)	1.00 (0.55, 1.79)	1.19 (0.65, 2.16)
>€2600	0.95 (0.45, 2.02)	1.12 (0.48, 2.63)	0.90 (0.43, 1.87)	1.06 (0.51, 2.22)
Financial strain				
No	Ref	Ref	Ref	Ref
Yes	1.61 (1.11, 2.33)	1.49 (0.91, 2.45)	1.45 (1.00, 2.09)	1.51 (1.05, 2.17)
Years of residence	1.01 (0.99, 1.03)	1.01 (1.00, 1.03)	1.01 (0.99, 1.02)	1.01 (0.99, 1.02)
Home ownership				
Renter	Ref	Ref	Ref	Ref
Home owner	1.28 (0.41, 3.96)	1.65 (0.29, 9.38)	1.27 (0.32, 4.96)	1.50 (0.44, 5.09)
Household size	0.98 (0.92, 1.05)	0.98 (0.91, 1.05)	0.98 (0.91, 1.06)	0.97 (0.91, 1.05)
Interaction terms				
Age x Social cohesion				
< 60		Ref		
>= 60		1.03 (0.87, 1.24)		
Educational level x Social cohesion				

Low				Ref	
Middle				1.07 (0.91, 1.25)	
High				0.98 (0.84, 1.14)	
Gender x Social cohesion					
Male					Ref
Female					1.04 (0.92, 1.18)
AIC [a]	5448	5152	5170	5163	5153
BIC [b]	5497	5380	5413	5419	5395

[a] average Akaike information criterion from the five imputed datasets,

[b] average Bayesian information criterion from the five imputed datasets

Chapter 3: Exploring how the interplay between neighborhood perceptions and social cohesion relates to self-assessed health: a four-way decomposition with a 10-year follow up

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Journal of Urban Health. 2026; 103: 406-415

Abstract

The present study investigated the extent to which the relationship between perceptions of neighborhood unsafety and disorder and self-assessed health (SAH) is explained by mediation, interaction, or a combination of both through perceived neighborhood social cohesion. We analyzed data on 5,650 respondents over a 10-year follow-up using the GLOBE study, a prospective cohort study in the Netherlands. Log-linear regression analyses were used to estimate the total effects of feeling unsafe and perceived neighborhood disorder with poor SAH. A four-way decomposition approach was used to decompose the total effects into four components: controlled direct effect (neither mediation nor interaction), pure indirect effect (mediation only), reference interaction effect (interaction only) and mediated interaction effect (both mediation and interaction). The results indicate that feeling unsafe had a positive estimated total effect on poor SAH (RR = 1.05, 95% CI: 1.01, 1.10). For perceived neighborhood disorder the estimated total effect was smaller (RR = 1.01, 95% CI: 1.00, 1.04). Decomposition analysis indicated that the majority of the estimated effect of perceived unsafety was attributed to the controlled direct effect (ERR = 0.09, 95% CI: 0.05, 0.13), with no evidence of mediation or interaction through social cohesion. None of the estimated decomposition components were significant for neighborhood disorder. These findings suggest that perceived neighborhood disorder and unsafety and perceived neighborhood social cohesion appear to influence health through independent pathways, rather than through their interplay.

Introduction

Over the past twenty years, there has been a growing body of research examining the relationship between neighborhood characteristics and health [1]. In this research, neighborhood conditions are often appraised by the individuals' perceptions of their neighborhood living environment [2]. Empirical evidence suggests that perceptions of neighborhood unsafety and disorder are linked to health outcomes [1]. Perceived neighborhood disorder refers to "visible cues indicating a lack of order and social control in the community" [3]. Such cues can be characterized as either physical disorder or social disorder. Neighborhoods with high physical disorder indicate the presence of litter, graffiti, and vandalism, whereas signs of social disorder include loitering, nuisances, and violence [3]. Previous research has shown that individuals who perceive their neighborhood as unsafe and having more disorder are more likely to have worse health outcomes than those who feel safe in their neighborhood and having less disorder [4-7]. However, the underlying pathways remain unclear.

A prominent framework for explaining the role of neighborhood disorder is the Broken Window Theory. This theory proposes that the presence of disorder may signal danger and threat, thereby hindering the development of social cohesion within communities [5,8]. Since higher perceptions of neighborhood cohesion are associated with positive health outcomes [9], it may partly mediate the association between perceptions of neighborhood unsafety and disorder and health. Indeed, a 2022 longitudinal mediation analysis found that lower engagement in social activities partly explained the association between perceived crime and depressive symptoms in older European adults [10].

In addition to exploring potential mediation effects, it is important to consider the possibility of an interaction effect between perceptions of neighborhood unsafety and disorder and perceived neighborhood social cohesion. Communities with high levels of cohesion tend to have trusting relationships among residents, which promotes collective efficacy, informal social control, and reciprocity [11]. Such mechanisms might buffer the negative impact of unsafe feelings and perceived neighborhood disorder on health [12]. While a few studies have tested this hypothesis, findings are not consistent [7,13,14]. Moreover, extant research has only examined either mediation or interaction in isolation, without considering the potential co-occurrence of both mechanisms. Results from previous mediation analysis are therefore likely to be biased, since traditional mediation analysis assumes the absence of an interaction between exposure and mediator [15,16].

This study draws on recent advances in counterfactual mediation analysis to assess both processes of mediation and interaction simultaneously, and to quantify the total effect between exposure and outcome into four components. Specifically, we aim to examine the extent to which the relationships between perceived neighborhood unsafety and neighborhood disorder and self-assessed health are explained by mediation, interaction, or combination of both through perceived neighborhood social cohesion [17].

Methods

Data

Data from this study come from the GLOBE Study, a prospective cohort study aimed at understanding socioeconomic inequalities in health in the Netherlands. Baseline measurements were taken in 1991 on

a representative sample of 27,070 adults from the city of Eindhoven and surrounding villages [18]. A smaller subset was followed up in subsequent waves via postal surveys and oral interviews [18]. More details about the GLOBE study are available elsewhere [18]. This analysis included data from the follow-up surveys in 2004, 2011, and 2014. Participants that relocated to a different neighborhood during the follow-up period were excluded (see Figure 1).

Outcome

The outcome variable is self-assessed health (SAH) that was reported in 2014. Respondents were asked the single-item question on their perceived health: How would you rate your health in general? The five response categories ranged from poor, fair, good, very good, and excellent. The variable was dichotomized into poor health (poor and fair) and good health (good, very good, and excellent), with good health serving as the reference.

Exposures

Perceived neighborhood unsafety was assessed in 2004 using three items. Respondents were asked the extent they agree with three statements about the safety of their neighborhood: 1) "In this neighborhood I am sometimes afraid to walk the streets alone at night", 2) "In this neighborhood I am sometimes afraid to walk the streets alone in the daytime", and 3) "In this neighborhood I am sometimes afraid to stay home alone at night". Response categories were 'disagree', 'neither agree nor disagree', and 'agree', ranging from 0 to 2, respectively. Following the work of Kamphuis et. al [19], a composite score was constructed by summing the three items, with a high score indicating more unsafe feelings.

Perceived neighborhood disorder was measured with eleven items, which asked respondents how often they think certain bad incidents occur in their neighborhood. Bad incidents included litter, vandalism, graffiti, youth nuisance, bicycle thefts, breaking into cars, breaking into houses, drunkenness on the street, harassment on the street, threats, and violent crimes. Response categories included almost never (1), sometimes (2), and often (3). Following previous research [20,21], we summed the 11 items to construct a composite score indicating an overall assessment of local problems with the higher score indicating greater problems in the neighborhood.

Mediator

Perceived neighborhood social cohesion was assessed in the 2011 follow-up survey using a four-item scale based on two widely used instruments [11,22,23]. Respondents were asked to what extent they agree or disagree with the following questions about their neighborhood: (a) People in this neighborhood get along with each other pleasantly, (b) People in this neighborhood are willing to help each other (c) I often feel alone in this neighborhood, and (d) I would move out of this neighborhood if I get the chance. The first two items capture perceived collective efficacy, whereas the last two items measure a sense of belonging [23]. Response categories were 'strongly agree', 'agree', 'neither agree nor disagree', 'don't

agree', and 'strongly don't agree', ranging from 1 to 5. The four items were summed and reverse coded so that higher values indicating less social cohesion.

Covariates

This analysis adjusted for the following individual sociodemographic characteristics from 2004: gender (male, female), age (years), living arrangement (living with a partner, living without an partner), educational level according to the International Standard Classification of Education (low = ISCED 0–2, middle = ISCED 3–4, high = ISCED 5–8), household income (<€1200, €1200–1800, €1800–2600, >€2600), employment status (employed, unemployed, retired), and baseline SAH (good health, poor health).

Data analysis

Descriptive statistics were used to describe the baseline sociodemographic characteristics and neighborhood perceptions of the study population in 2004, social cohesion measurements in 2011, and SAH in 2014.

Log-linear regression models were used to assess the overall relationships of perceptions of unsafe feelings and perceived neighborhood disorder and poor SAH, and to assess the relationship between perceived neighborhood social cohesion and poor SAH. Estimates were reported as relative risks with their 95% confidence intervals. Linear regression models were used to assess the relationships of the two exposures with perceived neighborhood social cohesion, with estimates reported as beta coefficients and 95% confidence intervals. Missing values for exposures, mediator, outcome and baseline characteristics were handled by using the multivariate imputation by chained equations package in R (M = 20) [24].

A four-way decomposition framework was used to estimate the mediating and interaction effects of perceived neighborhood social cohesion on the relationships between perceptions of unsafe feelings and perceptions of neighborhood disorder and poor SAH. This approach decomposes the total effect into four components: a controlled direct effect, a reference interaction, a mediated interaction, and a pure indirect effect [17]. A detailed description of each component's definition based on the counterfactual framework and their interpretation in the context of the current study are presented in Table 1. In addition to the consistency and positivity assumptions, the four-way decomposition requires the assumptions of no unmeasured confounding of the exposure–outcome, exposure–mediator, and mediator–outcome relationships, and that there are no mediator–outcome confounders that are themselves affected by the exposure [17]. These assumptions are encoded in the Directed Acyclic Graph depicted in Figure 2 that underlies our analytical approach. The four-way decomposition analysis was conducted in CMAverse package in R, which applied multiple imputation internally [25]. The reference level of the mediator was set to its median (i.e., 9) and 95% confidence intervals were obtained by normal distribution approximation. Estimates were expressed as excess relative risk (ERR), which was calculated as the relative risk minus one (ERR = RR – 1). All models in this study were adjusted for baseline sociodemographic and baseline health status. All analyses were performed in R 4.2.2 [26].

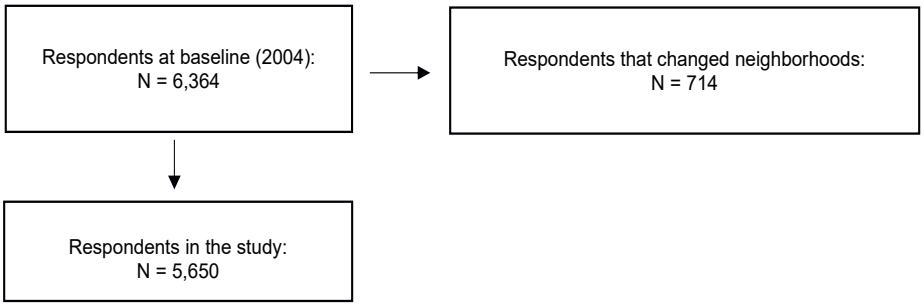


Figure 1. Flow chart of the respondents in the study.

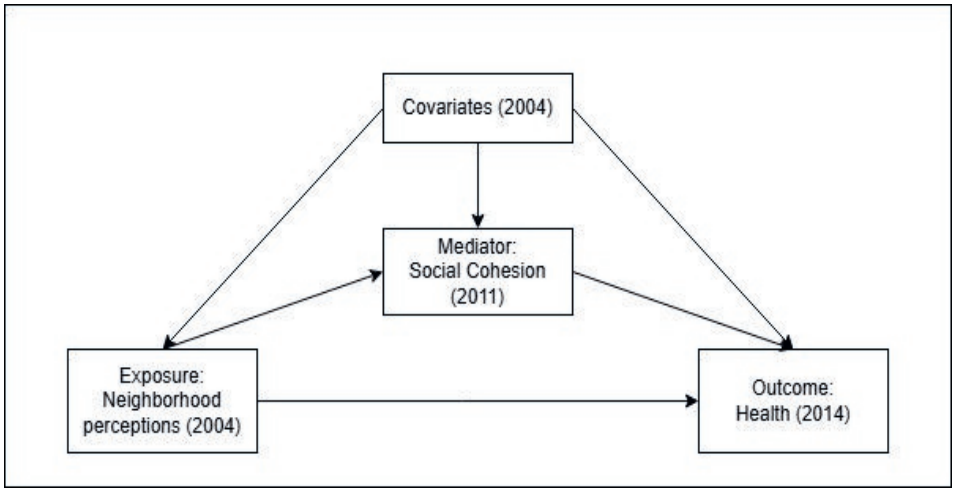


Figure 2. Directed acyclic graph for the hypothesized effect of neighborhood perceptions on self-assessed health, mediated by social cohesion, and adjusted for baseline covariates: gender, age, living arrangement, educational level, household income, employment status, and baseline self-assessed health.

Table 1. Definitions of the four-way decomposition as applied to the current study.

Causal Estimand	Notation[17]	Interpretation
Controlled direct effect (CDE)	$Y_{10}-Y_{00}$	The effect of perceived neighborhood disorder/unsafety on SAH that is neither mediated through nor modified by perceived neighborhood social cohesion. In other words, perceived neighborhood disorder/unsafety affects SAH through pathways completely independent of perceived neighborhood social cohesion.
Pure indirect effect (PIE)	$(Y_{01}-Y_{00})(M_1-M_0)$	The effect of perceived neighborhood disorder/unsafety on SAH that operates through perceived neighborhood social cohesion as a mediator, in the absence of interaction. This means perceived neighborhood disorder/unsafety improves health solely because it increases perceived neighborhood social cohesion, which in turn improves SAH.
Reference interaction (INTref)	$(Y_{11}-Y_{10}-Y_{01}+Y_{00})(M_0)$	The effect attributable to interaction between perceived neighborhood disorder/unsafety and perceived neighborhood social cohesion, but not through mediation. This means the effect of perceived neighborhood disorder/unsafety on SAH differs depending on the level of perceived neighborhood social cohesion, but this is not because perceived neighborhood disorder/unsafety caused perceived neighborhood social cohesion.
Mediated interaction (INTmed)	$(Y_{11}-Y_{10}-Y_{01}+Y_{00})(M_1-M_0)$	The effect of perceived neighborhood disorder/unsafety on SAH attributable to both mediation by and interaction with perceived neighborhood social cohesion. This means perceived neighborhood disorder/unsafety affects perceived neighborhood social cohesion, and perceived neighborhood social cohesion in turn modifies the effect of perceived neighborhood disorder/unsafety on health.

Table 2. Descriptive statistics of the study population.

	N (%) or mean (SD)	Median (min, max)
Sample size	5,650 (100.0%)	
Covariates		
Gender		
Male	2,631 (46.6%)	
Female	3,019 (53.4%)	
Age	56.6 (15.6)	59.0 (23, 90)
Missing	66 (1.2%)	
Living arrangements		
Living without a partner	1,145 (20.3%)	
Living with a partner	4,194 (74.2%)	
Missing	311 (5.5%)	
Education		
Low	2,555 (45.2%)	
Middle	1,192 (21.1%)	
High	1,500 (26.5%)	
Missing	403 (7.1%)	
Household income		
<1200	781 (13.8%)	
1200-1800	1,229 (21.8%)	
1800-2600	1,332 (23.6%)	
>2600	1,431 (25.3%)	
Missing	877 (15.5%)	
Employment status		
Employed	1,216 (44.6%)	
Retired	759 (27.9%)	
Unemployed	562 (20.6%)	
Missing	187 (6.9%)	
Baseline self-assessed health		
Good health	4,424 (78.3%)	
Poor health	1,062 (18.8%)	
Missing	164 (2.9%)	
Exposures		
Perceived unsafety	0.8 (1.3)	0 (0, 6)
Missing	142 (2.5%)	
Perceived disorder	14.7 (3.6)	14 (11, 33)
Missing	352 (6.2%)	
Mediator		
Social cohesion	8.8 (2.5)	8 (5, 20)
Missing	2,838 (50.2%)	
Outcome		
Self-assessed health		
Good health	2,107 (37.3%)	

Poor health	490 (8.7%)
Missing	3,053 (54.0%)

Table 3. Estimated effects of perceptions of feeling unsafe and perceptions of neighborhood disorder on reporting poor self-assessed health.

	Perceived unsafety		Perceived disorder	
	Model 1	Model 2	Model 1	Model 2
	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)
Perceived unsafety	1.05 (1.01, 1.10)	1.04 (0.99, 1.09)		
Perceived disorder			1.01 (1.00, 1.04)	1.01 (1.00, 1.03)
Social cohesion*		1.04 (1.01, 1.08)		1.04 (1.01, 1.08)
Gender				
Male	Ref	Ref	Ref	Ref
Female	0.99 (0.86, 1.14)	1.01 (0.87, 1.16)	1.02 (0.89, 1.19)	1.03 (0.89, 1.19)
Age	1.01 (1.00, 1.02)	1.01 (1.00, 1.02)	1.01 (1.00, 1.02)	1.01 (1.00, 1.02)
Living arrangement				
Living alone	Ref	Ref	Ref	Ref
Living with partner	0.85 (0.72, 1.01)	0.87 (0.74, 1.04)	0.86 (0.72, 1.02)	0.88 (0.74, 1.05)
Education level				
Low	Ref	Ref	Ref	Ref
Middle	0.74 (0.58, 0.95)	0.73 (0.57, 0.94)	0.73 (0.57, 0.94)	0.73 (0.57, 0.93)
High	0.64 (0.50, 0.83)	0.64 (0.50, 0.82)	0.64 (0.50, 0.82)	0.63 (0.49, 0.81)
Income				
<1,200	Ref	Ref	Ref	Ref
1,200-1,800	1.05 (0.84, 1.30)	1.06 (0.85, 1.31)	1.04 (0.84, 1.29)	1.05 (0.85, 1.30)
1,800-2,600	0.95 (0.74, 1.22)	0.98 (0.76, 1.26)	0.95 (0.73, 1.22)	0.97 (0.75, 1.25)
>2,600	0.87 (0.64, 1.19)	0.90 (0.66, 1.24)	0.87 (0.64, 1.19)	0.90 (0.66, 1.23)
Employment status				
Employed	Ref	Ref	Ref	Ref
Retired	1.17 (0.88, 1.57)	1.18 (0.88, 1.57)	1.19 (0.89, 1.58)	1.19 (0.89, 1.58)
Unemployed	1.13 (0.90, 1.43)	1.12 (0.89, 1.42)	1.13 (0.90, 1.42)	1.12 (0.89, 1.42)
Baseline health				
Good health	Ref	Ref	Ref	Ref
Poor health	3.73 (3.16, 4.41)	3.61 (3.04, 4.28)	3.76 (3.18, 4.45)	3.63 (3.06, 4.31)

Model 1 includes baseline covariates (measured in 2004). Model 2 includes baseline covariates (measured in 2004) and social cohesion (measured in 2011). Social cohesion was reverse coded so that a high value means less cohesion.

Table 4. Estimated effects of perceptions of feeling unsafe and perceptions of neighborhood disorder on perceived neighborhood social cohesion.

	Perceived unsafety	Perceived disorder
	β (95%CI)	β (95%CI)
Perceived unsafety	0.31 (0.23, 0.40)	
Perceived disorder		0.11 (0.08, 0.14)
Gender		
Male	Ref	Ref
Female	-0.42 (-0.62, -0.23)	-0.26 (-0.46, -0.06)
Age	-0.02 (-0.03, -0.01)	-0.02 (-0.03, -0.01)
Living arrangement		
Living alone	Ref	Ref
Living with partner	-0.60 (-0.85, -0.34)	-0.56 (-0.82, -0.31)
Education level		
Low	Ref	Ref
Middle	0.16 (-0.13, 0.45)	0.10 (-0.19, 0.39)
High	0.22 (-0.03, 0.47)	0.16 (-0.09, 0.41)
Income		
<1,200	Ref	Ref
1,200-1,800	-0.26 (-0.65, 0.13)	-0.33 (-0.71, 0.05)
1,800-2,600	-0.70 (-1.06, -0.33)	-0.73 (-1.10, -0.37)
>2,600	-0.84 (-1.21, -0.47)	-0.85 (-1.23, 0.48)
Employment status		
Employed	Ref	Ref
Retired	0.15 (-0.22, 0.51)	0.19 (-0.17, 0.56)
Unemployed	0.29 (0.02, 0.57)	0.29 (0.02, 0.56)
Baseline health		
Good health	Ref	Ref
Poor health	0.90 (0.62, 1.19)	0.14 (0.66, 1.22)

Table 5. Four-way decomposition of the estimated effects of perceptions of feeling unsafe and perceptions of neighborhood disorder mediated by perceived neighborhood social cohesion.

	Perceived unsafety	Neighborhood disorder
	ERR (95% CI)	ERR (95%CI)
CDE	0.09 (0.05, 0.13)	0.03 (-0.06, 0.11)
INTref	-0.00 (-0.06, 0.05)	0.00 (-0.08, 0.08)
INTmed	0.00 (-0.01, 0.01)	-0.00 (-0.00, 0.00)
PIE	0.01 (-0.00, 0.03)	0.01 (-0.00, 0.03)

ERR is excess relative risk, CDE is controlled direct effect; INTref is reference interaction; INTmed is mediated interaction; PIE is pure indirect effect. Models are adjusted for baseline covariates of gender, age, living arrangement, educational level, household income, employment status, and self-assessed health.

Results

Of the 6,463 respondents who participated at baseline, 714 were excluded due to moving to a different neighborhood during the study period, resulting in 5,650 participants for the analyses. Table 2 presents a summary of the study population. The average score for unsafe perceptions was 0.8 out of possible score of 6, while the average score for perceptions of neighborhood disorder was 14.7 out of possible score of 33. Approximately 9% of the study population reported poor SAH. The average age of the study population was 56.

The estimated effects of perceived unsafety and neighborhood disorder on reporting poor SAH are presented in Table 3. A one unit increase in feeling unsafe was associated with a 5% higher probability of reporting poor SAH while adjusting for baseline characteristics (RR = 1.05, 95% CI: 1.01, 1.10), while a one unit increase in perceptions of neighborhood disorder was associated with a 1% increase in the probability of reporting poor SAH (RR = 1.01, 95% CI: 1.00, 1.04).

The estimated effects of perceived neighborhood social cohesion on reporting poor SAH are also presented in Table 3. The results indicated that perceiving less social cohesion was associated with a higher probability of reporting poor SAH, controlling for either perceptions of unsafety or perceived neighborhood disorder (RR = 1.04, 95% CI: 1.01, 1.08).

Table 4 presents the estimated effects of perceived unsafety and neighborhood disorder on (reverse coded) perceived neighborhood social cohesion. We observed that a higher perceptions of feeling unsafe (β = 0.31, 95% CI: 0.23, 0.40) and more perceived neighborhood disorder (β = 0.11, 95% CI: 0.08, 0.14) were associated with less perceived neighborhood social cohesion.

The results of the four-way decomposition analysis are presented in Table 5. There was a positive direct effect estimate between perceptions of unsafe feelings and reporting poor SAH (CDE ERR = 0.09, 95% CI: 0.05, 0.13). The INTref (ERR = -0.00, 95% CI: -0.06, 0.05), INTmed (ERR = 0.00, 95% CI: -0.01, 0.01), and PIE (ERR = 0.01, 95% CI: -0.00, 0.03) were close to null. Results for perceptions of neighborhood disorder were similar, except that the positive direct effect estimate was much smaller and confidence intervals included the null (CDE ERR = 0.03, 95% CI: -0.06, 0.11).

Discussion

This study found that perceived neighborhood unsafety was associated with a higher probability of poor SAH, independently of perceived neighborhood social cohesion. Although perceived neighborhood social cohesion was also positively associated with SAH, the four-way decomposition analysis revealed that the estimated total effect of perceived neighborhood unsafety on SAH was attributable entirely to its pure direct effect, indicating that social cohesion neither mediated nor interacted with this relationship. The relationship between perceived neighborhood disorder and SAH was much weaker.

This study contributes to the literature in a number of ways. First, a key strength of this study is its longitudinal design, which allowed us to examine the pathways linking perceptions of unsafety and neighborhood disorder, social cohesion, and health outcomes while establishing temporal precedence. Second, we applied a four-way decomposition framework, which, to our knowledge, has not been used in this context to disentangle potential mediation and interaction effects of social cohesion on the relationships between perceptions of unsafe feeling, neighborhood order, and SAH.

However, this study also has several limitations to consider. An important limitation is the long interval between measurements: the exposure was measured in 2004, the mediator in 2011, and the outcome in 2014. While this study design establishes temporal precedence, the long gap limits the ability to capture causal dynamics between perceptions of neighborhood unsafety/disorder and social cohesion. As a result, measurement error in the mediator is possible, which can attenuate estimates of indirect effects and may partially explain the limited evidence for mediation [15]. Additionally, the reliance on self-reported data may introduce same-source bias and additional measurement errors. This could result in inflating the relationship between these variables [27]. Attrition bias due to a large loss to follow-up was another concern, which we try to mitigate using multiple imputation to account for missing data. However, this approach is only valid under the assumption that missingness was random given the observed data included in our imputation model. The four-decomposition analysis is based on the assumptions conditional exchangeability [17]. While we attempted to address this assumption by adjusting for baseline sociodemographic characteristics and baseline health status, unmeasured confounding, including potential time-varying confounders influenced by prior exposure, may still exist.

Our findings indicate that the relationship between perceived neighborhood unsafety and health is consistent with previous research, providing further evidence that perceiving the neighborhood as safe is beneficial to individual health [7,28]. This relationship seemed stronger for perceived unsafety than for perceived disorder, which aligns with previous research showing an inconsistent relationship between perceived neighborhood disorder and health [5,29]. One possible explanation for the stronger health impact of safety feelings is that feeling unsafe may trigger stronger stress responses than observing neighborhood disorder. Residents may not always interpret signs of neighborhood disorder as a personal threat, particularly if they have become accustomed to it. These findings suggest that policies aiming to improve population health should prioritize enhancing residents' sense of safety, rather than focusing solely on reducing visible signs of disorder.

The results from the four-way decomposition analysis indicate that the majority of the relationship between perceived unsafety and SAH was attributable to the direct pathway. Furthermore, we found no evidence that perceived neighborhood social cohesion mediated or interacted with this relationship. This suggests that social cohesion may not be a primary mechanism linking neighborhood perceptions to health. Few studies have investigated the mediating role of social cohesion in the association between

perceived (un)safety and health, limiting opportunities for comparison. This gap in the literature may reflect the difficulty of disentangling perceived safety from social cohesion, as these constructs show some conceptual and empirical overlap [30,31]. Future research could benefit from adopting a pluralistic approach, combining qualitative and quantitative methods to better capture the complex interplay of different neighborhood characteristics in shaping health outcomes.

In conclusion, this study found that perceived neighborhood safety was associated with better SAH independently of perceived neighborhood social cohesion. Although social cohesion was also associated with better SAH, it seems to neither carry nor modify the health benefits of higher perceived neighborhood safety. These findings suggest that neighborhood safety and social cohesion represent distinct and independent pathways to better health, and that interventions targeting either dimension may yield separate health benefits without relying on or amplifying the other.

Contributorship Statement

VC participated in study concept and design, data analyses, and writing and revising the manuscript. JOG participated in study concept and design and revising the manuscript. MAB participated in study concept and design and revising the manuscript. FJvL participated in study concept and design and revising the manuscript and serves as the guarantor.

Ethics Approval

The use of personal data in the GLOBE study is in compliance with the Dutch Personal Data Protection Act and the Municipal Database Act and has been registered with the Dutch Data Protection Authority (number 1248943).

Conflict of interest

The authors declare no conflicts of interest.

Funding

VC received funding from the European Commission HORIZON 2020 research as a part of the Marie Skłodowska-Curie Actions Innovative Training Networks [grant number 956780]; JOG received funding from the Erasmus Initiative 'Smarter Choices for Better Health'[no grant number]; and MAB received funding from the Netherlands Organization for Scientific Research (NWO/ZonMw) [grant number 09150161810158 / VI.Veni.194.041]. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. All authors and their institutions reserve intellectual freedom from the funders.

Data availability

The data underlying this article is available upon reasonable request and with specific restrictions. Access can be requested from the corresponding author.

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Chapter 4: Social network characteristics and levels of and fluctuations in momentary depressive symptomatology among older adults

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Journal of Epidemiology & Community Health. 2025; 79 (11): 828-834

Abstract

Background

Social networks are known to protect against depressive symptoms in older adults. However, most research relies on retrospective self-reported depression measures and cross-sectional data, which may introduce bias. Ecological Momentary Assessment (EMA) with longitudinal data overcomes these limitations by repeatedly measuring the subject's experience in the present moment. This study examined how social network characteristics relate to momentary depressive symptoms and their daily fluctuations in older adults.

Methods

We analyzed data from 216 older adults in Paris, France, using the HANC-MINDMAP studies. Social network characteristics included network size and frequency of in-person and digital interactions per week. Depressive symptomatology was assessed using a daily smartphone survey of the Center for Epidemiological Studies-Depression (CES-D8) over a week. Linear mixed-effect models estimated associations between social network characteristics and momentary depressive symptoms, while multivariable linear models examined relationships with daily symptom fluctuations.

Results

Network size and frequency of contact from digital communications per week were not associated with fewer depressive symptoms; however, there was suggestion that having more in-person contact was related to fewer depressive symptoms (exp(β) = 0.90, 95%CI 0.82, 1.00). Moreover, having a larger social network (exp(β) = 0.91, 95%CI: 0.85, 0.98) and more in-person contacts (exp(β) = 0.96, 95%CI: 0.93, 0.98) were associated with less fluctuations in daily depressive symptoms, but no association for the frequency of contact from digital communications was observed.

Conclusion

Findings from this study suggest that larger social networks and more in-person contact may promote more stable and better mental health among older adults.

Keywords

Ecological momentary assessment, depression, social network, older adults

What is already known on this topic

Depression in older adults is an important public health issue, especially since the world's population of people aged 60 years and older is expected to rise rapidly. Previous research has shown that certain social network characteristics protect against depressive symptoms in older adults. However, these findings are largely based on retrospective self-reported measures of depression and cross-sectional analyses, which are prone to measurement error, recall bias, and reverse causation.

What this study adds

Ecological momentary assessment (EMA) uses repeated collection of real-time data on subjects' behavior and experience in their natural environments. Using a longitudinal dataset with a baseline survey and repeated measurements of depression, this study found that having more frequent in-person contacts with members of the social network was related to less depressive symptoms; and that having a larger social network and more frequent in-person contacts with members of the social network were associated with less fluctuations in depressive symptoms.

How this study might affect research, practice or policy

This study provides further evidence that larger social networks and more in-person interactions might mitigate daily fluctuations in depressive symptoms among older adults. Developing interventions (e.g., in the form of contexts or events) that provide opportunities for building social ties could be a viable approach to promote a stable mental health among older adults.

Introduction

Depression in older adults is an important public health issue. Older adults with depression have a higher risk of morbidity, suicide, and mortality from other causes as well as less physical, cognitive, and social functioning compared to non-depressed older adults [1]. A recent systematic review and meta-analysis found that the overall global prevalence of depressive symptoms in older adults was 28.4% [2]. Further complicating matters, it is estimated that one in six people in the world will be aged 60 years or over by 2030, and this number is expected to increase to two billion people by 2050 [3]. Accordingly, this rapid growth in the world's population of people aged 60 years and older presents significant challenges to public health officials to prevent suffering and reduce healthcare costs related to depression in older adults.

Social relationships could play a crucial role in preventing and mitigating depression among older adults [4]. The social network, for example, is considered a key determinant of healthy ageing [5]. Social networks refer to the structure of social relationships and consist of multiple characteristics, such as the size of the network and the frequency of interactions [5]. Considered as a structural basis for social capital within public health research [6], social networks provide access to material resources and various forms of support, and can buffer the stress of adverse life events [5]. Such benefits are important to older adults who face declining mobility and more social isolation. Understanding the impact of social networks on depressive symptomatology in older adults is important for developing effective gerontological interventions.

Research on the influence of social network characteristics on depression has gained much needed attention. However, the evidence for certain social network characteristics is inconclusive and this research is marred by limitations [7]. A 2015 systematic review found that a larger social network was a protective factor against depressive symptoms, but it did not find consistent evidence for the role of frequency of social contact on depression [7]. The majority of the studies relied on retrospective self-reports to assess depressive symptomology, which is subject to recall distortion and can lead to measurement errors [8]. Furthermore, the analysis of purely cross-sectional survey data amplifies the risk of reverse causation, as depression can lead people to withdraw from their social network.

One approach that can attenuate recall error and memory distortion is ecological momentary assessment (EMA) [8-10]. EMA refers to a range of methods that uses repeated collection of real-time data on subjects' behavior and experience in their natural environments [11]. The appeal in applying EMA methodologies lies in its ability to assess the state of the participants' symptoms as they are experiencing it. As a result, EMA measurements, especially when repeated assessments are conducted for each participant, are considered more accurate than one-time, retrospective measurements [8, 10]. Furthermore, if measurements of the exposure (i.e., social networks structure) precede EMA measurements, then reverse causation can be minimized.

Another important application of EMA lies in its ability to detect fluctuations of symptoms over time [10]. Depressive symptoms are often characterized as dynamic processes that fluctuate in response to external environmental demands and internal regulatory forces [12]. Examining such fluctuations, also referred to as affective dynamics, offers further insight into psychological functioning and well-being. A widely used index of affective dynamics is the within-person variability calculated with the standard deviation [13]. This index captures the overall range of affect levels an individual may experience across a particular time period, where high variability indicates larger deviations from average emotional levels

[13]. In general, higher variability in negative affect has been shown to be associated with adverse mental health and well-being such as lower levels of psychological well-being [14] and higher risk for mild cognitive impairment [15]. However, to date no study has examined the relationship between social networks characteristics and fluctuations in depressive symptoms.

The first aim of this analysis is to assess the relationship between social network characteristics and momentary depressive symptomatology in older adults. We hypothesize that a larger social network and a higher frequency of contacts with members of the social network will be associated with fewer depressive symptoms. The second aim is to assess the relationship between social network characteristics and fluctuations in daily depressive symptoms. We hypothesize that a larger social network and a higher frequency of contacts will be associated with less variability in daily depressive symptoms.

Methods

Study design

The present analysis was based on a sample of 216 older adults (aged 60 and over) from the Paris region (France), which was collected from July 2019 to July 2021 [16]. The Healthy Aging and Networks in Cities (HANC) and Promoting Mental Well-Being and Healthy Aging in Cities (MINDMAP) sensor studies recruited participants among the 5,500 participants of the second wave of the RECORD study [16-18]. Inclusion criteria were being aged 60 or older, able to provide informed consent, and capable of completing a 7-day EMA protocol via smartphone, whereas, exclusion criteria included severe cognitive impairment or inability to use the mobile application [17]. We have shown that the RECORD study itself oversampled males, educated people, and residents of high socioeconomic status neighborhoods and low building density neighborhoods [19]. The selection of HANC and MINDAP participants within RECORD added another layer of selection; therefore, although the present study included a diversity of participants, it is not representative of the background population of the Paris region.

Using the framework of the HANC and MINDMAP projects, this analysis obtained information on participants' socioeconomic profiles, their social network characteristics, and their momentary depressive symptoms [17, 18, 20]. Momentary depressive symptoms were measured using smartphone-based EMA application over a seven-day period [17]. Participants were asked about their current mood four times a day at random times within the following slots: 9:00 a.m.-12:00 a.m., 12:00 a.m.-2:00 p.m., 2:00 p.m.-4:00 p.m., 4:00 p.m.-6:00 pm [17]. Prior to the EMA data collection, information about the respondents' sociodemographic profile were collected with a computer assisted personal interview questionnaire and information about the respondents' social network was collected with VERITAS, an interactive map-based questionnaire [21]. Since data collection coincided with the COVID-19 pandemic, participants who were surveyed after the lockdown (March 17, 2020 - May 28, 2021) were asked to answer questions regarding their social interactions and their social network before the lockdown. In-person briefings and ongoing technical support was provided to optimize compliance to the protocol.

Dependent variable

Depressive symptoms were assessed each day in the seven-day period with the short 8-item version of the Center for Epidemiological Studies-Depression (CES-D8) scale, a widely used and validated instrument of depression in large scale surveys [22]. Participants were asked two of the eight items within the four aforementioned time slots so that all eight items from the CES-D8 were offered during each day. The order of the items differed across days and participants, and participants were required to submit their answers within 90 minutes. The original items were translated to French and rephrased to inquire about the present moment as the following: 'At the moment, I…' 1. 'feel bothered by things that usually do not bother me', 2. 'feel depressed', 3. 'feel that everything done is an effort', 4. 'feel happy', 5. 'feel lonely', 6. 'enjoy life', 7. 'feel sad' 8. 'feel unmotivated or uninspired'. The four response options included 'no, not at all', 'no, not really', 'yes, somewhat', and 'yes, absolutely' and ranged from zero to three, respectively. The two positive items were reverse coded to reflect that a higher score indicates more depressive symptoms. A total score was calculated for each participant per day by summing the items. The daily CES-D8 score could range from 0 to 24. Some participants did not respond in the appropriate timeframe, which resulted in missing values. A summary of missingness can be found in Supplement Table 1. Within-person fluctuations in depressive symptoms were measured as the standard deviation of each participant's daily CES-D8 scores. The standard deviation was calculated for each participant based their CES-D8 scores across the week.

Independent variable

Prior to the EMA ambulatory study, respondents were asked to describe each member of their social network and how they are connected, yielding a number of social network characteristics [20, 23]. The size of the network and the frequency of contacts of the social network served as independent variables. Network size was defined as the number of people with whom the respondent usually performed social activities. Respondents were also asked how often they usually have contact with the members of their social network in a week from two modes of communication: digital communications such as internet and phone calls and in-person communication. Each social network variable was scaled to make the regression coefficients more understandable. The network size was divided by ten. Hence, a one unit increase in the scaled network size signifies an increase in ten persons in the network size. Both frequency of contacts variables (digital and in-person) were divided by 50, which means a one unit increase represents an increase in 50 interactions in a week.

Covariates

The following variables were taken into account to neutralize potential confounding effects: age (in years), gender (male; female), marital status (married/in a couple; divorced/widowed/unmarried), monthly household income per consumption unit (<€2000; €2000–4000; >€4000), employment status (employed; retired/other), and general health status self-assessed before the ambulatory study (good health; poor health). Following the work from Fancello and colleagues, education level was categorized as low-medium education (from none to the completion of high school), high education (high school + 2

to 4 years), and very high education (high school + 5 years and over) [24]. A binary variable was incorporated to account for the effects of the pre and post lockdown periods.

Data analysis

Descriptive analyses were conducted to characterize the study population, social network indicators, and depressive symptoms. The first part of the main analysis estimated the association between the social network characteristics and momentary depressive symptoms with three separate mixed effects linear models, one for each social network characteristic. Mixed effects models have the ability to take into account the hierarchical structure of nested data [25]. In this analysis, repeated daily measurements of CES-D8 (i.e., level-1) were nested within participants (i.e., level-2). In the second main analysis, three separate multivariable linear models were employed to estimate the association between the social network characteristics and the standard deviation of the daily CES-D8 scores. The CES-D8 scores and the standard deviations of the daily CES-D8 scores had skewed distributions. Therefore, we applied a natural logarithm transformation on both dependent variables. Because there were zero values, we used a log(x + 1) transformation to prevent undefined values at zero. All coefficients and their respective confidence intervals were exponentiated, and exponentiated coefficients of log-linear models can be interpreted as multipliers of the outcome of interest. As part of the sensitivity analysis, we reran both models with non-transformed outcomes. All models were adjusted for gender, age, marital status, education, household income, pre-ambulatory study health status, and Covid-19 pandemic period.

Missing variables including missing depressive symptoms reports were handled by using the multivariate imputation by chained equations (MICE) package in R [26]. Twenty imputed datasets were generated and pooled together to report the estimates and their 95% confidence interval. Following best practices for EMA studies, we tested model assumptions and verified consistency across both complete-case and imputed datasets (not reported). All analyses were conducted in R 4.2.2 [27].

Results

Descriptive analysis

Table 1 provides an overview of the study population demographics. Among the 216 older adults, 64% (n = 139) were males, 67% (n = 145) were married or in a couple, and 84% (n = 183) were retired or not employed. The average age of the study sample was 70.1 years (SD = 6.1). On average, participants completed 6.8 full CES-D8 surveys (SD = 0.4). The average size of the social network was 6.5 (SD = 3.2; IQR 4,8). Participants had, on average, 65.3 in-person contacts per week (SD = 44.6; IQR 33.5, 84.5) and 106.7 digital communications (SD = 76.5, IQR 59, 142.5) per week.

Association of social network characteristics with momentary depressive symptoms

Table 2 presents the associations between the social network characteristics and the log-transformed momentary depressive symptoms. For every 10 additional persons in the social network, momentary depressive symptoms were 10% lower, but the confidence interval included 1 (exp(β) = 0.90, 95%CI

0.70, 1.17). Regarding frequency of in-person contacts, having 50 more in-person contacts was associated with 10% less depressive symptoms. Although the confidence interval also included 1 (exp(β) = 0.90, 95%CI 0.82, 1.00), there was a suggestion of association. Every 50 extra digital communications was associated with 2% less depressive symptoms, but the confidence interval overlapped value 1 (exp(β) = 0.98, 95%CI 0.91, 1.06). All models met model assumptions and verified consistency across both complete-case and imputed datasets. The results from the sensitivity analysis were aligned with the main analysis, as there was also a suggestion of association where more in-person contacts were associated with less depressive symptoms but with a relatively wide confidence interval (Supplement Table 2).

Association of social network characteristics with fluctuation in depressive symptoms

The associations of social network characteristics with fluctuation in daily depressive symptoms, expressed as the log-transformed standard deviations, are presented in Table 3. Having ten more members in one's social network was associated with a having 9% less daily fluctuations in depressive symptoms (95%CI: 0.85, 0.98) after controlling for sociodemographic factors. In addition, having 50 more in-person contacts in a week was associated with less variability in daily depressive symptoms by 4% (95%CI: 0.93, 0.98); however, no association was observed regarding frequency of digital contacts in a week (exp(β) = 0.99 95%CI: 0.97, 1.01). The results of the sensitivity analysis (Supplement Table 3), which examined the associations between the social network characteristics and the non-transformed outcome, demonstrate that only network size (β = -0.30, 95%CI: -0.48, -0.11) and the frequency of in-person contacts (β = -0.09, 95%CI: -0.16, -0.01) were associated with a lower variability in daily depressive symptoms but not contact from digital communications (β = -0.01, 95%CI: -0.06, 0.04).

Table 1. Characteristics of the study population

	N (%) or Mean (SD)	Range (min, max)
Sample size, n (%)	216 (100)	
Individual characteristics		
Age, mean (SD)	70.1 (6.1)	(60, 90)
Gender, n (%)		
Female	77 (35.6)	-
Male	139 (64.4)	-
Marital status, n (%)		
Married/ In a couple	145 (67.1)	-
Divorced/widowed/unmarried	71 (32.9)	-
Education level, n (%)		
Low-medium	65 (30.1)	-
High education	70 (32.4)	-
Very high education	81 (37.5)	-
Household income, n (%)		
<2,000	32 (14.9)	-
2,000 – 4,000	128 (59.2)	-
>4,000	56 (25.9)	-
Employment, n (%)		
Employed	29 (13.4)	-
Retired/unemployed/other	183 (84.7)	-
Other	4 (1.9)	-
Self-assessed health, n (%)		
Good health	198 (91.7)	-
Poor health	17 (7.8)	-
NA	1 (0.5)	
COVID-19 lockdown, n (%)		
Pre-lockdown	76 (35.1)	-
Post-lockdown	139 (64.3)	-
NA	1 (0.5)	-
Social network characteristics, mean (SD)		
Network size	6.5 (3.2)	(1, 19)
In-person contacts per week	64.8 (44.5)	(0, 247)
Digital communications per week	42.5 (54.4)	(0, 544)
Number of completed CES-D8 per participant, mean (SD)	6.8 (0.4)	(5, 7)
CES-D8 scores, mean (SD) [a]	3.6 (2.9)	(0, 21)
Within-person variability CES-D8 scores, mean (SD) [a]	2.2 (1.0)	(0, 9.8)

[a] based on imputed data

Table 2. Exponentiated beta coefficients and 95% confidence intervals from the multilevel models estimating the associations between social network characteristics and the log-transformed momentary depressive symptoms

	Network size	In-person contacts	Digital communications
Intercept	2.78 (1.06, 7.27)	3.25 (1.23, 8.58)	2.78 (1.06, 7.30)
Network size [a]	0.90 (0.70, 1.17)		
In-person contacts [b]		0.90 (0.82, 1.00)	
Digital communications [b]			0.98 (0.91, 1.06)
Age	1.01 (0.99, 1.02)	1.01 (0.99, 1.02)	0.01 (-0.01, 0.02)
Gender			
Female	Ref	Ref	Ref
Male	1.01 (0.99, 1.02)	1.01 (0.99, 1.02)	1.01 (0.99, 1.02)
Marital status			
Married/ In a couple	Ref	Ref	Ref
Divorced/widowed/unmarried	1.07 (0.89, 1.3)	0.98 (0.79, 1.21)	1.08 (0.90, 1.31)
Education level			
Low-medium	Ref	Ref	Ref
High education	0.97 (0.79, 1.19)	0.95 (0.78, 1.17)	0.95 (0.78, 1.17)
Very high education	1.01 (0.81, 1.26)	0.99 (0.79, 1.23)	1.01 (0.81, 1.25)
Household income			
<2,000	Ref	Ref	Ref
2,000 – 4,000	1.01 (0.79, 1.28)	0.98 (0.77, 1.25)	1.01 (0.79, 1.28)
>4,000	1.00 (0.75, 1.33)	0.95 (0.71, 1.26)	0.99 (0.74, 1.32)
Employment			
Employed	Ref	Ref	Ref
Retired	0.86 (0.66, 1.12)	0.83 (0.64, 1.07)	0.87 (0.67, 1.13)
Unemployed/other	0.56 (0.30, 1.05)	0.56 (0.30, 1.04)	0.56 (0.30, 1.06)
Self-assessed health			
Good health	Ref	Ref	Ref
Poor health	1.28 (0.97, 1.70)	1.31 (0.99, 1.73)	1.28 (0.96, 1.70)
COVID lockdown			
Pre-lockdown	Ref	Ref	Ref
Post-lockdown	0.98 (0.82, 1.16)	0.96 (0.82, 1.13)	0.97 (0.82, 1.14)
Individual-level variance	0.301	0.296	0.302
Repeated measure variance	0.221	0.221	0.221
ICC [c]	0.576	0.572	0.577

[a] one unit increase means an increase by 10, [b] one unit increase means an increase by 50, [c] intra-level correlation coefficient

Table 3. Exponentiated beta coefficients and 95% confidence intervals from the linear models estimating the associations between social network characteristics and the log-transformed standard deviations in daily CES-D8 scores

	Network size	In-person contacts	Digital communications
Intercept	1.74 (1.34, 2.26)	1.86 (1.43, 2.42)	1.74 (1.34, 2.26)
Network size [a]	0.91 (0.85, 0.98)		
In-person contacts [b]		0.96 (0.93, 0.98)	
Digital communications [b]			0.99 (0.97, 1.01)
Age	1.01 (1.00, 1.01)	1.01 (1.00, 1.01)	1.01 (1.00, 1.01)
Gender			
Female	Ref	Ref	Ref
Male	1.02 (0.97, 1.07)	1.03 (0.98, 1.08)	1.03 (0.98, 1.09)
Marital status			
Married/ In a couple	Ref	Ref	Ref
Divorced/widowed/unmarried	1.17 (1.11, 1.24)	1.13 (1.07, 1.20)	1.18 (1.12, 1.25)
Education level			
Low-medium	Ref	Ref	Ref
High education	0.94 (0.87, 1.02)	0.91 (0.85, 0.98)	0.92 (0.85, 0.99)
Very high education	1.02 (0.94, 1.12)	1.00 (0.92, 1.10)	1.02 (0.93, 1.11)
Household income			
<2,000	Ref	Ref	Ref
2,000 – 4,000	0.84 (0.79, 0.90)	0.83 (0.78, 0.88)	0.84 (0.79, 0.89)
>4,000	0.90 (0.83, 0.97)	0.87 (0.81, 0.94)	0.89 (0.82, 0.96)
Employment			
Employed	Ref	Ref	Ref
Retired	0.96 (0.89, 1.03)	0.94 (0.88, 1.01)	0.96 (0.89, 1.03)
Unemployed/other	0.77 (0.64, 0.93)	0.77 (0.64, 0.92)	0.77 (0.64, 0.93)
Self-assessed health			
Good health	Ref	Ref	Ref
Poor health	1.26 (1.16, 1.37)	1.27 (1.17, 1.38)	1.26 (1.16, 1.37)
COVID-19 lockdown			
Pre-lockdown	Ref	Ref	Ref
Post-lockdown	1.05 (1.00, 1.10)	1.04 (0.99, 1.09)	1.04 (1.00, 1.09)

[a] one unit increase means an increase by 10, [b] one unit increase means an increase by 50

Discussion

This study did not find major evidence to support our hypothesis that the size of the network and the frequency of contact from digital communications per week were associated with fewer depressive symptoms. Nonetheless, although the 95% interval included value 1 just on its upper side, there was suggestion that the frequency of in-person contact was associated with slightly fewer depressive symptoms. When examining instability in depressive symptoms, our findings indicate that the size of the social network and the frequency of in-person contacts were associated with less variability in daily depressive symptoms.

The findings on the relationship between frequency of contacts and depressive symptoms are mixed [7]. While some studies found that more contact with the social network is associated with fewer depressive symptoms [28, 29], others did not find any associations [30, 31]. Researchers that did not observe any association postulated that the subjective components of social relationships, like the perceptions of the quality of social relationships, might be more critical to health than objective characteristics of one's social network [30, 31]. Our findings might provide some support for this argument. Although the confidence interval included value 1 on the margin, we found that more in-person contacts were linked with fewer symptoms of depression, and more so than contacts with digital communication. One possible explanation is that in-person communication offers a richer form of communication than digital communication among older adults [32]. In-person communications provides more interaction cues such as gestures, facial expressions, intonation, and body language than digital communications [32]. The lack of such cues when communicating with digital technologies could diminish older adults' ability to convey and experience interpersonal impressions and warmth as social presence theory posits [33]. Older adults also might lack the technical skills to properly use digital communications [34]. Digital communications could also lead to more exposure to negative content and misinformation that proliferated on the internet during the pandemic [35]. These barriers could suggest that digital communications is not a substitute for in-person interactions among older adults. Prior research has shown that older adults preferred in-person communication over digital communication during the COVID-19 pandemic [36, 37].

Our study adds to the literature by examining the relationship between social network characteristics and fluctuations in depressive symptoms. Our findings confirm our hypothesis that older adults with larger social networks and more in-person contact with their social network had less variability in depressive symptoms across a week. These results are in line with prior cross-sectional research emphasizing the protective effects of network size on depression in older adults [7, 38]. By relying on repeated real-time measures, our EMA-based design strengthens the validity of the associations between social networks and depressive symptoms in older adults by minimizing recall bias and allowing us to capture fluctuations in symptomatology, which are often missed in traditional designs.

Our findings provides evidence that social networks might buffer against the adverse effect of stressful events [39]. During the COVID-19 pandemic, many people experienced elevated and sporadic stress levels, especially older adults who were among the high-risk groups for adverse health effects from the COVID-19 virus. We believe participants' social networks may have mitigated sudden spikes in stress through social support. Additionally, participants with large networks and more in-person interactions may be less likely to feel loneliness, which could contribute to fluctuations in depressive symptoms.

Strengths and limitations

This study goes beyond existing literature by taking an EMA approach to assess momentary depressive symptoms, which is the main strength of this study. Moreover, social network characteristics were assessed prior to the assessment of depressive symptomatology. Although this approach does not eliminate reverse causation, we believe it minimizes it. There are some limitations that should also be considered. First, social network characteristics were assessed using a self-reported, time-invariant measure, which is susceptible to recall and reporting biases. Moreover, our sample was not representative of older adults in Paris due to selective participation bias [19], which makes it difficult to generalize the results to the broader population. In addition, nearly two third of our sample has been surveyed after the lockdown and were asked to answer questions about their social network before the lockdown. The threat of reverse causation remains, if an underlying depression status led to a reduction in the social network or in the frequencies of contacts. However, this is not an easy issue to solve, as we believe that adjusting for a CES-D8 indicator that was collected at the same time as the characterization of the social network may have represented an overadjustment of the model. Finally, although standard deviation is widely used for measuring the variability of affect levels, it does not take into account how affect changes over time [40]. The mean square successive difference is considered the preferred index of affective instability, because it captures both variability and temporal dependency [40].

Conclusions

The findings from this study suggest that certain social network characteristics protect against depressive symptoms in terms of levels but also stability. Given the rapid growth in the world's elderly population and the burden associated with depression, our findings have important policy implications. Intervention programs that provide older adults the opportunity to increase in-person interactions and to increase the size of their social networks such as providing contexts or events to meet are recommended to promote mental health.

Contributorship Statement

VC participated in study concept and design, data analyses, and writing and revising the manuscript. MAB participated in study concept and design and revising the manuscript. FJvL participated in study concept and design and revising the manuscript. JOG participated in study concept and design and revising the manuscript. GF participated in study concept and design and revising the manuscript. AM participated in study concept and design and revising the manuscript. CS participated in revising the manuscript. YK participated in revising the manuscript. JV participated in revising the manuscript. BC participated in study concept and design and revising the manuscript. BC is the guarantor.

Ethics Approval

The data collection was approved by the French Data Protection Authority (DR-2017-060).

Conflict of interest

YK holds shares in Polygon Research Inc., the company that markets the VERITAS application. The remaining authors declare no conflicts of interest.

Funding

The study was supported by a grant from the European Commission HORIZON 2020 research as a part of the Marie Skłodowska-Curie Actions Innovative Training Networks [grant number 956780]; Erasmus Initiative 'Smarter Choices for Better Health'[no grant number]; and the Netherlands Organization for Scientific Research (NWO/ZonMw) [grant number 09150161810158 / VI.Veni.194.041]. MINDMAP is funded by the European Commission HORIZON 2020 research and innovation action 667661. HANC is funded by a grant from the French National Research Agency (ANR-15-CE36-0005). The funders had no role in the study design or the analysis and interpretation of the data. All authors and their institutions reserve intellectual freedom from the funders.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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Appendix

Supplement Table 1. Description of missing CES-D8 items

Average number of missing EMA responses per respondent across the ambulatory period	7.2
Missing values by items n, (%)	
Item 1	200 (12.7)
Item 2	187 (11.8)
Item 3	220 (13.9)
Item 4	198 (12.5)
Item 5	173 (10.9)
Item 6	212 (13.4)
Item 7	196 (12.4)
Item 8	188 (11.9)
Total	1,574
Number of person-days with missing values n, (%)	
Person-days with no missing values	882 (62.8)
Person-days with one missing value	97 (6.9)
Person-days with two missing values	154 (10.9)
Person-days with three missing values	103 (7.3)
Person-days with four missing values	53 (3.7)
Person-days with five missing values	59 (4.2)
Person-days with six missing values	39 (2.7)
Person-days with seven missing values	17 (1.2)
Total number of person-days	1,404

Supplement Table 2. Beta coefficients and 95% confidence intervals from the multilevel models estimating the associations between social network characteristics and momentary depressive symptoms

	Network size	In-person contacts	Digital communications
Intercept	2.23 (-1.71, 6.17)	2.84 (-1.15, 6.82)	2.23 (-1.73, 6.19)
Network size [a]	-0.59 (-1.62, 0.44)		
In-person contacts [b]		-0.40 (-0.81, 0.01)	
Digital communications [b]			-0.09 (-0.39, 0.22)
Age	0.03 (-0.03, 0.09)	0.03 (-0.03, 0.09)	0.03 (-0.03, 0.09)
Gender			
Female	Ref	Ref	Ref
Male	-0.40 (-1.16, 0.35)	-0.34 (-1.08, 0.39)	-0.33 (-1.08, 0.41)
Marital status			
Married/ In a couple	Ref	Ref	Ref
Divorced/widowed/unmarried	0.38 (-0.41, 1.17)	0.02 (-0.86, 0.9)	0.43 (-0.35, 1.22)
Education level			
Low-medium	Ref	Ref	Ref
High education	-0.23 (-1.08, 0.61)	-0.30 (-1.13, 0.53)	-0.30 (-1.14, 0.54)
Very high education	-0.02 (-0.92, 0.88)	-0.10 (-1.00, 0.79)	-0.03 (-0.94, 0.87)
Household income			
<2,000	Ref	Ref	Ref
2,000 – 4,000	0.07 (-0.91, 1.05)	-0.05 (-1.03, 0.93)	0.05 (-0.93, 1.04)
>4,000	0.28 (-0.89, 1.45)	0.05 (-1.12, 1.22)	0.21 (-0.96, 1.38)
Employment			
Employed	Ref	Ref	Ref
Retired	-0.45 (-1.51, 0.62)	-0.60 (-1.68, 0.47)	-0.39 (-1.47, 0.68)
Unemployed/other	-1.96 (-4.53, 0.62)	-1.98 (-4.55, 0.58)	-1.92 (-4.52, 0.67)
Self-assessed health			
Good health	Ref	Ref	Ref
Poor health	1.21 (0.04, 2.38)	1.28 (0.11, 2.45)	1.21 (0.03, 2.38)
COVID lockdown			
Pre-lockdown	Ref	Ref	Ref
Post-lockdown	0.07 (-0.61, 0.76)	-0.02 (-0.69, 0.65)	0.02 (-0.66, 0.70)
Individual-level variance	5.045	4.992	5.081
Repeated measure variance	3.667	3.666	3.666
ICC [c]	0.579	0.577	0.581

[a] one unit increase means an increase by 10, [b] one unit increase means an increase by 50, [c] intra-level correlation coefficient

Supplement Table 3. Beta coefficients and 95% confidence intervals from the linear models estimating the associations between social network characteristics and standard deviation in CES-D8 scores

	Network size	In-person contacts	Digital communications
Intercept	0.97 (0.28, 1.67)	1.10 (0.39, 1.80)	0.96 (0.26, 1.66)
Network size [a]	-0.30 (-0.48, -0.11)		
In-person contacts [b]		-0.09 (-0.16, -0.01)	
Digital communications [b]			-0.01 (-0.06, 0.04)
Age	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)
Gender			
Female	Ref	Ref	Ref
Male	-0.01 (-0.15, 0.12)	0.03 (-0.1, 0.16)	0.03 (-0.1, 0.16)
Marital status			
Married/ In a couple	Ref	Ref	Ref
Divorced/widowed/unmarried	0.37 (0.23, 0.51)	0.31 (0.15, 0.46)	0.39 (0.25, 0.54)
Education level			
Low-medium	Ref	Ref	Ref
High education	-0.08 (-0.22, 0.07)	-0.11 (-0.26, 0.03)	-0.11 (-0.26, 0.03)
Very high education	0.04 (-0.13, 0.20)	0.01 (-0.16, 0.17)	0.02 (-0.15, 0.19)
Household income			
<2,000	Ref	Ref	Ref
2,000 – 4,000	-0.56 (-0.73, -0.39)	-0.59 (-0.76, -0.42)	-0.57 (-0.74, -0.40)
>4,000	-0.29 (-0.50, -0.09)	-0.36 (-0.57, -0.15)	-0.33 (-0.53, -0.12)
Employment			
Employed	Ref	Ref	Ref
Retired	0.03 (-0.16, 0.23)	0.01 (-0.18, 0.20)	0.05 (-0.14, 0.24)
Unemployed/other	-0.51 (-1.01, 0.00)	-0.52 (-1.02, -0.02)	-0.52 (-1.02, -0.01)
Self-assessed health			
Good health	Ref	Ref	Ref
Poor health	0.87 (0.64, 1.09)	0.87 (0.65, 1.10)	0.85 (0.63, 1.08)
COVID-19 lockdown			
Pre-lockdown	Ref	Ref	Ref
Post-lockdown	0.05 (-0.07, 0.18)	0.01 (-0.11, 0.13)	0.02 (-0.11, 0.14)

[a] one unit increase means an increase by 10, [b] one unit increase means an increase by 50

Chapter 5: Understanding the systems dynamics of neighborhood socioeconomic inequities in health in European cities: a causal loop diagram

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Health & Place. 2026; 97; 103595.

Abstract

Urban neighborhood inequities in health remain a persistent public health issue, despite many efforts to promote health equity. Given the complex nature of these inequities, a complex systems science approach is essential to identify and understand their underlying causes. In this study, a causal loop diagram (CLD) was developed to visualize the underlying mechanisms contributing to urban neighborhood inequities in self-assessed health. The CLD was based on the results from a scoping literature review and the input from an interdisciplinary group of researchers. Three overarching themes were identified: 1) Uneven power dynamic in decision-making, 2) Socioeconomic sorting through environmental factors, 3) Mutual reinforcement of social cohesion and the physical environment. The interplay of these themes demonstrates that addressing neighborhood inequities in health requires an integrated approach that is inclusive in the decision-making processes and empowers communities.

Keywords: complex systems, health inequities, causal loop diagram, feedback loops, urban health

Introduction

Urban neighborhood inequities in health, e.g. unjust differences in health between neighborhoods, are a persistent challenge in public health [1]. There is substantial evidence indicating that health is spatially patterned by a socioeconomic gradient at the neighborhood level, in which residents living in affluent neighborhoods tend to have lower morbidity and mortality rates, and higher perceptions of overall health than those residing in socioeconomically deprived neighborhoods [2-4]. Such inequities become increasingly important as the proportion of the global population living in urban areas is expected to rise in the coming decades [5]. However, effective strategies to address these inequities remain unclear. Emerging literature suggests that this challenge persists because the complexity and dynamics of the problem are not yet fully understood. [6, 7].

Cities exhibit key characteristics of complex systems [8, 9]. First, cities comprise many components at multiple levels of organizations. For example, shops and services operating across different neighborhoods serve residents and are governed by the city government [9, 10]. Second, these components are interconnected and interact, which suggests that changes in one feature can result in changes in other features in varying degrees. For example, increases in crime can affect the aesthetics of the built environment or the amount of social cohesion in varying degrees across different spatial contexts. Third, these interconnections might include feedback loops, which are circular chains of causal relationships in which a change in an element can either reinforce or balance further change [11]. For example, socioeconomically deprived neighborhoods often experience disinvestment in the local economy and surrounding aesthetics, which has negative effects on the labor market and economic prosperities, leading to more deprivation [12]. Fourth, the interplay of single elements produces macro-level patterns that cannot be explained by any individual element alone, which is known as emergence. To that end, urban neighborhood inequities in health are increasingly seen as “an outcome of a multitude of interdependent elements within a connected whole” [11]. Adding to the complexity, changes in neighborhood characteristics influence changes in the composition of residents in the neighborhood, and vice versa. Currently, recommendations on how to tackle neighborhood inequities in health insufficiently capture these complex processes. [6, 13].

There are increasing calls among public health researchers to apply complex systems thinking approaches to address health inequities [6, 11]. At the core of complex systems thinking lies the goal of understanding the dynamic interrelations between the elements of a system by viewing the system as a whole [14]. This perspective aligns closely with the need to address urban neighborhood inequities in health, where understanding the implications of the interrelations between neighborhood characteristics may be more insightful than isolating the causal effects of single neighborhood factors [11]. Taking a systems approach, could therefore provide valuable guidance for local policymakers in designing more integrated policies and interventions that target the underlying dynamics of neighborhood inequities in health.

A tool in complex systems thinking to visualize the interconnections within the system is a causal loop diagram (CLD) [15]. Previous CLDs have examined the impact of several urban features on health including the food environment [16], chronic stress [17], and urban densification [18], but there has not been one that visualizes how the interplay of neighborhood factors contribute to the development of urban neighborhood inequities in health. The aim of this study is to develop a CLD to better understand

how the dynamic interplay of neighborhood factors contribute to the development of urban neighborhood inequities in self-assessed health in cities in high-income European countries.

Methods

Study design

We constructed the CLD based on the results from a scoping literature review and the insights from Group Model Building (GMB) sessions. GMB is a participatory method that integrates the knowledge of different stakeholders in a structured setting to form a consensus-driven shared representation of the system of interest [19]. The scoping review brings evidence from international literature that complements the shared knowledge of those participating in the GMB. Our multistep, iterative procedure is based on the procedures used in developing previous CLDs that were created from literature reviews and subject matter experts [17, 20] and established guidelines for developing CLDs [15].

Core Modeling Team

The core modeling team (CMT) was responsible for developing the CLD. It consisted of an interdisciplinary group of researchers with expertise in social epidemiology, urban population health, and sociology (VC, MB, FtE, JOG, FJvL). FtE facilitated the GMB sessions. The remaining members served as modelers and hypothesized causal connections within the model.

Define systems the boundaries

Defining the boundary of the system involves determining what will and will not be in the model. According to system science literature, the model should not include every possible variable and causal connection, but only the most relevant ones that will illustrate the dynamics of the system under study [15]. The CMT decided to limit the systems map to the local level and focus solely on neighborhood-level factors that have the potential to be intervened upon through local policies, and excluded factors at the national or international levels. In addition, the systems map focused on urban environments specifically in high-income European countries, because there are differences in access to resources and living standards between high and low-income countries that would imply different dynamics. Furthermore, we included only European countries and excluded the United States of America, because the US has a unique history dealing with racial relationships that has shaped neighborhood inequities differently than in European countries.

Factors in CLDs have an unique set of attributes. First, factors must be measurable and quantifiable, which means that the variable, in theory, must be able to increase or decrease. This allows us to visualize how a change (i.e., increase or decrease) in one factor in the model changes other factors in the model. Categorical factors do not fit this criteria and were not included in the systems map. For example, 'the weather' cannot increase or decrease, but the amount of precipitation or the temperature can increase or decrease. Second, when possible the name of the variable was phrased in neutral

manner to minimize confusion, which follows conventional practices from previous CLDs [16, 20]. For example, 'income level' would be the preferred naming convention instead of 'low-income', because an increase or decrease would clearly indicate the directions of the changes.

Identify neighborhood-level factors from literature review

A scoping literature review was conducted to identify a list of neighborhood-level factors that have been shown to influence neighborhood inequities in self-assessed health. Self-assessed health is a widely used measure of health in public health research [21], because its measurement is easily administered and has been shown to be associated with mortality [21], morbidity, and objective health [22] across multiple different populations. Because of its ability to account for multiple dimensions of health and to predict mortality, self-assessed health is a viable measure to use in a CLD. A detailed description of the review protocol is listed in the Appendix 1. This list of neighborhood-level factors was then used as a basis to build the base systems map.

Core structure of the system

The central feature of the systems map for this analysis lies in its core structure. Inspired by previous work [23], the CMT conceptualized a core stock and flow diagram as a way to visualize the flow of the distribution of poor health across neighborhoods from an equitable distribution of poor health (i.e., a reduction in such inequities) to an inequitable distribution of poor health (i.e., growing neighborhood inequities in health). During the mapping and analyzing process, the CMT expanded the core structure to better visualize the connection between the flow of the distribution of poor health across neighborhoods and neighborhood factors. The CMT conceptualized neighborhood inequities as a function of neighborhood composition and neighborhood effects. They further divided neighborhood effects into those that promote health and those that harm health. As a result, three core factors were added to the core structure to show that the flow of the distribution of health was jointly influenced: 1) the amount of harmful environmental exposures and 2) the amount of health enhancing environmental conditions, which represent the context of the neighborhood and 3) the number of socioeconomic material resources in the neighborhood, which represent the composition of the neighborhood (See Figure 1). CMT chose socioeconomic material resources (i.e., income and education) to represent neighborhood composition, because they are often used in public health literature as a proxy for compositional characteristics and it aligns best with visualizing neighborhood socioeconomic inequities in health.

Building the model

The first GMB session took place in December 2022. The agenda was structured by an established GMB methodology [19] and was based scripts from the online tool Scriptapedia [24]. The CMT used Kumu, an online mapping software, to develop and visualize the CLD [25].

Using the list of factors from the scoping review, the CMT selected the factors they believed were connected to the core structure and drew a causal connection from the factor to the core structure

according to their shared perspective. For the purpose of this analysis, the causal connections identified were not causal in the strict epidemiological sense, but were instead hypothesized by the CMT based on their expert understanding of the systems. As more factors were added to the base model, the CMT discussed which factors were related to each other and drew connections between those. When two factors exhibited bidirectional connections, the CMT members discussed these connections and jointly chose the direction of the connection they believed was stronger. For each causal connection, the CMT determined the polarities of the connections, which could be either positive or negative. A positive relationship indicates that an increase (or decrease) in one variable leads to an increase (or decrease) in the other variable, whereas a negative relationship indicates that an increase (or decrease) in one variable leads to a decrease (or increase) in the other variable [15].

It should be noted that the CMT was not required to use all factors from the scoping review. Furthermore, the list of factors was not considered an exhaustive list that explained neighborhood inequities in health. As the systems map expanded and pathways emerged, the CMT could include new variables they believed were most relevant to understand the system's dynamics . The CMT decided unanimously on the names and causal connections of all variables in the systems map.

Evaluations by domain experts

The CLD was evaluated twice by external domain experts (see Supplemental Table 1 for a summary of all contributors). The CMT discussed which field of expertise could enrich the CLD and invited two researchers with expertise in urban geography and public administration to participate in a GMB session. The first external evaluation took place in January 2022. The participants were given a copy of the CLD and information about the project beforehand. During the GMB session, the participants were instructed to provide their feedback, such as whether they agreed or disagreed with causal links and whether factors should be added or removed from the model.

The second evaluation took place in March 2023. The CLD was evaluated by members of the SURREAL consortium, a Marie Skłodowska-Curie Innovative Training Network (ITN) about urban health inequalities. The SURREAL consortium consists of academics and stakeholders across ten institutions in seven countries. The CMT received feedback from four domain experts with expertise in environmental health, urban geography, and public health policy.

After both rounds of evaluations, the CMT discussed the feedback from the domain experts. In both occasions, the domain experts largely agreed with the overall structure of the CLD and had minor discrepancies, which included refining the names of some factors and adding new factors to the CLD. The CMT only incorporated the feedback that improved the comprehensibility of the pathways.

Theme analysis

Following GMB sessions, VC was responsible for examining the feedback loops using Kumu. Feedback loops refer to a closed chain of connections between multiple elements. In order to be a feedback loop, the directions of all the associations must flow in the same direction (i.e., element A ➔ element B ➔ element C ➔ element A). Loops are considered reinforcing when all the connection polarities in the loop

were positive or if the loop has an even number of negative polarities. Balancing loops occur when there was an odd number of negative connections in the loops [15]. Once all feedback loops were identified and labelled, VC identified feedback loops that had reoccurring patterns in the pathways, which could indicate a general theme. In follow-up GMB sessions, the CMT inspected the feedback loops and discussed whether these patterns were valid according to their expertise and theorized how and why these patterns occurred. At this time, the CMT also proposed changes to the systems map (i.e., either adding or removing variables, or changing causal connections) that reflected the theories from the discussion. VC took the feedback from the CMT and modified the systems map accordingly, which created new feedback loops. This process was repeated until the CMT decided that themes sufficiently described the underlying pathways.

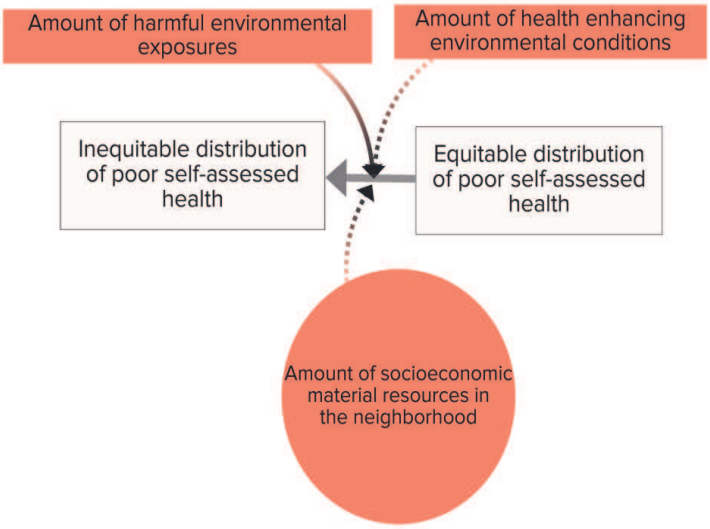


Figure 1. The systems' core structure showing the flow of the distribution of health and the three core factors, which represents the composition of the neighborhood and the context of the neighborhood. Causal links with solid lines indicate the causal relationship has a positive polarity in the direction of the arrow, whereas inverse causal links with dashed lines indicate a negative polarity.

Results

Descriptive summary of studies

The initial database search yielded 6,332 articles, which was reduced to 2,877 after the removal of duplicates. After the title and abstract screenings, 2,550 articles were excluded, leaving 327 remaining for the full text assessment. Of these, 242 were excluded for the following reasons: non-European context (n = 96), did not examine relevant self-assessed health measurements (n = 68), did not focus on neighborhood inequities (n = 29), did not examine neighborhood-level factors (n = 27), setting was not in an urban area (n = 11), not a peer reviewed article (n = 5), not an empirical analysis (n = 4), not in English (n = 1), and dealing with specific population (n = 1) (Supplemental Figure 1). The remaining 85 articles were used in the review and are summarized in Supplemental Table 2. Most of the studies were conducted in the Netherlands (n = 23), followed by United Kingdom with fifteen and Spain with six.

Structure of CLD

Figure 2 presents the CLD, which consists of 22 factors and 64 connections. A summary of the factors is presented in Table 1. Eleven factors were directly extracted from the literature review, five factors were extracted from the literature review but were afterwards slightly modified by the CMT, and six factors were not represented in the literature review at all and were added by the CMT. Five of these six factors created by the CMT were part of the core model as described in the methods section. The factors were classified into five categories: core structure, physical environment, social environment, socioeconomic environment, and well-being. Causal links with solid lines indicate the causal relationship has a positive polarity in the direction of the arrow, whereas inverse causal links with dashed lines indicate a negative polarity.

Table 1. Summary of factors in a causal loop diagram on urban neighborhood inequities

Name of factor	Categories	Definition	Origin
Amount of harmful environmental exposures	Core structure	the amount and intensity of physical or social environmental variables that harm health	Created by CMT (core model)
Amount of health enhancing environmental conditions	Core structure	the amount of physical or social environmental variables that enhances health	Created by CMT (core model)
Accessibility to public transport	Physical environment	the ease in which residents can access public transit	Literature review
Accessibility to the labor market	Socioeconomic	the ease in which residents can find employment	Modified by CMT
Amount of car traffic in the neighborhood	Physical environment	the density of vehicles on the roads	Created by CMT
Amount of neighborhood influence in decision making	Social environment	the ability of a community to develop, sustain, and grow an organized base of people who can mobilize resources and influence public policy	Modified by CMT
Amount of green and blue spaces	Physical environment	the total land covered by vegetation or green space, including trees, lawns and gardens, parks, crop land, and forested wetlands set apart for recreational purposes, and natural or artificial bodies of water, including lakes, canals, and fountains	Literature review
Density and variety of local amenities	Physical environment	the amount and variety of local retail shops and public and healthcare services (e.g., library, clinics, grocery stores etc.)	Literature review
Equitable distribution of poor self-assessed health	Core structure	how evenly poor self-assessed health is distributed between neighborhoods	Created by CMT (core model)
Housing prices in the neighborhood	Socioeconomic	the amount of money to buy a house or rent a residence property	Modified by CMT
Inequitable distribution of poor self-assessed health	Core structure	how unevenly poor self-assessed health is distributed between neighborhoods	Created by CMT (core model)
Level of pollution	Physical environment	the amount of pollutants, noise, or heat in the area that cause adverse effects	Literature review
Level of neighborhood disorder	Physical environment	the observed or perceived physical and social features of neighborhoods that may signal the breakdown of order and social control (e.g., vandalism, litter, disturbances, etc.)	Literature review

Level of stress in the neighborhood	Well-being	the cumulative amount and intensity of chronic stress in the neighborhood	Literature review
Neighborhood social cohesion	Social environment	the connection through shared values, beliefs, and behaviors among residents	Literature review
Neighborhood stigma	Social environment	negative attitudes and beliefs toward the neighborhood	Modified by CMT
Number of socioeconomic material resources in the neighborhood	Core structure	the proportion of households in the neighborhood with economic resources and power	Created by CMT (core model)
Perceived safety in the neighborhood	Social environment	the residents' perceptions of how safe a person feels in their neighborhood	Literature review
Perceived unfair treatment	Social environment	day-to-day discrimination, in the form of chronic, routine, or relatively minor experiences that makes an individual feel less fairly treated	Literature review
Quality of green and blue space	Physical environment	the perceptions of the aesthetics and maintenance of greenspace and blue space	Literature review
Quality of housing conditions	Physical environment	the objective state of the physical and sanitary conditions of the house	Literature review
Quality of schools in the neighborhood	Socioeconomic	the perceptions of the schools in the neighborhood based on academic performance, funding, and lack of social disorder	Modified by CMT

Neighborhood-level factors

The neighborhood factors are color-coded according to the different categories to make the model easier to read. The factors in the physical environment group include density and variety of local amenities, quality and amount of surrounding green and blue space, amount of car traffic, amount of pollution, quality of housing conditions, access to public transport, and amount of neighborhood disorder. The social environment group consists of the amount of neighborhood influence in decision making, perceived safety, social cohesion, and perceived unfair treatment. Neighborhood disorder could, in fact, be assigned to either physical and social environment domains, but it was assigned to the physical environment domain, because we referred to the physical disorder more often than the social disorder when formulating our themes. The socioeconomic group consists of housing prices in the neighborhood, access to labor market, and quality of the schools in the neighborhood. The sole well-being factor is the amount of stress in the neighborhood.

Social cohesion, density and variety of amenities, amount of surrounding green and blue spaces, quality of green spaces, and quality of housing conditions feed into the amount of health enhancing environmental factors. The amount of stress in the neighborhood, pollution, neighborhood stigma, and disorder in the neighborhood feed into the amount of harmful environmental factors.

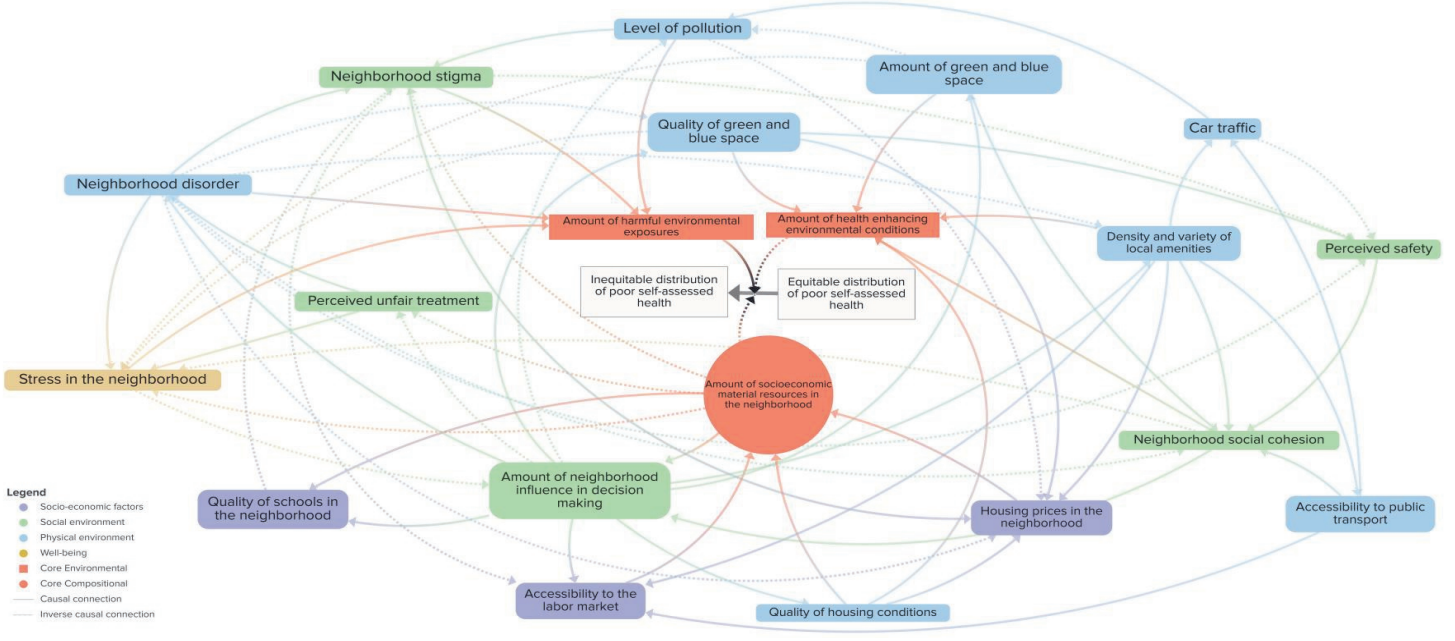


Figure 2. Causal loop diagram of neighborhood inequities in health as an outcome of the interplay between neighborhood factors

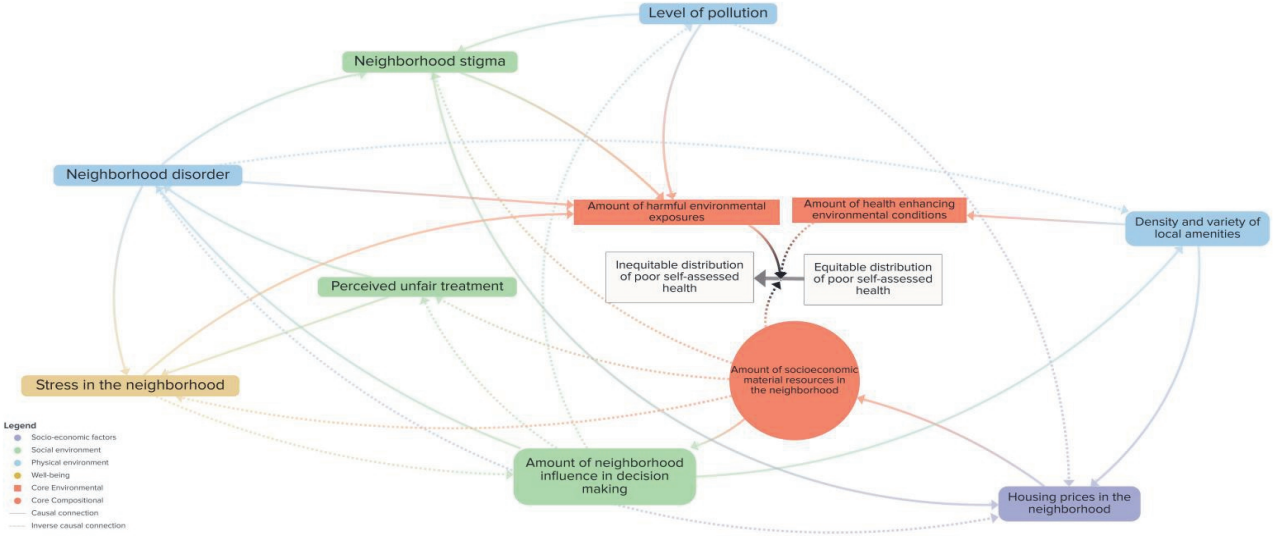


Figure 3. Theme 1: Health inequities as an outcome of the interplay between uneven power dynamic in decision-making and neighborhood environment

Themes of CLD

The CMT identified three overarching themes comprising reoccurring pathways that show how the interconnections between neighborhood factors contribute to neighborhood inequities in health (see Supplemental Table 3).

Theme 1: The interplay between uneven power dynamic in decision-making and neighborhood environment

The first theme (Figure 3) consists of pathways that show how the interplay between the amount of neighborhood influence in decision-making and neighborhood environment lead to inequities in environmental determinants in health. The amount of neighborhood influence in decision-making refers to the collective power of residents to mobilize their individual resources to influence those who make decisions about the changes to the local environment. Such influence could motivate public officials or entrepreneurs to invest in the upkeep of the neighborhood. This investment could reduce the amount of environmental stressors such as pollution (e.g., air and noise), systemic unfair treatment, and neighborhood disorder in a neighborhood. Furthermore, neighborhoods with more environmental stressors and less amenities tend to develop negative reputations, which can lower housing prices in the neighborhood. Conversely, neighborhoods with less environmental stressors and more amenities tend to have positive reputations, which makes them more desirable and more expensive to live. Housing and rental prices, in turn, influence who can afford to live in which neighborhood. Hence, neighborhoods with higher housing prices tend to have a higher proportion of households with more socioeconomic material resources than neighborhoods with lower housing prices. These mechanisms lead to a disproportionate distribution of socioeconomic resources across neighborhoods. The composition of the neighborhood by the number of socioeconomic resources influences how well residents in the neighborhood can engage in public decision making, completing the reinforcing feedback loops. An important factor that can influence the amount of neighborhood influence in decision making is the level of stress in the neighborhood. The accumulation of chronic stress from financial strain or residential instability are generally more prominent in the neighborhoods comprised of households with less socioeconomic resources. More stress in a neighborhood can make residents feel powerless and inhibit them to engage with public officials, which, in turn, hinders the neighborhood from protecting itself against environmental stressors and maintaining the physical environment.

In summary, this theme indicates that the neighborhood's ability to influence public policy influences the amount of exposure to stressors in a neighborhood and the amount of local amenities, and these relationships reinforce themself. As a result, inequities in the amount of exposure to stressors in a neighborhood and in the amount of neighborhood influence on public policy widen over time. Since neighborhood stressors are associated with poor health outcomes, the growing disproportionate amount of exposure to environmental stressors contribute to neighborhood inequities in health.

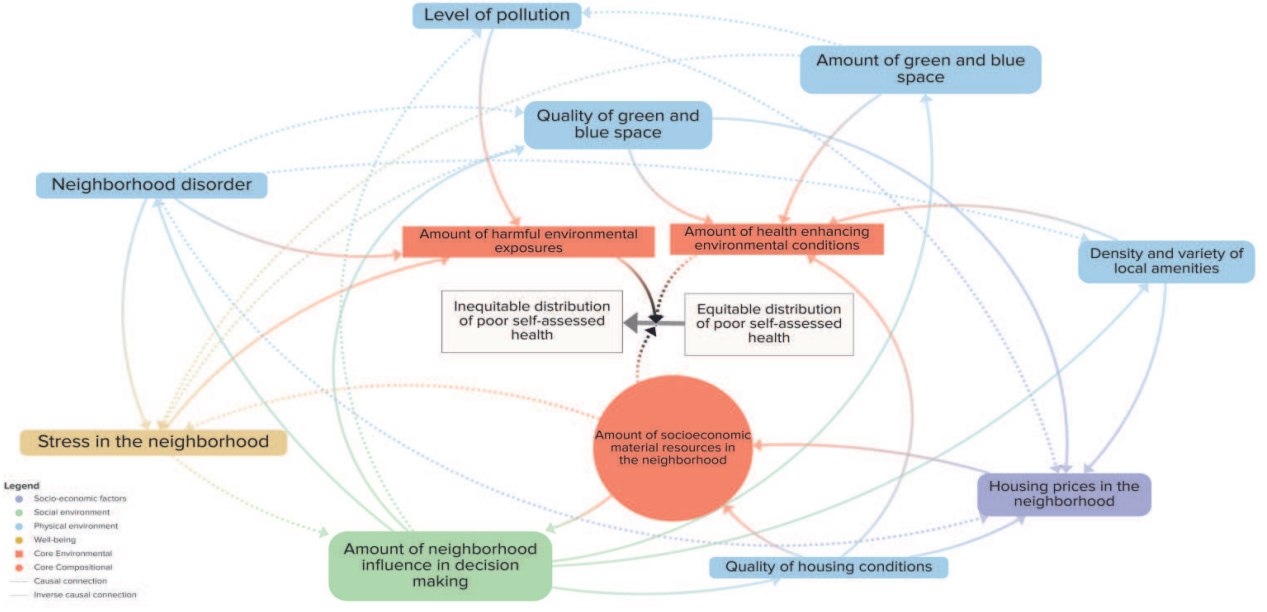


Figure 4. Theme 2: Health inequities as an outcome of neighborhood socioeconomic sorting through environmental factors

Theme 2: The neighborhood socioeconomic sorting through environmental factors

Theme 2 (see Figure 4) contains pathways that show the interplay between the physical environment and the composition of residents in the neighborhood. Neighborhoods with more aesthetic green and blue space, better housing conditions, and more diversity of local amenities are generally more desirable to live in, which results in higher housing and rental prices. Housing prices determine who can afford to live in particular neighborhoods; households with more socioeconomic resources tend to live in the neighborhoods with higher housing prices. Hence, neighborhoods are sorted by socioeconomic position (SEP). The neighborhoods primarily composed of households with higher socioeconomic resources tend to have high aesthetics in physical environment and more diversity in local amenities and services. These neighborhood factors make certain areas more desirable to live and results in increasing housing prices and ensuring that affluent neighborhoods remain composed of households that can afford higher housing costs. On the contrary, neighborhoods with worse physical surroundings and less diversity in amenities have lower housing value, and these neighborhoods are where households with less socioeconomic resources tend to reside. These cycles partly explain how the composition of neighborhoods are created and maintained.

In summary, this theme suggests that the local physical environment contributes to the growing differences in neighborhood composition, particularly by the amount of household socioeconomic resources in a neighborhood. Since health is influenced by household socioeconomic resources, this theme shows another dynamic that contributes to neighborhood inequities in health.

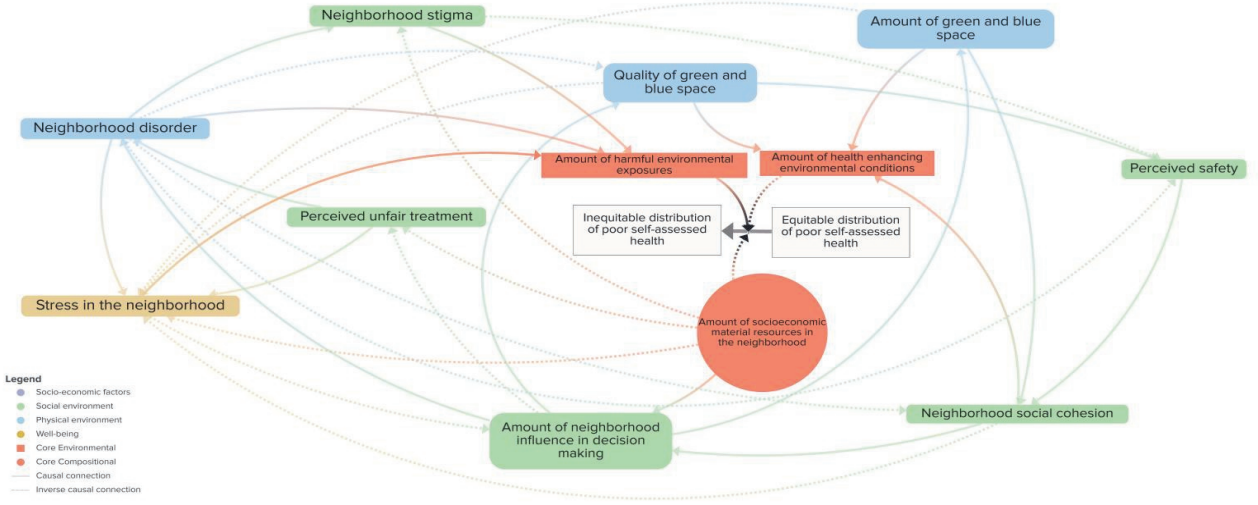


Figure 5. Theme 3: Health inequities as an outcome of the mutual reinforcement of social cohesion and the physical environment

Theme 3: The mutual reinforcement of social cohesion and the physical environment

The pathways from Theme 3 (see Figure 5) shows the interplay between the social and physical environmental factors. A central element in this theme is social cohesion, which refers to the strength of social bonds in a neighborhood. The development of neighborhood social cohesion is promoted when residents have a positive perception of safety and local places to socialize. Since urban green and blue spaces offer a place for residents to gather and meet people, neighborhoods with more and better quality (and safe) green and blue spaces are likely to have stronger social bonds among their residents. Consequently, these neighborhoods have more trustworthiness among their residents, which can maintain social order through informal control and promote the distribution of resources via reciprocity. As a result, neighborhoods with more cohesion can protect against neighborhood disorder as well as promote the upkeep of green and blue spaces. On the contrary, residents living in neighborhoods with low quality green and blue spaces tend to perceive their living environment more often as less safe and have less opportunities to interact with their neighbors. As a result, these neighborhoods tend to have less social cohesion, which hinders residents to work with and trust one another. Moreover, neighborhoods with less cohesion tend to have more disorder and more stigma associated with them, which further perpetuates residents' perceptions of unsafe feelings.

In summary, this theme shows how neighborhoods with stronger social connections can resist the breakdown of the social and physical infrastructure, while neighborhoods with less social bonds are more susceptible to spiraling into deprivation. Since both physical aspects such as green space and social aspects such as social cohesion are associated with better health, neighborhood inequities in health will emerge as inequities in the amount and quality of elements from the physical and social environments widen.

Discussion

By using a complex systems thinking perspective to improve understanding of the underlying mechanisms contributing to urban neighborhood inequities in health, we identified three overarching themes. These themes indicate that neighborhood characteristics are not only interconnected, but also reinforce each other and contribute to the sorting of residents by their socioeconomic resources over time.

Interpretation of findings

The first theme of our systems model suggests that imbalances in neighborhood influence in decision - making can lead to health inequities. As our system model illustrates, such influence is a key factor in shaping the surrounding living environment and neighborhoods with less socioeconomic resources tend to have less influence. Over time, socioeconomically deprived neighborhoods are more susceptible to the proliferation of environmental stressors and less likely to upkeep the local amenities. One possible explanation for these power imbalances is that the prevalence of chronic stress and neighborhood disorder that are generally found in deprived neighborhoods can lead to collective threat, which, in turn, can elevate mistrust between residents and a sense of powerlessness among residents to take action [26, 27]. As a result, communities that lack the power to improve the living conditions remain threatened by the deleterious conditions and the sense of mistrust and powerlessness are reinforced. Public health practitioners are turning to community empowerment initiatives as a strategy to address health equities [28]. The central aim of community empowerment initiatives is to help residents living in deprived communities develop and exercise collective control [29]. Some empirical evidence suggest that increasing collective control in a community can improve social determinants of health and population health outcomes [30]. However, understanding how to collectively build community power to advance health equity is still developing [28].

The second theme of our systems model aligns with the processes that produce residential segregation of socioeconomic groups. As illustrated in our model, residents with higher SEP generally have more agency to attain their housing and neighborhood preferences than residents with lower SEP. Thus, high SEP households generally populate the neighborhoods with better living conditions and more access to amenities since the cost of housing in these areas are the most. This mechanism partly explains why there are concentrations of low SEP households residing in neighborhoods with less access to amenities and poor living conditions. The accumulation of poverty is the primary reason why residential segregation is considered problematic for population health [31]. In addition to providing reduced educational and employment opportunities, more deprived neighborhoods tend to have more crime, pollutants, and deteriorating living conditions, and fewer options for purchasing healthy food and more options for purchasing alcohol compared to affluent neighborhoods [29]. Living in these environments increases risks for adverse physical and mental health outcomes [1]. Over time, these spatial clusters of affluence and poverty are reinforced by neighborhood characteristics such as housing prices, neighborhood stigmatization, and neighborhood disorder as illustrated by our model. Our model also illustrates that the interplay of neighborhood characteristics and neighborhood composition feedback on each other, which explains why inequities in neighborhood characteristics are maintained and can even widen over time.

The third theme highlights the reciprocating effects between urban green space and the development of social connections in a neighborhood. Our model illustrates that neighborhoods with ample, well-kept green space are perceived as safe and promote social interactions, which leads to more cohesion in the neighborhood. Neighborhoods with more social cohesion are characterized as having more collective efficacy, reciprocity among residents, and informal control. These mechanisms might explain why neighborhoods with more social cohesion tend to have maintained green spaces. The relationship between aspects of green space and social cohesion has been examined extensively [32]. One systematic review posited that the relationships between physical characteristics of green space and social cohesion are jointly mediated by perceptions of the environment and use patterns of the green space [32]. These insights from our system model and the literature have implications for designing and managing urban green spaces to enhance social cohesion, especially in deprived neighborhoods. Community gardens, for example, serve multiple purposes. First, they offer places within urban settings where residents can have social activities and build a sense of belonging through gardening. Second, community gardens improve the aesthetics of the neighborhood, which can increase the perceived safety among residents [32].

Policy Implications

Our model provides insight into why existing policies aimed at promoting health equity have not produced the desired results despite being rooted in sound evidence-based recommendations. For example, urban regeneration, a popular policy approach for countering residential segregation, refers to the process of renewal or redevelopment of the environment especially in deprived urban areas [33]. Through a wide range of policies and interventions, urban regeneration aims to improve the surrounding physical, social, and economic environments thereby creating safer streets, better mobility, improved aesthetics, and stronger social cohesion, all of which are associated with better health [34]. Despite being widely implemented across various contexts, the evidence on the impact of urban regeneration programs on health or socioeconomic outcomes is mixed [35]. Urban regeneration policies can also lead to the displacement of long-term residents with less socioeconomic resources who are unable to afford the rising property values and costs of living. [36]. The transition from low and working-class neighborhoods to a middle and upper-class neighborhoods is generally referred to as gentrification, and has been linked to increased psychosocial stress from disruptions to daily activities and a loss of social networks, and from stigmatization and discrimination before and after displacement [36, 37]. Consequently, by failing to consider the functioning of the wider system in which they take place, well-intended policies can lead to unintended consequences, in this example an increased risk of adverse health outcomes among displaced residents [37].

Because urban health inequities are the result of a complex interplay of factors at the individual and neighborhood levels, it is clear that addressing health equity will require an integrated approach that takes into account the wider socioeconomic and contextual factors affecting health [38]. This approach should involve long-term multisectoral collaboration between public health practitioners, urban planners, and other local officials to create holistic, systemic solutions [38]. In addition, this approach should include community organizations and community members in the decision-making and scientific research processes. Community members can be involved in a range of activities such as defining the problem, collecting data, and co-creating policies [39]. Including community members, especially those

living in neighborhoods most affected by urban inequities, can not only empower communities to exert control over their environments, but it also provides first-hand and diverse perspectives of health inequities that are typically not represented in decision-making [39]. That is why public health initiatives are increasingly employing citizen science frameworks to address health equity [39].

Strengths and limitations

Our model is the first system map to visualize how the interplay of neighborhood characteristics contribute to urban neighborhood inequities in health. This is an important first step towards applying complex systems thinking to address health inequities. The model was developed under a structured and well-established systems mapping protocol. Moreover, the creation of the model involved scoping the literature to identify relevant neighborhood-level factors and the critical reflection from an interdisciplinary team of researchers. Using group model building methodologies, we integrated the perspectives from social epidemiology, urban health, and urban geography to create a comprehensive model of the urban environment.

This study should be interpreted in light of several limitations. The scope of the model was intended to reflect high income European countries; however, most of the researchers in the CMT and majority of the articles from the scoping review are from the Netherlands. Despite this overrepresentation, we still expect that the main mechanisms are quite generalizable to other high income European contexts. More research is needed show urban dynamics in other contexts. For example, segregation is more pronounced in the United States than in European countries, given their unique history on racial discrimination. Our model conceptualized compositional characteristics as socioeconomic circumstances, but does not include other aspects that has been shown to be related to neighborhood inequities and segregation like ethnicity and lifestyle preferences. Although socioeconomic position is often used in public health research to reflect compositional characteristics, it does not encompass all personal attributes. Therefore, our model might not capture certain mechanisms related to other compositional characteristics, such as ethnicity. Additionally, our model only visualized the dynamics between local, neighborhood-level factors, and did not include factors at other levels, such as the national level. Therefore, it is likely that our model did not capture all possible mechanisms that explain urban health inequities, including those associated with national and supranational influences. Future research can apply the methods from the current analysis to understand other aspects of urban health inequities that incorporates national level. In addition, the causal connections within our model were hypothesized by the CMT, which is subject to bias. Other methods in systems science such as agent-based modeling are better suited at testing the causality of relationships in a model [40]. By taking such an approach future research can better understand the implications of conceptual models. Another limitation is the lack of representation in the mapping process from other perspectives. The model was primarily developed from an academic perspective and could benefit from including the perspectives from residents, (nonprofit) organizations, governments, or local activists.

Conclusion

In conclusion, we developed a CLD based on the results of a scoping literature review and the input from an interdisciplinary group of researchers. We visualized how the interplay of neighborhood characteristics contributes to neighborhood inequities in health. By taking a complex systems science approach we were able to identify three overarching themes that indicate that neighborhood inequities in health, particularly between deprived and affluent neighborhoods, emerge from multiple reinforcing feedback loops. The interplay of neighborhood-factors suggests that addressing urban inequities in health will require an integrated approach that is inclusive in the decision-making processes and empowers communities.

Conflict of interest

The authors declare no conflicts of interest

Funding

The study was supported by a grant from the European Commission HORIZON 2020 research as a part of the Marie Skłodowska-Curie Actions Innovative Training Networks [grant number 956780]; Erasmus Initiative 'Smarter Choices for Better Health'[no grant number]; Netherlands Organisation for Health Research and Development (ZonMw) [project number 55.500.2033]; and the Netherlands Organization for Scientific Research (NWO/ZonMw) [grant number 09150161810158 / VI.Veni.194.041]. The funders had no role in the study design or the analysis and interpretation of the data. All authors and their institutions reserve intellectual freedom from the funders.

Data availability

The data used in this article are qualitative data specific to the developed system model and are not suitable or available for other research activities.

Appendix 1. Description of the literature review protocol

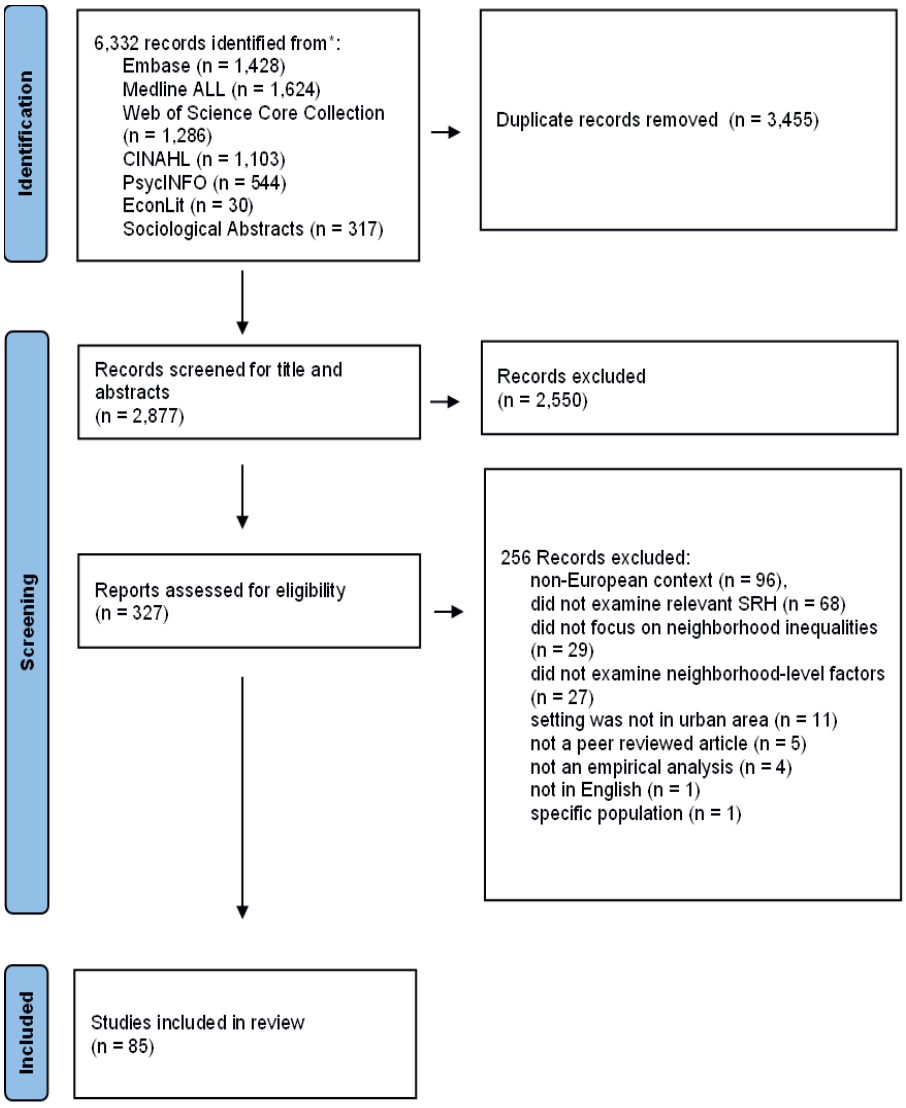
In April 2022, seven electronic databases were searched to retrieve relevant papers: Medline ALL, Embase, Web of Science Core Collection, CINAHL, PsycINFO, EconLit, Sociological Abstracts, and Web of Science. The search strategy was created in collaboration with an experienced medical librarian. The key terms in the search strategy included: 'self-rated health', 'inequality', 'neighborhood characteristics', and 'urban environment'. The final search results were exported into EndNote, and duplicates were removed by the librarian.

To be included in this review, the study: (1) examined predominantly adults (>18 years old); (2) took place predominantly in urban environments or cities, characterized as a densely populated area [41]; (3) took place in high/upper middle income European countries classified by the World Bank; (4) examined city and neighborhood characteristics including individual, social, physical, economic, political factors as predictors or intervening factors; (5) examined these factors in the context of neighborhood inequities in health; (6) examined general health using a single item measure of self-assessed health status on a four- or five-point scale from excellent to poor (i.e. self-rated health, self-assessed health, or self-perceived health) either as an explanatory, mediator, or outcome variable; and (7) must be a peer-reviewed publication in the English language. Articles were excluded if: (1) the study population had specific health-related issues or specific characteristic (i.e. autoimmune, genetic disorders, cancer patients, pregnant women, etc.); (2) the self-assessed indicator measured a specific state of health (i.e. oral-health, mental health, etc.); or (3) protocol papers.

Titles, abstracts, and keywords were screened by VC. A random sample of titles and abstracts were screened by MB. The full texts of relevant records were screened against the inclusion and exclusion criteria by VC. Any disagreements at phases of the screening process were discussed until a consensus was met.

Information from the articles that met the inclusion criteria were entered and organized in a data spreadsheet. VC extracted (1) reference information, (2) study objective, (3) study type, (4) study design, (5) location of the study (i.e. city, country), (4) description of the study population (i.e. demographics, sample size), (5) factors (i.e. explanatory or mediator factors) examined, (6) outcome variable, (7) study results.

Factors in CLDs have an unique set of attributes. First, factors must be measurable and quantifiable. This means that the variable, in theory, must be able to increase or decrease. Categorical factors (e.g., race) do not fit this criteria and were not included in the systems map. Second, the name of the variable should be neutral to minimize confusion. For example, 'income level' would be the preferred naming convention instead of 'low-income', because an increase or decrease would clearly indicate the directions of the changes. Factors from the literature review were modified by VC, FvL, JOG, and MB to match the aforementioned naming conventions.



Supplemental Figure 1. Search strategy flow chart

Supplemental Table 1. Background of contributors

Name	Role	Title	Discipline	Institution
Vernon Cail	Modeler (CMT)	PhD Candidate	Public Health	Erasmus MC University Medical Center
Mariëlle A. Beenackers	Modeler (CMT)	Assistant Professor	Urban Health	Erasmus MC University Medical Center
Fleur ter Ellen	Facilitator (CMT)	PhD Candidate	Systems Thinking	Erasmus MC University Medical Center
Joost Oude Groeniger	Modeler (CMT)	Assistant Professor	Sociology	Erasmus MC University Medical Center
Frank van Lenthe	Modeler (CMT)	Professor	Social Epidemiology	Erasmus MC University Medical Center
Amit Birenboim	External Reviewer	Senior Lecturer	Urban Geography	Hebrew University of Jerusalem
Usha Dahal	External Reviewer	PhD Candidate	Environmental Health	Tartu University
Beitske Boonstra	External Reviewer	Assistant Professor	Urban Development	Erasmus University Rotterdam
Martin Dijst	External Reviewer	Professor	Urban Geography	Luxembourg Institute Socio-Econ Research
Mariël Droomers	External Reviewer	Senior Researcher	Public Health Policy	Municipality Utrecht
Erik Timmermans	External Reviewer	Assistant Professor	Environmental Health	University Medical Center Utrecht
Daina Kosite	Note Taker	PhD Candidate	Mental Health	Erasmus MC University Medical Center

Supplemental Table 2. Summary of articles

Title	Authors	Year	Study design	Place	Description of Population	Factors	Findings
Social inequalities in the associations between urban green spaces, self-perceived health and mortality in Brussels: Results from a census-based cohort study	Rodriguez-Loureiro et al.	2021	cross-sectional study	Brussels, Belgium	571,558 individuals aged 16–80	greenspace	Urban greenspace was associated lower odds of poor self-assessed health.
A multilevel perspective on the health effect of social capital: Evidence for the relative importance of individual social capital over neighborhood social capital	Lagaert et al.	2021	cross-sectional study	Ghent, Belgium	2,730 adults	social capital indicators	Social support was associated with better health.
Promoting social capital, self-management and health literacy in older adults through a group-based intervention delivered in low-income urban	Blancafort Alias et al.	2021	randomized clinical trial	Spain	intervention: 194 control: 164	community intervention	Self-perceived health was not affected by the intervention.

areas: results of the randomized trial AEQUALIS							
The health potential of neighborhoods: A population-wide study in the Netherlands	Dekker et al.	2021	cross-sectional study	Netherlands	over 400,000 inhabitants	neighborhood socioeconomic position	There were disparities in self-assessed health both within and between neighborhoods by neighborhood socioeconomic position.
Neighborhood characteristics, neighborhood satisfaction, and well-being: The links with neighborhood deprivation	Mouratidis	2020	cross-sectional study	Oslo, Norway	951 adults aged 19-94	neighborhood deprivation	Neighborhood deprivation was not associated with health but income, unemployment, and education were.
Involuntary staying and self-rated health: A multilevel study on housing, health and neighbourhood effects	Kemppainen et al.	2020	cross-sectional study	Finland	7,369 Finnish-speaking residents aged 25–74	involuntary staying	Involuntary staying was associated with a lower self-rated health.
Assessing the role of criminality in neighbourhood safety feelings and self-reported health: results from a	Putrik et al.	2019	cross-sectional study	Maastricht, Netherlands	9,656 adults	neighborhood disorder	Perceived frequency of violent crime and perceived frequency of traffic nuisance were associated with poor health.

cross-sectional study in a Dutch municipality							
Distinguishing between self-control and perceived control over the environment to understand disadvantaged neighbourhood health and lifestyle outcomes	Gillebaart & de Ridder	2019	cross-sectional study	Utrecht, Netherlands	3,758 adults aged 19-96	self-control	Higher self-control was associated with better self-reported general health. Perceived control mediated the association between neighbourhood socioeconomic status and self-reported general health.
Neighbourhood blue space, health and wellbeing: The mediating role of different types of physical activity	Pasanen et al.	2019	cross-sectional study	England	21,097 respondents	blue space/ green space	Living nearer the coast was associated with better self-reported general and mental health.
Comparing subjective and objective neighbourhood deprivation and their association with health over time among older adults in England	Godhwani et al.	2019	longitudinal study	England	10,469 sample members	neighbourhood deprivation	Both objective and subjective neighbourhood composite scores independently predicted poor health.
Social network resources and self-rated health in a	Tanggaard Andersen et al.	2018	cross-sectional study	Korskærparken, Denmark	408 adults in 2008 and 405 in 2013	social network	Residents with a better social network had higher

deprived Danish neighborhood							odds of having good self-rated health.
The moderating effect of functional social support on the association between unfair treatment and self-rated health: A study of the resilience of a community-based sample of Irish migrants in London	Moore	2018	cross-sectional study	United Kingdom	790 immigrants	unfair treatment, social support	Higher levels of support was associated with reduced poor health. Higher levels of instrumental or practical support moderated the effect of unfair treatment on self-rated health.
Does the ethno-religious diversity of a neighbourhood affect the perceived health of its residents?	Jonsson	2018	cross-sectional study	England	13,236 minorities and 15,021 white British	neighbourhood diversity	Residing in areas of greater diversity had a differential impact on minorities when compared to Whites, where diversity appeared to be more beneficial for minorities.
Community action for health in socioeconomically deprived neighbourhoods in Barcelona: Evaluating its effects on health and social class health inequalities	Palència et al.	2018	quasi-experimental	Barcelona, Spain	The study sample consisted of 3,068 non-institutionalised individuals aged ≥15 in 2001 and 1,336 in 2011	community intervention	Self-rated health improved in women, especially those living neighbourhoods with the community action intervention.

Social Quality and Health: Examining Individual and Neighbourhood Contextual Effects Using a Multilevel Modelling Approach	Holman & Walker	2018	cross-sectional study	England	8,139 individuals	social quality	Individual-level experience of social quality was generally more important for individual-level health than neighbourhood-level social quality.
The relationship between ethnic composition of the residential environment and self-reported health among Turks and Moroccans in Amsterdam	Veldhuizen et al.	2017	cross-sectional study	Amsterdam, Netherlands	2,661 Moroccan adults and 2,701 Turkish adults	neighborhood ethnic density	Higher density of the other ethnic groups were associated with better self-rated health.
Residential Surrounding Greenness, Self-Rated Health and Interrelations with Aspects of Neighborhood Environment and Social Relations	Orban et al.	2017	cross-sectional study	Bochum, Essen, and Mülheim/Ruhr, Germany	4,480 adults	greenspace	Higher greenness was associated with better self-rated health.
Changes in Health Following Housing Improvement in a Vulnerable Population in	Novoa et al.	2017	quasi-experimental	Barcelona, Spain	232 families	housing conditions	Most of the observed associations with health improvements was related to housing affordability issues.

Spain: A Follow-up Study							
Are area-level and individual-level socioeconomic factors associated with self-rated health in adult urban citizens? Evidence from Slovak and Dutch cities	Behanova et al.	2017	cross-sectional study	Bratislava and Kosice, Slovakia Amsterdam and Utrecht, Netherlands	2,652 adults	neighborhood deprivation	Neighborhood deprivation was associated with poor self-rated health.
Social capital, deprivation and self-rated health: Does reporting heterogeneity play a role? Results from the English Longitudinal Study of Ageing	O'Doherty et al.	2017	cross-sectional study	England	2,341 aged 50 years and older	social capital indicators	Low local area trust and poor social networks were associated with worse self-rated health.
Evaluation of the health impact of an urban regeneration policy: Neighbourhood Renewal in Northern Ireland	Mohan et al.	2017	quasi-experimental	Northern Ireland	adults aged 16 and over	urban renewal intervention	There was a small, non-significant trend towards a reduction in the gap of good self-rated health between neighbourhood renewal areas and controls.

Housing Type and Neighbourhood Safety Behaviour Predicts Self-rated Health, Psychological Well-being and Frequency of Recent Unhealthy Days: A Comparative Cross-sectional Study of the General Population in Sweden	Berglund et al.	2017	Repeated, cross-sectional study	Sweden	90,845 adults	housing type	People not living in private housing and residents who did not go out for safety reasons reported lower self-rated health.
Neighbourhood social capital: measurement issues and associations with health outcomes	Mackenbach et al.	2016	cross-sectional study	Belgium, France, Hungary, the Netherlands and the United Kingdom	5,900 adults	social cohesion	Higher neighbourhood social capital was associated with better self-rated health.
Exploring why residents of socioeconomically deprived neighbourhoods have less favourable perceptions of their neighbourhood environment than	Mackenbach et al.	2016	cross-sectional study	Belgium, France, Hungary, the Netherlands and the United Kingdom	5,205 adults	perceptions of physical environmental	Self-rated health was only associated with neighbourhood perceptions in the Randstad region.

residents of wealthy neighbourhoods							
The impact of neighborhood social capital on life satisfaction and self-rated health: A possible pathway for health promotion?	Maass et al.	2016	cross-sectional study	Malvik, Norway	865 adults	social capital	Social capital was associated with self-rated health.
Restoration in urban spaces: Nature views from home, greenways, and public parks	Honold et al.	2016	cross-sectional study	Berlin, Germany	32 adults	greenspace	Exposure to greenspace was not associated with self-reported health.
The impact of intervening in green space in Dutch deprived neighbourhoods on physical activity and general health: results from the quasi-experimental URBAN40 study	Droomers et al.	2016	quasi-experimental	Netherlands	48,132 adults	greenspace	Greening interventions did not achieve short-term health gains among adults.
Is it better to invest in place or people to maximize population health? Evaluation of the	Droomers et al.	2016	quasi-experimental	Netherlands	66,800 respondents	greenspace	Greening interventions did not achieve short-term health gains among adults.

general health impact of urban regeneration in Dutch deprived neighbourhoods							
The interplay between neighbourhood characteristics: The health impact of changes in social cohesion, disorder and unsafety feelings	Ruijsbroek et al.	2016	Repeated, cross-sectional study	Netherlands	43,635 adults	neighbourhood disorder, unsafe feeling	Reduced social cohesion and unsafety feelings in the area were associated with poor health, while improvement in social cohesion was associated with better general health. Changes in physical and social disorder were not associated with the general health of the population.
Association between Self-Rated Health and the Ethnic Composition of the Residential Environment of Six Ethnic Groups in Amsterdam	Veldhuizen et al.	2015	cross-sectional study	Amsterdam, Netherlands	4,673 adults aged 19-34	neighborhood ethnic density	The presence of own ethnic group was associated with higher odds of reporting poor health among Surinamese, but not among other groups.
Objective exposure to road traffic noise, noise annoyance and self-rated poor	Riedel et al.	2015	cross-sectional study	Dortmond, Germany	1,192 adults aged 24-74	road traffic noise and traffic-related noise annoyance	Exposure to road traffic noise was associated with poor health.

health - framing the relationship between noise and health as a matter of multiple stressors and resources in urban neighbourhoods							
Living environment matters: relationships between neighborhood characteristics and health of the residents in a Dutch municipality	Putrik et al.	2015	cross-sectional study	Maastricht, Netherlands	9,879 adults	quality and accessibility of facilities, safety and nuisance, quality of housing, perceptions of traffic and the built environment, social capital	Better feeling of safety, more social cohesion and less car and railway traffic nuisance were associated with lower odds of having poor self-rated health.
The Influence of Social Capital on Individual Health: Is it the Neighbourhood or the Network?	Mohnen et al.	2015	cross-sectional study	Netherlands	53,269 adults	social cohesion/ social capital	Neighbourhood social capital and individual social capital were associated with better health.
The relationship of green space, depressive symptoms and perceived general health in urban population	Reklaitiene et al.	2014	cross-sectional study	Kaunas, Lithuania	6,944 adults aged 45-72	greenspace	Greenspace was associated with self-assessed health only for women.

The effects of an urban renewal project on health and health inequalities: a quasi-experimental study in Barcelona	Mehdipanah et al.	2014	quasi-experimental	Barcelona, Spain	adult population	urban renewal intervention	Intervened neighborhoods had a significant decrease in poor self-rated health.
Healthy Mixing? Investigating the Associations between Neighbourhood Housing Tenure Mix and Health Outcomes for Urban Residents	Lawder et al.	2014	cross-sectional study	Aberdeen, Dundee, Edinburgh and Glasgow, Scotland	3,703 adults	neighborhood housing tenure mix	Neighborhood with a social renting was associated with poor self-reported health.
Early-life school, neighborhood, and family influences on adult health: A multilevel cross-classified analysis of the aberdeen children of the 1950s study	R. L. Dundas, A. H.; MacIntyre, S.	2014	longitudinal study	Aberdeen, Scotland	6,285 adults	school socioeconomic status	There were small contextual associations between childhood school environment and neighborhood environment and adult self-rated health.
Neighbourhood social capital and individual self-rated health in Wales	Tampubolon et al.	2013	cross-sectional study	Wales	13,557 adults	social cohesion	Neighbourhood social capital was associated with self-rated health.

A Regional Measure of Neighborhood Multiple Environmental Deprivation: Relationships with Health and Health Inequalities	Richardson et al.	2013	cross-sectional study	Scotland	398 neighborhoods	environmental deprivation index	Environmental deprivation was associated with increased rates of self-reported ill health.
Social capital, health behaviours and health: a population-based associational study	Nieminen et al.	2013	cross-sectional study	Finland	8,028 adults	social capital indicators	Social support, trust, and reciprocity were associated with better self-rated health.
You have to be there to enjoy it? Neighbourhood social capital and health	Mohnen et al.	2013	cross-sectional study	Netherlands	65,990 adults	social cohesion	The length of stay in the same neighbourhood was not associated with individual health.
Association of personality, neighbourhood, and civic participation with the level of perceived social support: the HUNT study, a cross-sectional survey	Grav et al.	2013	cross-sectional study	Norway	35,797 adults	sense of community	There was an association between the level of perceived social support and personality, sense of community in the neighbourhood, and civic participation, and interactions were observed self-rated health.
Streetscape greenery and health: stress,	de Vries et al.	2013	cross-sectional study	Utrecht, Rotterdam, Arnhem, Den	1,641 adults	greenspace	Quantity and quality of streetscape greenery were associated with

social cohesion and physical activity as mediators				Bosch, Netherlands			better perceived general health.
Health in the cities: When the neighborhood matters more than income	M. C. Bilger, V.	2013	cross-sectional study	Italy	61,429 individuals	neighborhood disorder	Low quality neighborhoods are associated with poor health.
Critical urban areas, deprived areas and neighbourhood effects on health in France	Debrand et al.	2012	cross-sectional study	France	16,505 adults	“economic and social condition”, “residential stability” and “generational”	Living in a deprived neighborhood, a low mobility neighborhood, or a neighbourhood without a mix of population and housing positively increased the probability of self-reporting poor health.
Individual social capital, neighbourhood deprivation, and self-rated health in England	Verhaeghe et al.	2012	cross-sectional study	England	25,366 respondents	social capital indicators	Social capital indicators were associated with better self-rated health.
Linking green space to health: a comparative study of two urban neighbourhoods in Ghent, Belgium	Van Herzele et al.	2012	cross-sectional study	Ghent, Belgium	190 adults	greenspace	Neighbourhood greenness was more strongly related to general well-being or happiness than it is with health.
Greenspace in urban neighbourhoods	van Dillen et al.	2012	cross-sectional study	Netherlands	1,641 adults	greenspace	Quantity of greenspace was associated with

and residents' health: adding quality to quantity							better self-reported health indicators.
Income inequality and self-rated health in Stockholm, Sweden: A test of the 'income inequality hypothesis' on two levels of aggregation	Rostila et al.	2012	cross-sectional study	Stockholm, Sweden	31,182 adults aged 18-84	city income inequality	No detrimental effect by income inequality on self-rated health at the neighbourhood-level was found.
Community resilience and health: The role of bonding, bridging, and linking aspects of social capital	W. Poortinga	2012	cross-sectional study	England	17,572 respondents	social capital indicators	Social capital indicators were associated with better community health after controlling for neighborhood deprivation.
Examining the differential association between self-rated health and area deprivation among white British and ethnic minority people in England	Bécares et al.	2012	cross-sectional study	England	12,175 respondents	neighborhood deprivation	For all ethnic minority groups examined in this study, the association between area deprivation and self-rated health was less strong than that found for white British people.
Neighborhood social capital and individual health	Mohnen et al.	2011	cross-sectional study	Netherlands	61,235 respondents	social cohesion	Neighborhood social capital was associated with better health.

Quality and quantity: the role of social interactions in self-reported individual health	Fiorillo and Sabatini	2011	cross-sectional study	Italy	216,994 observations	social capital indicators	The quantity and quality of social interactions were associated with better self-reported health.
How relevant are district characteristics in explaining subjective health in Germany? A multilevel analysis	Diehl et al.	2011	cross-sectional study	Germany	5,542 respondents	employment rate	Living in areas with a higher unemployment rate was associated with increased odds of poorer self-reported health.
Self-rated health, ethnicity and social position in a deprived neighbourhood in Denmark	Andersen et al.	2011	cross-sectional study	Korskærparken and Fredericia, Denmark	1,842 adults	neighbourhood ethnic density	Ethnicity was not associated with self-rated health.
Perceived characteristics of the neighborhood and its association with physical activity behavior and self-rated health	Stronegger et al.	2010	cross-sectional study	Graz, Austria	997 adults aged 15-60	social cohesion/social capital	Perceived social-environmental quality of the residential environment was associated with self-rated health.
Green space as a buffer between stressful life events and health	van den Berg et al.	2010	cross-sectional study	Netherlands	4,529 Dutch respondents	greenspace	The relationship of stressful life events with perceived general health were moderated by greenspace.

Neighbourhood characteristics, social capital and self-rated health--a population-based survey in Sweden	Lindén-Boström & Eriksson	2010	cross-sectional study	Sweden	2,386 adults aged 18-84	social cohesion/social capital	Social capital was associated with better self-rated health.
Housing deprivation and health status: evidence from Spain	Navarro et al.	2010	longitudinal study	Spain	adult population	housing conditions	Housing deprivation was associated with poor health.
Healthy communities: The challenge of social capital in the Lisbon Metropolitan Area	Nogueira et al.	2009	cross-sectional study	Lisbon, Portugal	4,577 adults	social capital indicators	Linking and bonding social capital were associated with better self-rated health.
Physical activity as a possible mechanism behind the relationship between green space and health: a multilevel analysis	Maas et al.	2008	cross-sectional study	Netherlands	4,899 Dutch people	greenspace	Green space was associated with self-rated health, but was not explained by physical activity.
Neighbourhood deprivation and self-rated health: The role of perceptions of the neighbourhood and of housing problems	Poortinga et al.	2008	cross-sectional study	Wales	10,892 adults	neighborhood deprivation	Neighbourhood deprivation was associated with better self-rated health.

Area deprivation and trends in inequalities in self-rated health in Spain, 1987-2001	Daponte-Codina et al.	2008	Repeated, cross-sectional study	Spain	84,567 respondents	neighborhood deprivation	Living in deprived neighborhoods were associated with poor health.
Pathways from deprivation to health differed between individual and neighborhood-based indices	van Jaarsveld et al.	2007	cross-sectional study	Glasgow, Scotland	5,253 adults aged 55e64	neighborhood deprivation	Individual and neighborhood deprivation were associated with poor health.
Area deprivation and its association with health in a cross-sectional study: Are the results biased by recent migration?	Piro et al.	2007	cross-sectional study	Oslo, Norway	14,608 adults	neighborhood deprivation	Area deprivation was associated self-rated health.
The association of neighbourhood psychosocial stressors and self-rated health in Amsterdam, the Netherlands	Agyemang et al.	2007	cross-sectional study	Amsterdam, Netherlands	2,914 adults	neighborhood disorder	Neighborhood-level psychosocial stressors were associated with poor self-rated health.
Social relations or social capital? Individual and community health effects of bonding social capital	Poortinga et al.	2006	cross-sectional study	England	7394 adults	social capital indicators	Social trust variable was associated with better self-rated health.

A simultaneous analysis of neighbourhood and childhood socio-economic environment with self-assessed health and health-related behaviours	Monden et al.	2006	cross-sectional study	Eindhoven, Netherlands	8,000 adults	neighborhood socioeconomic position	Neighborhood socioeconomic position was associated with better self-assessed health.
Do perceptions of neighbourhood environment influence health? Baseline findings from a British survey of aging	Bowling et al.	2006	cross-sectional study	England	999 adults aged 65 and older	perceptions of facilities/neighborhood disorder	Perceptions of the neighborhood environment were associated with self-assessed health. Perceptions of problems in the area were predictive of poorer health.
Gender differences in the associations between health and neighbourhood environment	Stafford et al.	2005	cross-sectional study	United Kingdom	8,440 respondents	social cohesion	Physical environment, amenities, and indicators of neighborhood deprivation were associated with self-rated health over and above individual socioeconomic characteristics.
Social capital, geography and health: a small-area analysis for England	Mohan et al.	2005	cross-sectional study	England	7,578 individuals	social capital indicators	Neighborhood social capital was not associated with self-rated health.

Residential instability in socioeconomically deprived neighbourhoods, good or bad?	Drukker et al.	2005	cross-sectional study	Maastricht, Netherlands	3,469 adults	neighbourhood socioeconomic deprivation and residential instability	Residential instability appeared to protect against negative effects of neighbourhood poverty.
Neighbourhood environment and its association with self rated health: Evidence from Scotland and England	Cummins et al.	2005	cross-sectional study	United Kingdom	13,899 adults aged 16 or over	neighborhood disorder/social capital	Poor self-rated health was significantly associated with poor physical quality residential environment, left wing political climate, low political engagement, high unemployment, lower access to private transport, and lower transport wealth.
Neighbourhoods and self rated health: A comparison of public sector employees in London and Helsinki	Stafford et al.	2004	cross-sectional study	London, England and Helsinki, Finland	London 5,301 adults aged 39–63 and Helsinki 4,287 adults aged 40–60	neighborhood deprivation	Neighborhood socioeconomic context was associated with health.
Effect evaluation of a comprehensive community intervention aimed at reducing socioeconomic health inequalities in the Netherlands	Abbema et al.	2004	quasi-experimental	Arnhem, Netherlands	General population	community intervention	No significant effects on improved perceived health or health-related problems were found.

Neighbourhood deprivation and health: Does it affect us all equally?	Stafford & Marmot	2003	cross-sectional study	London, England	5,539 civil servants	neighbourhood deprivation	Neighbourhood deprivation was associated with poor self-rated health.
Social participation and health in a community rich in stock of social capital	Hyyppä et al.	2003	cross-sectional study	Ostrobothnia, Finland	2,000 adults	social capital indicators	Social capital was associated with better self-rated health.
Neighbourhood socioeconomic context and self reported health and smoking: A secondary analysis of data on seven cities	Reijneveld et al.	2002	cross-sectional study	Netherlands	23,269 adults	neighbourhood socioeconomic position	Neighbourhood socioeconomic position was associated self-assessed health.
Ethnicity, environment and health: putting ethnic inequalities in health in their place	Karlsen et al.	2002	cross-sectional study	England	adult population	neighborhood ethnicity	There was no ethnic density effect on self-assessed health.
Neighborhood problems as sources of chronic stress: Development of a measure of neighborhood problems, and	Steptoe et al.	2001	cross-sectional study	London, England	654 adults	neighborhood disorder	Neighborhood problems, area deprivation, and individual deprivation were associated with poor self-rated health.

associations with socioeconomic status and health							
Characteristics of individuals and characteristics of areas: investigating their influence on health in the Whitehall II study	Stafford et al.	2001	cross-sectional study	London, England	10,308 civil servants	neighborhood deprivation	The level of deprivation in the area, housing and neighborhood quality, and social integration were associated with health but did not fully explain differences between areas.
Perceptions of place and health in socially contrasting neighbourhoods	Ellaway et al.	2001	cross-sectional study	Glasgow, Scotland	640 adults	neighbourhood disorder/social cohesion	Self-assessed health was associated with perceived neighbourhood problems and perceived neighbourhood cohesion scores.
The impact of area deprivation on differences in health: Does the choice of the geographical classification matter?	Reijneveld et al.	2000	cross-sectional study	Amsterdam, Netherlands	5,121 adults	neighborhood socioeconomic position	Neighborhood socioeconomic position was associated with health.
Neighborhood environment and self-reported health status: A multilevel analysis	Malmström et al.	1999	cross-sectional study	Sweden	9,240 adults aged 25-74	neighborhood deprivation	Neighborhood socio-economic environment was associated with self-reported health.

The impact of individual and area characteristics on urban socioeconomic differences in health and smoking	Reijneveld	1998	cross-sectional study	Amsterdam, Netherlands	5,121 adults	neighborhood deprivation	Poor health status in deprived areas was mainly due to a lower individual socioeconomic status and not to contextual factors.

Supplemental Table 3. Pathways by Themes

Theme 1	Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) pollution -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) perceived unfair treatment -> (+) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) pollution -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) pollution -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) pollution -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) pollution -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) pollution -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) stress in the neighborhood -> (-)

	Neighborhood influence in decision making -> (-) pollution -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (+) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) pollution -> (+) stigma -> (-) housing prices -> (+) household material and social resources -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stress in the neighborhood -> (-)
Theme 2	Neighborhood influence in decision making -> (+) quality of housing conditions -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (+) density of local amenities -> (+) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) quality of green and blue spaces -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of housing conditions -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of green and blue spaces -> (-) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) density of amenities -> (+) housing prices -> (+) household material and social resources -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (+) density of local amenities -> (+) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (+) quality of green and blue spaces -> (+) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of housing conditions -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) density of local amenities -> (+) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of green and blue spaces -> (-) housing prices -> (+) household material and social resources -> (-) stress in the neighborhood -> (-)

Theme 3	Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) social cohesion -> (+) Neighborhood influence in decision making -> (+) surrounding green and blue spaces -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (+) surrounding green and blue spaces -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (+) quality of green and blue spaces -> (+) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) social cohesion -> (+) Neighborhood influence in decision making -> (+) quality of green and blue space -> (+) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (+) stigma -> (-) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of green and blue spaces -> (-) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) neighborhood disorder -> (+) stigma -> (-) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) neighborhood disorder -> (-) quality of green and blue spaces -> (-) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stigma -> (-) perceived safety -> (+) social cohesion -> (+) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) quality of green and blue spaces -> (+) perceived safety -> (+) social cohesion -> (+)

	Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (+) stigma -> (-) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-) Neighborhood influence in decision making -> (-) unfair treatment -> (+) neighborhood disorder -> (-) quality of green and blue spaces -> (+) perceived safety -> (+) social cohesion -> (-) stress in the neighborhood -> (-)

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Chapter 6: General discussion

The overarching aim of this thesis is to understand how the social environment contributes to urban health and urban health inequities. This chapter begins by summarizing the main findings of the studies in this thesis. It goes on to address methodological considerations and discuss the interpretation of main findings. The chapter concludes with implications for policy and directions for future research.

Summary of main findings

Chapter 2 examined whether higher perceived social cohesion was associated with better self-assessed health (SAH) and whether within individual changes in perceived neighborhood social cohesion were associated with changes in SAH in a cohort of Dutch adults with 17-year follow-up. This study further determined whether the relationship between perceived neighborhood social cohesion and health varies across age, socioeconomic position (SEP), and gender. The findings showed that residents with higher perceptions of neighborhood social cohesion were less likely to report poor SAH. However, the analysis did not find conclusive evidence that increases in perceived social cohesion within individuals were associated with improvements in their health over time. Additionally, the study did not observe any differences in these associations based on age, SEP, or gender.

Chapter 3 investigated the extent to which the relationship between perceptions of neighborhood unsafety and disorder and self-assessed health (SAH) is explained by mediation, interaction, or a combination of both through perceived neighborhood social cohesion. This analysis was based on a sample of 5,650 respondents over a 10-year follow-up. The total effects of feeling unsafe and perceived neighborhood disorder with poor SAH were estimated using log-linear regression analyses. A four-way decomposition approach was used to decompose the total effects into four components: controlled direct effect (neither mediation nor interaction), pure indirect effect (mediation only), reference interaction effect (interaction only) and mediated interaction effect (both mediation and interaction). The results showed that feeling unsafe had a positive estimated total effect on poor SAH. For perceived neighborhood disorder, the estimated total effect was smaller. Decomposition analysis indicated that the majority of the estimated effect of perceived unsafety was explained by the controlled direct effect, and provided no evidence of mediation or interaction through social cohesion. None of the estimated decomposition components were significant for neighborhood disorder. These findings suggest that perceived neighborhood disorder and unsafety and perceived neighborhood social cohesion appear to influence health through independent pathways, rather than through their interplay.

Chapter 4 analyzed ecological momentary assessment (EMA) data to examine how social network characteristics relate to momentary depressive symptoms and their daily fluctuations in older adults. Social network characteristics included network size and frequency of in-person and digital interactions per week. Depression symptoms were measured using a daily smartphone survey based on the Center for Epidemiological Studies-Depression (CES-D8) scale over the course of a week. The results showed that the size of the network and the frequency of contact from digital communications per week were not associated with fewer depressive symptoms. Nonetheless, although the 95% interval included the value of 1 just on its upper side, there was a suggestion that the frequency of in-person contact was

associated with slightly fewer depressive symptoms. The study also found that having a larger social network and more frequent in-person interactions were associated with less fluctuations in daily depressive symptoms. The findings from this study suggest that providing older adults the opportunity to increase in-person interactions and to increase the size of their social networks may promote mental health.

Chapter 5 took a systems thinking approach to better understand the underlying mechanisms contributing to urban neighborhood inequities in health. A causal loop diagram (CLD) was developed to illustrate how the dynamic interplay of neighborhood factors contributes to the development of urban neighborhood inequities in health in high-income European countries. The CLD was informed by a list of neighborhood factors derived from a scoping literature review and the insights gathered from an interdisciplinary group of researchers during Group Model Building (GMB) sessions. GMB is a participatory method that integrates knowledge of different stakeholders in a structured setting to create a shared understanding of the system being studied. The modeling team identified three overarching themes. The first theme of our systems model suggests that imbalances in neighborhood influence in decision-making can lead to an unequal distribution of resources and services across neighborhoods. The second theme reflects the processes that drive residential segregation of socioeconomic groups. The third theme highlights the reciprocal relationship between elements of the physical environment like urban green space and the development of social connections within a neighborhood. These themes demonstrate how neighborhood factors are interconnected, reinforcing one another, and contributing to the sorting of residents by their socioeconomic resources over time. Given this complex interplay, addressing urban inequities in health requires an integrated approach that fosters inclusivity in the decision-making processes and empowers community engagement.

Methodological considerations

Conceptualization of the social environment

This thesis conceptualized the social environment using indicators of social capital, which is widely used in social epidemiology and public health research as a proxy for community-level social interactions, networks, and support systems [1]. While social capital captures some dimensions of the social environment, it does not encompass all of its complexities. The social environment is a multifaceted, multidimensional construct that includes behaviors, interactions, and structural factors that influence health [2]. Notably, aspects such as power dynamics, social exclusion, and cultural norms were not directly represented in the epidemiological studies because they were not measured in the follow-up surveys. Their exclusion means that this thesis did not fully capture all aspects of the social processes that influence health outcomes. However, in the systems model, perceived neighborhood disorder and stigma were incorporated to reflect some of these social processes. Power imbalances also emerged as an overarching theme in the systems model, reflecting their role in shaping health inequities.

Social capital was operationalized through individuals' self-reported perspectives of social cohesion and social network. In particular, two studies assessed social cohesion by measuring the respondents' perceptions of collective efficacy and sense of belonging in their neighborhood [3], while another study assessed the size of the social network and frequency of contact. With these perspectives, this thesis

tried to capture the structure and quality of social relationships, which have been linked to health through mechanisms such as social support, trust, reciprocity, and collective efficacy [4]. Although the instruments implemented in this thesis are widely used in social capital research [3, 5, 6], there are other ways to operationalize social capital that may provide different insights when examining urban health [7]. Bridging social capital, for example, refers to social resources that may be accessed across groups of different socioeconomic or sociodemographic characteristics [7]. This form of social capital may be particularly relevant for evaluating whether interventions fostering connections between socioeconomic groups can improve health outcomes. Given its multiple dimensions, it is important to consider how other forms of social capital relate to health outcomes, as they might reveal distinct social processes that underlie this relationship [7]. Understanding these processes is crucial for developing effective health policies.

Epidemiological methods and systems approaches

This thesis provides an innovative approach to understanding the role of social environment on urban health by integrating two key methodological developments: advanced epidemiological methods and a complex systems thinking perspective. While both epidemiological methods and the systems thinking perspective offer distinct advantages, they also have their limitations. Epidemiological methods are valuable for quantifying specific relationships and testing hypotheses about the effects of one variable on another. For example, in Chapter 2, random-effects within-between (REWB) models were employed to disentangle the within-individual and between-individual components of the association between social cohesion and SAH [8]. An advantage of this model is that individuals act as their own control, effectively removing confounding biases from unobserved time-invariant factors such as inherent personality traits. As such, these models are better able to isolate the effect of temporal changes in the social environment on health outcomes [15]. In addition, a four-way decomposition analysis was conducted to examine the mediating and interaction effects of social cohesion in the association between perceptions of the neighborhood and SAH. This technique draws on recent advances in counterfactual mediation analysis to assess both processes of mediation and interaction simultaneously, by quantifying the overall relationship between an exposure and an outcome into four components [9]. Both of these advanced models provide a more nuanced understanding of the impact of social cohesion on individual health, which is valuable for advancing the development of effective public health interventions and policies.

However, by isolating the effects between exposures and outcomes, epidemiological methods may oversimplify the complexity of real-world processes [10]. For example, epidemiological methods are less capable of accounting for nonlinear feedback loops that may shape health outcomes over time. Assessing this complex feature is important for understanding the dynamic interrelations between social cohesion, individual health, and other aspects of the environment [10]. Additionally, epidemiological methods, especially based on causal inference frameworks, often rely on stringent assumptions about confounding variables, which may not align with the complex and nonlinear dynamics in the social environment.

The systems thinking approach excels in understanding the complexity and interdependencies inherent in real-world systems, as demonstrated in the systems model in Chapter 5 [10]. By recognizing feedback

loops, interdependent relationships, and the dynamic nature of health and social processes, systems thinking offers a more holistic view of how multiple factors interact and influence one another [11]. This approach is particularly useful for exploring the broader mechanisms driving health inequities over time [12]. Furthermore, integrating expert knowledge through GMB methods enables the creation of more nuanced model that captured these complexities.

Despite its advantages, the systems thinking approach also presents limitations. Systems models reflect the knowledge and perspectives of the modelers, introducing a degree of subjectivity. For example, a systems model created by community stakeholders may differ from the one presented in Chapter 5, which was developed primarily by an interdisciplinary team of scholars and health scientists. Using multiple sources of information can mitigate this subjectivity [13], which was done in Chapter 5, where the CLD was informed by both the literature review and insights from GMB sessions.

Given their unique attributes, both approaches complement each other. Epidemiological methods focus on isolating the effects of two variables to determine whether a causal effect exists. This approach provides clear, quantifiable evidence of the relationship but may overlook external factors, which limits its ability to capture the complexity of real-world phenomena [10]. On the other hand, systems approaches take a broader, holistic view, considering the entire system and how all the relationships within it are interconnected. This "bird's-eye view" offers clarity and context on how different factors influence one another and contribute to the overall system, but building these models requires many assumptions about the existence of causal relationship [10, 14]. When used together, both approaches enhance one another. Insights from systems approaches can be further tested through epidemiological methods, while evidence from epidemiological methods informs the development of new systems models. Therefore, integrating both methods offers a more comprehensive understanding, which is essential for better understanding complex public health problems [14].

Longitudinal study design considerations

The epidemiological studies in this thesis contribute to the literature on social capital and health by examining their longitudinal relationship across multiple timeframes. Selecting appropriate time intervals in longitudinal studies is crucial, as different social processes operate at different rates and influence health outcomes in unique ways. Shorter time intervals are ideal for analyzing rapidly changing variables, such as mental health symptoms, as demonstrated by the EMA study in Chapter 4, where fluctuations can occur on a daily basis. However, shorter intervals also require more frequent data collection, which can be burdensome for participants and costly for researchers.

In contrast, longer time intervals are necessary for capturing more gradual social processes that evolve over time, such as building trusting relationships. These processes may take years to unfold and are best examined over extended periods of time, as seen in the REWB analysis with its 17-year follow-up. However, the GLOBE study's time intervals between follow-up surveys ranged from four to seven years, which may have been too long to detect changes that could have occurred sooner. This could partly explain the absence of any within-individual associations between social cohesion and SAH. Determining the appropriate time intervals for measuring changes in social cohesion is challenging, since the rate of change can be influenced by various factors, such as neighborhood size, available resources, and efforts to foster connections. While the ideal period for measuring changes in social cohesion remains unclear,

assessing social cohesion and health more frequently, such as on a yearly basis, may have captured greater within-individual variations in social cohesion and SAH over time.

Examining the association between social capital and health across multiple timeframes provides a more comprehensive understanding of how these relationships evolve over time. By capturing both short-term fluctuations and long-term changes, researchers gain insight into the immediate and sustained impacts of social capital on health. This approach allows for a better understanding of the dynamic nature of social processes, ensuring that interventions can be tailored to address both rapid and gradual shifts in social capital.

Interpretation of main findings

The first overarching aim of this thesis sought to understand how the social environment contributes to urban health. This thesis provided evidence that individuals who perceived high levels of social cohesion in their neighborhood tended to have better SAH, which aligns with previous literature [15]. Higher levels of social cohesion are theorized to contribute to health through mechanisms such as informal social control and collective efficacy, both of which are particularly important during times of distress [4]. For example, in socially cohesive neighborhoods, residents are more likely to intervene when witnessing unlawful behavior, which reduces reliance on law enforcement officers and promoting safer communities [5]. Furthermore, close-knit communities are better equipped to mobilize after natural disasters [16] and collectively maintain neighborhood conditions [17]. Based on these mechanisms, improving perceptions of social cohesion should lead to better health outcomes. However, contrary to these expectations, this thesis did not find conclusive evidence that changes in perceptions of social cohesion were related to changes in health across the population at large or across subgroups based on age, SEP, and gender. The lack of association may be due to a limited variation in social cohesion within the individuals over the study period, which may occur more gradually. Additionally, as mentioned earlier, the extended intervals between follow-up surveys may have further limited the ability to capture changes in social cohesion and health outcomes. Since shifts in social connections and community dynamics often occur gradually and may not be easily observable within a study's timeframe, detecting changes in perceived social cohesion is inherently challenging.

Although changes in social cohesion may not have been directly linked to changes in health, the presence of social cohesion is still expected to provide significant health benefits. These benefits are particularly essential for people living in deprived neighborhoods, where crime, disorder, and deviant behaviors are prevalent. Moreover, deprived neighborhoods tend to be underinvested, resulting in less access to healthcare and amenities than affluent neighborhoods [18, 19]. In communities lacking formal support systems, neighbors stepping in to meet basic needs is essential [20]. For example, residents might support each other by offering childcare or transportation at a time of need. Neighbors may also offer financial relief or share information on job leads, with the expectation of reciprocity during times of financial hardships. In this sense, social cohesion might be considered an informal social safety net that protects against the adverse effects of poverty [20]. Although the studies in this thesis did not find an interaction effect between SEP and level of social cohesion, previous research has shown that high social cohesion can buffer the effects of poverty [20]. Specifically, research has shown that the negative impact of poverty on mental health was significantly reduced in areas with high social cohesion and exacerbated in areas with low social cohesion [21]. In addition, living in socially cohesive communities has also been

shown to protect against psychological distress among unemployed, disabled, and financially struggling residents [22]. These findings suggest a nuanced relationship between social cohesion and health. While measuring the processes that lead to changes in social cohesion is difficult, it is clear that living in communities with strong social cohesion provides significant health benefits.

This thesis also provides some evidence of the value of social networks in relation to mental health. Having a network of people and maintaining frequent contact with them may contribute to more stable and better mental health outcomes. However, it is important to acknowledge that not all forms of social interactions impact well-being equally. More in-person contact was associated with fewer depressive symptoms and less fluctuation in depressive symptoms in older adults, while contact through digital communications showed no such association. This suggests that when developing interventions aimed at improving mental health, the modality of social interaction should be carefully considered to maximize their effectiveness.

There is no denying that the world is becoming more digital, and these changes present both opportunities and challenges for health and well-being. Smartphones and social media platforms enable people to stay connected with family and friends from virtually anywhere, which protects against loneliness, especially in older adults [23]. However, communicating through digital technologies often lacks depth and richness of in-person communications [24]. Studies suggest that virtual interactions can diminish emotional attachment in relationships and may not offer the same level of social support as face-to-face encounters [25]. Moreover, older adults might lack the technical skills to properly use digital communications [26]. As the older population continues to grow, this raises important questions about the quality of digital connections and their long-term effects on mental and physical health. While digital communication can supplement in-person interactions, it cannot replace the benefits of direct, personal contact, which remains essential for building deep, supportive relationships. As society continues to shift toward digital communication, it will be important to balance the accessibility of technology with the need for more meaningful, in-person connections.

The second overarching aim of this thesis was to understand how the social environment contributes to urban health inequities. This thesis identified several underlying mechanisms that perpetuate urban health inequities. These vicious cycles highlight a core dimension of complex systems approaches: complex problems, such as urban health inequities, emerge from interplay of multiple factors and cannot be fully understood by examining individual components in isolation [10]. Although aspects of the social environment are an integral part of the urban system, understanding why urban health inequities persist requires examining the system as a whole.

A key underlying factor in the systems model was household income, as it determines where people live and their position in society. People with more wealth have greater agency to afford housing in the most desirable, and often most expensive neighborhoods, while individuals with less wealth are often confined to areas with fewer resources and poorer living conditions. Over time, this results in a clear divide between affluent and deprived areas, which is why income and wealth inequalities are considered fundamental drivers of residential segregation between socioeconomic groups [27]. Empirical evidence has shown rising levels of income inequality in European cities correlating with rising levels of socioeconomic segregation [27, 28]. This growing segregation has significant implications for population health. Socioeconomic segregation affects the distribution of resources, with deprived areas often lacking essential resources such as housing, healthcare, and education. These neighborhoods also

experience higher crime rates, greater exposure to environmental pollutants, and fewer options for purchasing healthy food compared to affluent areas [29, 30]. As a result, people living in deprived neighborhoods are at greater risk for physical and mental issues, as well as higher mortality rates. The high risk of morbidity in these areas also makes it difficult for residents to improve their social standing, further exacerbating inequalities [31].

As implied by the systems model, socioeconomic segregation contributes to the erosion of the social fabric, which in turn contributes to widening health inequalities. In segregated societies, different groups have fewer opportunities for positive interactions, making it more difficult to develop empathy for people with different demographics. Segregation also limits the sharing of resources and knowledge between groups (i.e., bridging social capital). Without these interactions, people may become more susceptible to negative stereotypes and prejudice, which deepens divisions and perpetuates ignorance. As a result, segregation fosters fear and mistrust between groups, which can lead to social unrest and conflict [31]. It is no surprise that the rise in societal polarization across Europe coincides with increased levels of segregation and the weakening of social bonds and shared values. Currently, distrust between groups is widespread, and with the rise in populism, migrant populations are often being scapegoated for societal issues. This polarization is further exacerbated by the rise of misinformation and echo chambers created by social media and other online platforms [32]. As income inequality and socioeconomic segregation continue to grow, the erosion of trust and its associated risks are likely to intensify.

Implication for policy and practice

As European urban areas become more densely populated, with increasingly diverse and more segregated populations, policymakers and urban planners face significant challenges in creating healthy and equitable urban environments. A primary focus must be placed on improving the living conditions of low SEP households and those living in deprived areas. Improving access to housing, transport, and employment is essential for promoting healthy urban populations. However, due to the interconnectedness of factors within urban environments, policymakers must be aware of potential unintended consequences. For example, improving neighborhood infrastructure could drive up living costs, displacing long-term residents from their homes [33]. To mitigate such unintended effects, it is crucial to examine the urban environment as a whole, identify its underlying mechanisms, and understand the feedback loops that shape these dynamics [34].

In addition to improving living conditions, policymakers should focus on facilitating social cohesion in urban areas as a strategy to promote urban health and mitigate urban health inequities. Social cohesion is often described as the invisible glue that holds a community together. In socially cohesive neighborhoods, residents feel supported and valued, which encourages the sharing of resources and fosters a sense of belonging. Communities with high levels of social cohesion are more resilient to crises and are better equipped to uphold social norms without the need of authorities. Urban design and planning have an important role in promoting social cohesion. Policymakers and urban planners should ensure that public spaces are available for all, which would create opportunities for regular in-person social interactions [35]. Incorporating social cohesion into urban policy and design provides a foundation for more equitable and healthier cities, where residents are empowered to support one another and thrive together.

The responsibility of creating healthier and more equitable cities does not rest solely on local officials. Growing recognition in public health literature suggests that involving residents in community decision-making is a viable strategy for addressing health inequities [36]. This bottom-up approach empowers these groups by providing them with a sense of control over their destiny, which is considered a fundamental social determinant of health [36-38]. Policymakers should collaborate with and share their decision-making power with those directly facing inequities [36]. Their perspectives offer valuable insights into the causes of and barriers to solutions that might otherwise be overlooked. Such collaborations can also strengthen trust between residents and public institutions. Empowering residents, therefore, creates inclusive and equitable communities.

Given the rising levels of socioeconomic segregation in European cities, policymakers and urban planners must be mindful of the increased risk for social isolation and loneliness. Social isolation refers to the objective absence of social connections while loneliness describes the perceptions of feeling isolated [39]. A substantial body of evidence links both social isolation and loneliness to physical and mental health issues, as well as mortality, with social isolation being a stronger predictor [39]. Because low SEP populations often reside in deprived areas with more crime and less access to high quality green space, they face fewer opportunities for in-person social connections and they are more susceptible to social isolation. The risk of social isolation is also particularly high for older adults with less education and wealth, since they tend to experience a shrinking social network as they age [40, 41]. In cases where in-person contact is no longer possible, digital communities may become a vital alternative for maintaining social connections.

Although this thesis did not focus specifically on migrant populations, the findings have important policy implications for migrants, a rapidly growing group in Europe. Migrants face numerous challenges. Upon arrival in Europe, they must adapt to a new culture, secure housing and employment, and learn a new language, each of which can be sources of significant stress [42-44]. Additionally, many migrants face discrimination with the rise of populism across Europe [42]. These challenges can make it difficult for migrants to establish a sense of belonging. Without adequate support systems, their health may be negatively affected [43, 45]. As European cities continue to attract increasing numbers of migrants, the importance of creating neighborhoods that promote social integration becomes even more critical [44]. Ensuring that these communities foster trust, support, and collective efficacy can help mitigate some of the stressors migrants face [43]. The role of social cohesion in supporting migrant populations highlights the need for policies that prioritize the development of inclusive, supportive neighborhoods that facilitate social integration [44].

Future research

The growing interest in adopting complex systems approaches to address major public health issues is well justified, as demonstrated in this thesis. By developing a CLD, this thesis applied a complex systems approach to understand how the underlying mechanisms of neighborhood factors contribute to urban health inequities. However, complex systems approaches have more to offer than just conceptual models. Future research applying complex systems approaches can benefit from the following considerations. One important methodology in the complex systems approach is the use of computer simulations to test the functionality and the implications of proposed conceptual models. Two powerful computational tools used for simulating system behavior are system dynamics models and agent-based

models. System dynamics models take a top-down approach by focusing on broader system characteristics such as feedback loops, stocks, and flows, to model system-wide behavior over time [46]. In contrast, agent-based modeling takes a bottom-up approach, focusing on how individuals (i.e., agents) interact with others and their environment according to predefined rules to create emergent properties at the population level [47]. Both approaches can provide valuable insight into how urban health inequities emerge as well as how interventions affect health and health inequities. Additionally, future CLD's can benefit from applying a triangulation approach, which integrates domain expertise from GMB, literature review, and data-driven causal discovery [13]. The CLD in this thesis was informed by both the literature review and GMB, as using multiple sources of information improves the reproducibility and validity of CLDs [48]. However, this approach still relies on modelers' assumptions, which can introduce biases [13]. Integrating causal discovery, a data-driven methodology for identifying causal relationships between variables from observational data, alongside GMB and literature reviews further strengthen causal inferences, resulting in higher-quality CLDs [13]. Finally, to support the next generation of evidence within public health and complex systems approaches, future research can consider implementing the Health Complexity Framework [14]. This framework offers a broader conceptualization of the research questions necessary to understand complex public health problems. By combining three types of evidence (i.e., causal evidence, intervention evidence, and implementation evidence) with the three dimensions of complex systems (i.e., mechanisms, dynamics, and patterns), this framework offers nine categories of evidence generation. This framework could be a valuable tool for framing future research questions, designing research projects, and developing evidence-based policies that address health inequities [14].

The epidemiological studies in this thesis advanced research on social capital and health, but there are areas for further exploration in future research. This thesis focused on social cohesion and social networks as indicators of social capital [49]. However, social capital can be operationalized in various ways with each capturing different aspects of the social environment [49]. Since these forms of social capital may influence health through distinct social processes, future studies should examine their effects on health outcomes [49]. Additionally, this thesis relied on SAH as the primary health outcome. While SAH is widely used as a proxy for overall health, it limits our understanding of the specific mechanisms through which social capital affects health [15]. Future studies should explore the effects of social capital on a broader range of health outcomes, which may help identify the distinct mechanisms linking social to various health outcomes [15]. Finally, while the epidemiological methods used in this thesis aimed to establish causal relationships between social capital and health, observational studies are inherently susceptible to confounding factors. A key challenge in causal inference in the social sciences is addressing endogeneity, which arises from individuals' choices and preferences [50]. Future research on social capital and health should incorporate natural experiment study designs, which can help mitigate endogeneity and provide more robust evidence of causal relationships [51].

Finally, given the rapid changes in population density and diversity, it is unclear how to effectively build social cohesion in these unprecedented contexts. As urban areas become more urbanized and multicultural, the process of building trust, understanding, and common purpose becomes more complicated. It is likely that there is no one-size-fits-all solution to this challenge, as different communities may require tailored approaches that take into account local contexts and social dynamics. Given these complexities, further research is essential to explore strategies for promoting social cohesion in diverse communities, where residents may come from different cultural, ethnic, and socioeconomic

backgrounds. Including residents in this decision-making process is essential for promoting inclusive and equitable societies.

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Summary

Introduction

Over half of the world's population currently resides in urban areas, with projections indicating that two-thirds of people will live in cities by 2050. Europe has become one of the most urbanized regions, with 75% of its population living in urban areas. Urbanization has significant public health implications since living in urban areas brings both health benefits and risks. Urban areas can provide access to economic opportunities, healthcare, and other essential services. However, rapid urban growth can also result in overcrowded living conditions, inadequate infrastructure, and increased exposure to environmental pollutants, which disproportionately affect disadvantaged neighborhoods. As urban populations continue to grow, it is crucial to identify the key drivers of health in urban areas for informing effective public health interventions.

Empirical research indicates that both the physical and social environment are associated with urban health. The physical environment includes aspects such as air pollution, noise, climate, and the physical infrastructure; the social environment involves social cohesion, trust, and community organization. While research on the physical environment and its impact on health is well-established, studies examining the social environment's influence on health are rapidly advancing for two reasons. First, urbanization trends have made urban areas denser and more diverse than ever before, which have affected the way residents form new relationships and interact with one another. Second, with advances in digital technology people now rely on the internet and communication devices to build and maintain social relationships through. These changes to the social environment underscore the need for further research into how modern social environments shape public health.

Another critical concern of growing urban populations is the persistence of health inequities, particularly systematic differences in health outcomes within cities. These inequities remain prevalent across Europe despite ongoing efforts to address them. Within-city health inequities primarily stem from the unequal distribution of material and social resources, as well as environmental conditions. These disparities are reinforced by socioeconomic residential segregation, where higher-income households are able to access better infrastructure and services compared to lower-income households. Understanding the complex interactions between these factors is crucial for developing interventions that address the root causes of urban health inequities.

While research on the social environment to health is extensive, there are areas to build upon these findings. This research would benefit from examining these relationships from a longitudinal perspective as both the social environment and health are dynamic. Additionally, public health researchers have turned to complex systems approaches, as a complement to conventional epidemiological methods, to better understand the complexity underlying public health issues.

Research aim

The overarching aim of this thesis is to further understand how the social environment contributes to urban health and urban health inequities.

To address this aim, this thesis adopted a mixed-methods approach to examine how various aspects of the social environment shape health and contribute to inequities in urban contexts. Each empirical chapter focuses on a different aspect of the social environment and employs a different methodological approach. Collectively, these chapters offer a comprehensive understanding of how social contexts influence urban health and contribute to urban health inequities.

Summary of findings

Chapter 2 explored the relationship between perceived neighborhood social cohesion and self-assessed health (SAH) in a cohort of Dutch adults over a 17-year follow-up period. The study aimed to determine whether higher levels of perceived social cohesion were associated with better SAH and whether changes in individuals' perceptions of neighborhood cohesion were linked to changes in their health over time. Additionally, it examined how these relationships varied by age, socioeconomic position (SEP), and gender. The findings revealed that individuals with higher perceptions of social cohesion in their neighborhoods were less likely to report poor SAH. However, no conclusive evidence was found to suggest that improvements in perceived social cohesion within individuals led to corresponding improvements in their health. The analysis also found no differences in these associations across age, SEP, or gender.

Chapter 3 investigated the extent to which the relationship between perceptions of neighborhood unsafety and disorder and SAH is explained by mediation, interaction, or a combination of both through perceived neighborhood social cohesion in Dutch cohort of 5,650 respondents over a 10-year follow-up. Log-linear regression analyses were used to estimate the total effects of feeling unsafe and perceived neighborhood disorder with poor SAH. A four-way decomposition approach was used to decompose the total effects into four components: controlled direct effect (neither mediation nor interaction), pure indirect effect (mediation only), reference interaction effect (interaction only) and mediated interaction effect (both mediation and interaction). The results indicated that feeling unsafe had a positive estimated total effect on poor SAH. For perceived neighborhood disorder, the estimated total effect was smaller. Decomposition analysis indicated that the majority of the estimated effect of perceived unsafety was attributed to the controlled direct effect, with no evidence of mediation or interaction through social cohesion. None of the estimated decomposition components were significant for neighborhood disorder. These findings suggest that perceived neighborhood disorder and unsafety and perceived neighborhood social cohesion appear to influence health through independent pathways, rather than through their interplay.

Chapter 4 analyzed ecological momentary assessment (EMA) data to examine how social network characteristics relate to momentary depressive symptoms and their daily fluctuations in older adults. Social network characteristics included network size and frequency of in-person and digital interactions per week. Depression symptoms were measured using a daily smartphone survey based on the Center for Epidemiological Studies-Depression (CES-D8) scale over the course of a week. The results showed that the size of the network and the frequency of contact from digital communications per week were not associated with fewer depressive symptoms. There was a suggestion that the frequency of in-person contact was associated with slightly fewer depressive symptoms, as the 95% interval included the value of 1 just on its upper side. The study also found that having a larger social network and more frequent in-person interactions were associated with less fluctuations in daily depressive symptoms. The findings

from this study suggest that providing older adults the opportunity to increase in-person interactions and to increase the size of their social networks may promote mental health.

Chapter 5 employed a systems thinking approach to explore the underlying mechanisms contributing to urban neighborhood health inequities. A causal loop diagram (CLD) was developed to illustrate how the dynamic interplay of various neighborhood factors shapes health inequities in high-income European countries. The diagram was created using Group Model Building (GMB), a participatory method that brings together stakeholders to build a shared understanding of the system. A scoping review of international literature complemented the insights gathered during the GMB sessions. The modeling team identified three overarching themes. The first theme of our systems model suggests that imbalances in neighborhood influence in decision-making can lead to an unequal distribution of resources and services across neighborhoods. The second theme reflects the processes that drive residential segregation of socioeconomic groups. The third theme highlights the reciprocal relationship between elements of the physical environment such as urban green space and the development of social connections within a neighborhood. These interconnected themes reveal how neighborhood factors reinforce one another, driving the socioeconomic sorting of residents over time. To address urban health inequities, the study suggests the need for an integrated, inclusive approach that empowers communities and involves them in decision-making processes.

Interpretations of findings

The findings from this thesis indicate that high levels of social cohesion are linked to better health outcomes. However, it does not find conclusive evidence that increasing perceptions of social cohesion leads to improved health. This finding was unexpected and may be due to the inherent challenges in detecting changes in perceived social cohesion, as there was little variation in the levels of social connections and extended timeframes between follow-up periods.

Additionally, findings of this thesis indicate that in-person contact is associated with better mental health outcomes among older persons, while digital interactions showed no such effect. This might suggest that not all forms of social interaction impact well-being equally. Although the world is becoming increasingly digital, it remains important to engage in meaningful in-person interactions when possible.

Using a systems thinking approach, this thesis identified three underlying mechanisms that perpetuate these inequities. Within these vicious cycles, income inequality and socioeconomic segregation were found to play a significant role in driving health inequities. High-income residents have greater freedom to choose to live in neighborhoods with better resources and more influence in shaping their environments, than lower-income households who are often confined to deprived areas with fewer opportunities. This ongoing cycle of poverty and inequality contributes to poorer health outcomes, and if not addressed, can heightened social unrest, and further reinforce segregation.

Policy implications

Policymakers and urban planners face significant challenges in creating healthy and equitable urban environments. A key focus must be placed on improving the living conditions of deprived areas and

fostering neighborhood social cohesion. Additionally, policymakers must be mindful of social isolation among migrants and low SEP populations. Finally, it is important that policymakers include residents from marginalized communities in the decision-making process in shaping their communities, as this promotes empowerment and trust in institutions. Empowering those shaped by social disadvantage is essential for building more inclusive and equitable societies.

Samenvatting

Meer dan de helft van de wereldbevolking woont momenteel in stedelijke gebieden en prognoses wijzen erop dat in 2050 zelfs twee derde van de mensen in steden zal wonen. Europa is één van de meest verstedelijkte regio's geworden, waar 75% van de bevolking in stedelijke gebieden woont. Verstedelijking heeft belangrijke gevolgen voor de volksgezondheid, omdat wonen in stedelijke gebieden zowel gezondheidsvoordelen als gezondheidsnadelen met zich meebrengt. Stedelijke gebieden kunnen toegang bieden tot economische kansen, gezondheidszorg en andere essentiële diensten. Verstedelijking kan echter ook leiden tot voor de gezondheid ongunstige woonomstandigheden, inrichting van de gebouwde omgeving en tot een verhoogde blootstelling aan milieu gerelateerde schadelijke stoffen. Deze nadelen komen vaak onevenredig vaak voor in wijken waar mensen minder te besteden hebben. Naarmate de stedelijke bevolking blijft groeien, is het cruciaal de belangrijkste factoren die de gezondheid in stedelijke gebieden beïnvloeden te identificeren, zodat effectieve volksgezondheidsinterventies kunnen worden ontwikkeld.

Empirisch onderzoek wijst uit dat zowel de fysieke als de sociale omgeving van belang is voor de gezondheid van mensen in steden. De fysieke omgeving omvat aspecten zoals luchtvervuiling, geluid, klimaat en fysieke infrastructuur; bij de sociale omgeving gaat het om de mate van sociale cohesie, vertrouwen en sociale orde in buurten. Hoewel onderzoek naar de fysieke omgeving en de impact ervan op de gezondheid mede door het groeiende besef van klimaatverandering veel aandacht heeft, blijft onderzoek naar de invloed van de sociale omgeving op gezondheid belangrijk om tenminste twee redenen. Ten eerste maakt de toenemende verstedelijking gebieden diverser, wat van invloed kan zijn op de manier waarop bewoners nieuwe relaties vormen en met elkaar omgaan. Ten tweede vertrouwen mensen door de vooruitgang in digitale technologie steeds meer op internet en digitale communicatiemiddelen om sociale relaties op te bouwen en te onderhouden.

Een ander belangrijk aandachtspunt bij groeiende stedelijke bevolkingen is de persisterende gezondheidsongelijkheid binnen steden. Deze ongelijkheden blijven wijdverspreid in Europese steden, ondanks inspanningen ze aan te pakken. Ongelijkheden binnen steden ontstaan voornamelijk door de ongelijke verdeling van materiële en sociale middelen van mensen en de verschillen in omgevingsfactoren. Deze verschillen worden versterkt door sociaaleconomische segregatie, waarbij huishoudens met een hoger inkomen betere toegang hebben tot infrastructuur en diensten in vergelijking met huishoudens met een lager inkomen. Het begrijpen van de complexe interacties tussen deze factoren is cruciaal voor het ontwikkelen van interventies die de onderliggende oorzaken van gezondheidsongelijkheden binnen steden aanpakken.

Tegen deze achtergrond is het overkoepelende doel van dit proefschrift beter te begrijpen hoe de sociale omgeving bijdraagt aan de volksgezondheid in steden en aan gezondheidsongelijkheden binnen steden. Om dit doel te bereiken, richt elk empirisch hoofdstuk zich op een ander aspect van de sociale omgeving en maakt gebruik van een andere methodologische benadering.

Hoofdstuk 2 beschrijft een studie waarin de relatie tussen sociale cohesie (zoals ervaren door mensen) in de buurt en zelfgerapporteerde ervaren gezondheid werd onderzocht in een cohort van Nederlandse volwassenen gedurende een follow-up periode van 17 jaar. De studie had tot doel te onderzoeken of meer sociale cohesie geassocieerd was met betere ervaren gezondheid en of veranderingen in de ervaren sociale cohesie in de buurt samenhingen met veranderingen in ervaren gezondheid. Daarnaast werd onderzocht hoe deze relaties varieerden naar leeftijd, sociaaleconomische positie (SEP) en

geslacht. De bevindingen toonden aan dat mensen die meer sociale cohesie ervoeren in hun buurt minder vaak een slechte gezondheid rapporteerden. Er werd echter geen sluitend bewijs gevonden dat mensen die verbeteringen in de ervaren sociale cohesie rapporteerden overeenkomstige verbeteringen in hun ervaren gezondheid hadden. De analyse liet ook geen verschillen zien in deze verbanden zien voor groepen mensen op basis van hun leeftijd, geslacht of sociaaleconomische positie.

Hoofdstuk 3 beschrijft een studie waarin werd onderzocht in hoeverre de relatie tussen enerzijds percepties van onveiligheid en sociale wanorde in de buurt en anderzijds ervaren gezondheid verklaard en/of versterkt worden door de mate van ervaren sociale cohesie in de buurt. Dit werd onderzocht in een Nederlands cohort van 5.650 respondenten gedurende een follow-up periode van 10 jaar. Log-lineaire regressieanalyses werden gebruikt om de totale effecten van het gevoel van onveiligheid en sociale wanorde op de ervaren gezondheid te schatten. Een relatief nieuwe decompositietechniek werd gebruikt om de totale effecten op te splitsen in vier componenten: een gecontroleerd direct effect (geen mediatie, geen interactie), puur indirect effect (alleen mediatie), referentie-interactie-effect (alleen interactie) en gemedieerd interactie-effect (zowel mediatie als interactie). De resultaten toonden aan dat een groter gevoel van onveiligheid gepaard ging met een slechtere ervaren gezondheid. Voor de maten van ervaren sociale wanorde in buurten was dit verband kleiner. De decompositieanalyse wees uit dat het grootste deel van het geschatte effect van ervaren onveiligheid op de ervaren gezondheid niet verliep via, of versterkt werd door de mate van sociale cohesie. Deze bevindingen suggereren dat het waarschijnlijker is dat ervaren onveiligheid en sociale wanorde in buurten en de mate van ervaren sociale cohesie in de buurt de gezondheid beïnvloeden via onafhankelijke wegen.

Hoofdstuk 4 beschrijft een analyse hoe kenmerken van sociale netwerken samenhangen met depressieve symptomen en de dagelijkse schommelingen daarin bij oudere volwassenen uit Parijs. Om die schommelingen te kunnen meten, gaven deelnemers aan de studie via een mobiele telefoon een week lang en meerdere keren per dag aan hoe zij zich voelden. Kenmerken van sociale netwerken omvatten de netwerkgrootte en de frequentie van persoonlijke en digitale interacties per week. Depressieve symptomen werden gemeten met een dagelijkse enquête via de mobiele telefoon. De resultaten toonden aan dat de grootte van het netwerk en de frequentie van digitale communicatie per week niet geassocieerd waren met depressieve symptomen. De resultaten suggereerden dat een hogere frequentie van persoonlijk contact geassocieerd was met minder depressieve symptomen, al was dit niet statistisch significant. De studie toonde ook aan dat een groter sociaal netwerk en meer persoonlijke interacties samenhingen met minder fluctuaties in dagelijkse depressieve symptomen. De bevindingen suggereren dat het uitbreiden van het aantal persoonlijke interacties en het vergroten van het sociale netwerk de mentale gezondheid van ouderen zou kunnen bevorderen.

Hoofdstuk 5 beschrijft een studie waarin de onderliggende mechanismen die bijdragen aan gezondheidsongelijkheden in stedelijke buurten werden onderzocht. Vanuit het perspectief dat het hier gaat om een complex systeem, werd een 'causal loop diagram' (CLD) ontwikkeld dat de dynamische interactie van verschillende buurtfactoren visualiseerde, die leiden tot ongelijkheden in gezondheid binnen steden. Het diagram werd gemaakt met Group Model Building (GMB), een participatieve methode die verschillende stakeholders, in dit geval experts uit verschillende vakgebieden, samenbracht om een gezamenlijk begrip van het systeem te ontwikkelen. Een review van internationale literatuur vulde de inzichten uit de GMB-sessies aan. Zo werden drie overkoepelende thema's geïdentificeerd. Het eerste thema van het systeemmodel suggereerde dat ongelijkheden in de mate van invloed op besluitvorming kunnen leiden tot een ongelijke verdeling van middelen en diensten tussen buurten. Het tweede thema weerspiegelde de processen die leiden tot sociaaleconomische segregatie in steden. Het derde thema benadrukte de wederzijdse relatie tussen elementen van de fysieke omgeving (zoals

stedelijk groen) en de ontwikkeling van sociale verbanden binnen een buurt. Deze onderling verbonden thema's laten zien hoe buurtfactoren elkaar versterken en de spreiding van bewoners op basis van hun sociaaleconomische positie in de loop van de tijd beïnvloeden. Om de ongelijkheid in gezondheid binnen steden te verkleinen is een integrale inclusieve aanpak nodig die gemeenschappen versterkt en hen betrekt bij besluitvormingsprocessen.

De resultaten van het proefschrift onderstrepen zo het belang van de sociale omgeving voor de gezondheid van bewoners van steden. Tegelijkertijd wordt duidelijk dat het voor de onderbouwing van oorzakelijke verbanden en de ontwikkeling van interventies en beleid belangrijk is in onderzoek rekening te houden met de tijd tussen het meten van kenmerken van de sociale omgeving en de gezondheid en de complexe samenhang tussen factoren en processen die elkaar kunnen versterken.

Tot slot, beleidsmakers staan voor de aanzienlijke uitdaging gezonde en rechtvaardige stedelijke omgevingen te creëren. Daarbij moet een belangrijke focus liggen op het bevorderen van sociale cohesie in buurten met een lage sociaaleconomische welstand. Daarbij is het belangrijk dat bewoners worden betrokken bij besluitvormingsprocessen over de leefomgeving, ook omdat dit vertrouwen in instituties kan bevorderen. Het versterken van mensen die leven in minder gunstige omstandigheden , is essentieel voor het bouwen van inclusievere en rechtvaardigere samenlevingen.

List of Publications

2026

Cail V., Oude Groeniger J., Beenackers M.A., van Lenthe F.J. Exploring How the Interplay Between Neighborhood Perceptions and Social Cohesion Relates to Self-Assessed Health: A Four-Way Decomposition with a 10-Year Follow Up. Journal of Urban Health. 2026; 103: 406–415; https://doi.org/10.1007/s11524-026-01083-1.

Cail V., Beenackers M.A., ter Ellen F., Droomers M., Dijst M., Oude Groeniger J., van Lenthe F.J. Understanding the systems dynamics of neighborhood socioeconomic inequities in health in European cities: a causal loop diagram. Health & Place. 2026; 97; https://doi.org/10.1016/j.healthplace.2025.103595.

2025

Cail V., Beenackers M.A., Van Lenthe F.J., Oude Groeniger J., Fancello G., Montanari A., Sueur C., Kestens Y., Vallée J., Chaix B. Social network characteristics and levels of fluctuations in momentary depressive symptomatology among older adults. Journal of Epidemiology & Community Health. 2025; 79 (11): 828-834; https://doi.org/10.1136/jech-2024-222959.

2024

Cail V., Oude Groeniger J., Beenackers M.A., van Lenthe F.J. Changes in perceived neighborhood social cohesion and self-assessed health: 17-year follow-up of the Dutch GLOBE study, European Journal of Public Health. 2024; 34 (6): 1079-1085; https://doi.org/10.1093/eurpub/ckae168.

Portfolio

PhD Student: V.E. Cail

University: Erasmus University Rotterdam

Faculty: Erasmus MC

Department: Public Health

PhD Period: 2021-2026

Promotor: Prof. Dr. F.J. van Lenthe

Co-promotors: Dr. M.A. Beenackers, Dr. J. Oude Groeniger

	Date	ECTs
Courses		
Erasmus MC - Introduction session	Oct-21	0.2
Reviews: Project Management, multiple databases, and EndNote	Apr-22	1.0
Biostatistics I	May-22	2.0
Social Epidemiology	Aug-22	0.7
The Practice of Epidemiologic Analysis	Aug-22	0.7
Scientific Integrity	Sep-22	0.3
Public Health Across the Life Course	Mar-23	2.0
Repeated Measurements in Clinical Studies	Apr-23	1.7
Causal Inference	Aug-23	1.4
Causal Mediation Analysis	Aug-23	1.4
Biomedical Writing for PhD Candidates	Nov-23	1.5
SURREAL Network Schools		
Network School, Utrecht, The Netherlands	Jun-22	1.0
Network School, Paris, France	May-23	1.0
Network School, Barcelona, Spain	Mar-24	1.0
Network School, Luxembourg	Jun-24	1.0
Secondments		
Academic secondment at INSERM, Paris, France [1]	Sep-23	17.1
Nonacademic secondment at Munich Municipality, Munich, Germany [2]	Jul-24	11.4
Conferences		
Healthy City Conference, Rotterdam, The Netherlands	Apr-23	1.0
WEON Conference, Rotterdam, The Netherlands	Jun-23	1.0
Presentations		
Research Seminars Department of Public Health		3.0
Section Meetings Social Epidemiology		1.0
Total		51.5

[1] 12 weeks at 40 hours per week, [2] 8 week at 40 hours per week, *1 ECT per 28 hours

About the author

Vernon Elbert Cail was born on March 20, 1987, in Chicago, Illinois, USA. He earned a Bachelor of Science in Kinesiology from the University of Illinois at Urbana-Champaign in 2009. In 2011, he graduated with a dual Master of Public Health (MPH) and Master of Public Administration (MPA) from the University of Illinois at Springfield. After completing his graduate studies, Vernon worked as a Research Study Coordinator at Rush University Medical Center in Chicago. In this role, he focused on childhood obesity research within underserved communities. In 2015, he relocated to Munich, Germany, where he enrolled in the Master's program in Epidemiology at Ludwig Maximilian University of Munich. During this time, Vernon contributed to various research projects on environmental health and chronic disease management at Helmholtz Zentrum München. Upon earning his Master of Science in Epidemiology, he returned to Chicago, where he worked as an Analytics Consultant at Health Care Service Corporation. From 2021 to 2026, Vernon conducted his PhD research at the Department of Public Health at Erasmus MC University Medical Center in Rotterdam as a part of the SURREAL consortium.

Vernon Elbert Cail werd geboren op 20 maart 1987 in Chicago, Illinois, USA. In 2009 behaalde hij een Bachelor of Science in Kinesiologie aan de Universiteit van Illinois in Urbana-Champaign. In 2011 voltooide hij een dubbele masteropleiding in Public Health (MPH) en Public Administration (MPA) aan de Universiteit van Illinois in Springfield. Na het afronden van zijn masterstudies, werkte Vernon als Research Study Coordinator bij Rush University Medical Center in Chicago, waar hij zich richtte op onderzoek naar kinderobesitas in achtergestelde gemeenschappen. In 2015 verhuisde hij naar München, Duitsland, om de masteropleiding Epidemiologie te volgen aan de Ludwig Maximilian Universiteit van München. Gedurende deze periode droeg hij bij aan verschillende onderzoeksprojecten op het gebied van milieugezondheid en chronisch ziektebeheer bij Helmholtz Zentrum München. Na het behalen van zijn Master of Science in Epidemiologie keerde Vernon terug naar Chicago, waar hij werkte als Analytics Consultant bij Health Care Service Corporation. Van 2023 tot en met 2026 deed hij promotieonderzoek bij de afdeling Maatschappelijke Gezondheidszorg van het Erasmus MC in Rotterdam.

Acknowledgements

Completing this thesis has been a long and challenging journey, and it would not have been possible without the incredible support of so many people.

First and foremost, I owe my gratitude to my supervision team: Prof. Dr. Frank van Lenthe, Dr. Mariëlle Beenackers, and Dr. Joost Oude Groeniger. Your mentorship, guidance, and belief in me gave me the courage to tackle difficult questions and pursue ambitious ideas. I am proud of the work we have accomplished together, and I could not have asked for a better group of people to learn from.

I am also grateful to the other contributors to my manuscripts for sharing their expertise and providing valuable feedback, which greatly enriched the quality of my work.

Being part of the SURREAL consortium has been a truly unique experience. It was an honor to collaborate with talented early-stage researchers (ESRs) and senior researchers from around the world who share my passion for public health. I am especially grateful to Daina Kosite, who shared this journey with me from the very beginning. It was a joy to work alongside you.

To my colleagues and staff at MGZ, thank you for your support, encouragement, and camaraderie. You made the challenges lighter and Rotterdam feel like home.

I am deeply grateful to my parents, Eugene Cail Jr. and Ivanona Cail, for instilling in me the values of hard work and perseverance. Your example has guided me every step of the way.

To my siblings, Vernetta, Vincent, and Vanessa, thank you for your constant encouragement, support, and belief in me. I am grateful for the bond we share and for always knowing that I could count on you.

I am also grateful to my family and friends in Germany and the United States who supported me in countless ways throughout this journey. Your encouragement, kindness, and continued support have been invaluable.

Thank you, Frances, for always being there, cheering me on, and believing in me, especially during the moments when I needed it most. I could not have completed this journey without your love and support.

Lastly, I dedicate this thesis to my three sons: Noah, Nelson, and Nathan. Like my parents did for me, I hope to inspire you to pursue your dreams. May this thesis serve as a testament that with determination, hard work, and persistence, you can achieve anything you set your mind to.