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Neighborhoods and health: where are we and were do we go from here?:

Environnement résidentiel et santé: état de la question et perspectives pour le futur

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Summary

In recent years there has been an explosion of interest in neighborhood health effects. Most existing work has relied on secondary data analyses and has used administrative areas and aggregate census data to characterize neighborhoods. Important questions remain regarding whether the associations reported by these studies reflect causal processes. This paper reviews the major limitations of existing work and discusses areas for future development including (1) definition and measurement of area or ecologic attributes (2) consideration of spatial scale (3) cumulative exposures and lagged effects and (4) the complementary nature of observational, quasi-experimental, and experimental evidence. As is usually the case with complex research questions, consensus regarding the presence and magnitude of neighborhood health effects will emerge from the work of multiple disciplines, often with diverse methodological approaches, each with its strengths and its limitations. Partnership across disciplines, as well as among health researchers, communities, urban planners, and policy experts will be key.

Keywords

Neighborhood environment; Health; Measurement; Causality; Ecological attributes; Spatial scale

The recent interest in neighborhood health effects within epidemiology and public health is closely linked to several interrelated trends within these fields. The first of these is a growing sense that purely individual-based explanations of the causes of ill-health are insufficient and fail to capture important disease determinants. This has been reflected in multiple discussions of the need to consider not only individual characteristics but also characteristics of the groups or contexts to which individuals belong in understanding the distribution of health and disease [1–4]. Neighborhoods (or residential areas more broadly) have emerged as a potentially relevant group or context because they clearly possess both physical and social attributes which could plausibly affect the health of individuals. A second trend contributing to interest in neighborhood health effects has been the revitalized interest in understanding the causes of social inequalities in health. Because place of residence is strongly patterned by social position, neighborhood characteristics could be important contributors to health inequalities by socioeconomic indicators or race/ethnicity. A third factor has been a perception that epidemiology needs to be more closely linked to policy broadly understood. A correlate of this

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is that health researchers need to consider the health effects of policies which are not traditionally thought of as health policies but that could have important health implications. Many of these non-health policies (such as housing policy or urban planning policy) could affect health through their impact on the contexts in which individuals live and work. Neighborhoods are clearly an important context for these policies and thus the study of neighborhood health effects becomes directly policy-relevant and could have broad impact on a range of policies far beyond the traditional purview of health policy. A fourth factor has been the increasing availability and popularity of methods especially suited to the study of neighborhood health effects, first multilevel analysis [5–7] and more recently the explosion of Geographic Information Systems (GIS) and spatial analysis techniques which allow the examination of space in a much more detailed and sophisticated manner than has been possible in the past [8].

Investigation of the effects of neighborhood characteristics on the health of residents is not new. Over thirty years ago Harburg et al. examined whether living in a neighborhood characterized as “high stress areas” affected blood pressure after controlling for the potentially confounding effects of individual characteristics [9]. Results indicated that living in a “high stress area” was associated with higher systolic and diastolic blood pressure independently of individual-level characteristics. Areas were defined based on available census-defined geographic units (census tracts) and were classified as high or low stress based on combinations of aggregate variables derived from a national census. Subsequent work on area or neighborhood health effects, including the large number of contextual or multilevel studies published over the last decade and reviewed in detail elsewhere [10] have followed an approach very similar to that used by Harburg *et al.* thirty years ago, although employing more sophisticated analytical techniques such as multilevel analysis to account for the clustering of persons within areas or neighborhoods and, sometimes, to decompose the variance in the outcome being studied into between and within neighborhood components. Multiple different health outcomes have been investigated using these approaches including chronic disease morbidity and mortality, mental health, infant health and birth outcomes [10]. One of the domains most frequently investigated in relation to neighborhoods has been cardiovascular disease and its risk factors[11–16]. For this reason, much of this paper will use cardiovascular disease as an example, although the issues to be discussed are relevant to all health outcomes.

LIMITATIONS OF USING CENSUS AGGREGATE MEASURES AS PROXIES FOR RELEVANT AREA-LEVEL VARIABLES

To date the vast majority of contextual and multilevel studies of neighborhood health effects on cardiovascular disease and its risk factors have been secondary analyses of data collected with other purposes [10,17–19]. As a result, the only available neighborhood-level data were aggregate census characteristics for pre-defined census areas, such as census-tracts or block-groups in the US or wards in the UK. Census-derived measures, such as area poverty or deprivation indices combining various census socioeconomic measures, were used as proxies for the variety of physical and social features of areas hypothesized to be relevant to health. A consistent picture has emerged from these contextual and multilevel studies now replicated across multiple populations and with multiple different datasets. A key finding has been the repeated observation of an association between neighborhood deprivation or neighborhood disadvantage and increased cardiovascular risk, as assessed by morbidity, mortality or risk factor prevalences [10,18]. These associations persist after statistical control for person-level indicators of socioeconomic position using multiple regression techniques. A second finding has been that when multilevel analysis has been used to estimate the percent of total variance in the outcome that is between neighborhoods (the intraclass correlation coefficient (ICC) for neighborhoods) this percent has generally been found to be low, usually well under 10%. Although this fact is sometimes used as an indication that neighborhood effects must therefore not be important, drawing conclusions on the presence or magnitude of neighborhood causal effects based on the ICC has important limitations discussed in detail elsewhere [20,21]. Misspecification of neighborhoods (a large problem in neighborhood health effects) is likely to result in important underestimation of neighborhood ICCs. In addition, even low intraclass correlation coefficients may coexist with important fixed effects of contextual variables. Public health is full of examples of risk factors that explain very little inter-individual variance but are considered important predictors of health outcomes. Thus, as Duncan *et al.* have noted [20], low ICCs are compatible with important and policy-relevant effects of neighborhood characteristics on health. Contextual and multilevel analyses of neighborhood effects using census data to characterize neighborhoods have important methodological limitations as repeatedly noted by researchers working in the field [18,19]. The chief limitation is that these measures are imperfect and obviously very crude proxies for the physical and social features of neighborhoods hypothesized to affect health. This generates two problems. First, their use necessarily results in misestimates of the overall causal effects of neighborhoods on health simply because of the measurement error inherent in using neighborhood socioeconomic characteristics as a proxy for the direct measure of the relevant construct. A second problem is that their use does not allow identification of the specific neighborhood features that are relevant, or of the processes by which neighborhoods affect health. Identifying these features and these processes is key to developing health promoting interventions targeted at neighborhood conditions. Nevertheless it is important to emphasize that the causal effect of interest even in studies that use aggregate neighborhood socioeconomic characteristics is not the literal effect of neighborhood socioeconomic composition per se, but rather the causal effect of the social and physical neighborhood attributes which neighborhood socioeconomic position (SEP) is proxying. The counterfactual contrast can therefore be clearly articulated, although the treatment or "exposure" is measured with error and its effective components cannot be identified. These social and physical features of neighborhood are external to the individual and are also modifiable and therefore perfectly valid as potential causal factors. The "treatment" being investigated is changing these social and physical attributes, and not moving rich people into poor neighborhoods or vice versa, as is sometimes implied [22]. Even though neighborhood SEP may appear endogenous to individual SEP (because it is constructed by aggregating personal SEP) the dependence of the aggregate measures on a single individual is trivial; moreover the aggregate SEP measures is used to proxy a variety of clearly exogenous characteristics. Of course they may be poor proxies; hence the need to move beyond this initial approach to direct measurement of the neighborhood constructs of interest.

A second limitation of using neighborhood socioeconomic indicators as proxies for relevant neighborhood attributes pertains to difficulties in estimating associations of neighborhood socioeconomic context with health outcomes independently of person-level socioeconomic position. Person-level socioeconomic position is often perceived as a key confounder of any neighborhood health effects because of the known relationship between socioeconomic position and health, and because of the strong residential segregation by socioeconomic position that exists in most of today's societies. It has been argued for example, that the limited overlap in personal SEP between wealthy and poor neighborhoods makes personal SEP adjusted estimates of neighborhood effects questionable because they are based on extrapolations well beyond the range observed in the data [22]. The extent to which this is true is an empirical question that can be examined in each specific dataset. Careful analyses of neighborhood effects have investigated the overlap in the distributions before making any adjustments as one would with any adjustment variable [21]. The amount of overlap that is sufficient is ultimately a matter of judgement. The whole purpose of adjustment is to compare groups with different distributions, how different these distributions have to be for the adjusted results to be questionable is a matter of debate. Of course, as in any analysis, showing the data and making assumptions explicit is key.

Because of the limitations noted above, considerable debate still exists on whether the associations observed reflect causal processes, and if they do, what the specific relevant aspects of neighborhoods -aspects that we could potentially intervene on to improve health - might be. Identifying these specific features is crucial not only for strengthening evidence regarding the presence of causal neighborhood effects but also because it would indicate aspects that could be intervened on to improve health. A large body of recent work has begun to focus on investigating area or neighborhood effects in much more detail. The fundamental questions that these studies are trying to address are: (a) What is it about areas that matters or what are the specific area characteristics relevant to health? (b) How does it matter or what are the specific processes through which these characteristics affect health? (c) What are the spatial scales at which these processes operate and are different scales relevant for different health outcomes? and finally, (d) Can we change area characteristics and show an effect on health? Fundamental to answering these questions is the development of conceptual models of the specific processes through which neighborhoods or areas may affect a given health outcome. These models are crucial to developing operational hypotheses which can be tested with empirical data. Much greater specificity in the hypotheses and empirical tests carried out to date is necessary to strengthen inferences regarding causal effects of neighborhoods on health. The development of these conceptual models as well as the empirical testing of hypotheses derived from them will require addressing a set of key issues that include definition and measurement of area or ecologic attributes, consideration of spatial scale, cumulative exposures and lagged effects, and complementary study designs. Each of these is discussed in detail below.

DEFINING AND MEASURING AREA ATTRIBUTES

Conceptualizing and measuring the area or neighborhood-level factors hypothesized to be relevant to a particular health outcome continues to be a major challenge. Beginning with an explicit conceptual model of what the most relevant factors might be, as well as clearly hypothesized pathways through which they may affect health outcomes is key. An example of such a model for cardiovascular disease is shown in Figure 1. In contrast to the sophistication of the measurement of individual characteristics in epidemiology, the measurement of the attributes of areas or neighborhoods remains in its infancy. Thus developing measures of neighborhood or area-level constructs and documenting their validity and reliability continues to be an important need in the field. Two basic approaches have been used to characterize neighborhoods or areas to date: Geographic Information Systems (GIS), and reports of neighborhood conditions by onsite human observers (be they the participants in a health study themselves, a separate sample specifically surveyed to assess neighborhood conditions, or a trained set of raters).

The recent development of GIS has led to an enormous growth in the capability to construct spatially referenced measures. In the health field GIS has been used in conjunction with a variety of geo-referenced databases to construct measures of the density and accessibility of resources, as well as measures of features of the built environment related to urban form, road networks, land use and density [23]. The bulk of this work has focused on studying the area-level determinants of physical activity and to a lesser extent, diet. The geographic accessibility of resources has long been studied in the health field, with a specific focus on the accessibility of health care services [24]. Recent work has applied variants of the spatial accessibility measures previously used including sophisticated versions of density measures such as kernel densities (which allow smoothing of densities over space) [25] as well as variants of the gravimetric model (which measures accessibility based on a function of distance from a point location to all resources within a geographically bounded area) to quantify the accessibility of physical activity resources [26]. Sophisticated versions of these measures also incorporate weights based on the size, quality, and desirability of a given resource [26]. Another major application of GIS has been its use to characterize features of the built environment hypothesized to be related to physical activity. Examples of the types of measures constructed include measures of mixed (commercial and residential) land use, street connectivity, and housing density [23]. In general the technical capability to construct these GIS measures has far outrun theorizing on which measures may be the most relevant to health behaviors and health outcomes. A multiplicity of different measures for different sizes of areas can be constructed but existing theory on the ways in which these attributes might affect the behavior of individuals provides little guidance on which measures are likely to be the most relevant. For this reason a large part of this work remains more exploratory than hypothesis driven.

A second approach increasingly used to measure attributes of neighborhoods or areas is the use of human observers who report on conditions in an area or neighborhood. This approach is used for logistic or feasibility reasons or when the construct of interest is simply not amenable to the GIS approach (for example social cohesion). In the simplest version of this approach, participants in a health study are administered a questionnaire in which they report on various conditions in their neighborhoods using a set of scales. These measures of neighborhood conditions are then examined in relation to health outcomes measured in the same study participants in a purely individual-level analysis.(e.g. [27]) A limitation of this approach is the possibility of same-source bias, that is, the possibility that the use of self-reported data for both the outcome and the neighborhood characteristic generates a spurious association between the two because the measurement error in both reports is correlated or because the outcome affects the perception or report of the neighborhood attribute. For example persons who are more physically active may be more likely than those who are less active to report resources in their neighborhood, irrespective of the actual condition on the neighborhood. Persons who are depressed may be more likely to report less connection and cohesion between neighbors than those who are not. The same-source bias problem is obviously not present when the health outcome is directly measured by the investigator as opposed to self-reported. But even in the case of directly measured outcomes a limitation of the use of participant reports is that each measure is based on the report of a single participant, and individual reports of neighborhood conditions may have substantial error. This error may arise from simple lack of knowledge of the resident on certain conditions in the neighborhood and from the necessarily subjective nature of perceptions. Of course, if it is hypothesized that an individual’s perception of neighborhood conditions is the construct relevant to health (as opposed to the objective condition) then participant self-reports are the measure of choice, although the interpretation of results may be rendered complex by the same-source bias issue alluded to above.

An alternative to the use of each participant’s own self-report of neighborhood characteristics is to combine the responses of several residents of the same neighborhood [28]. Theoretically, by averaging over measurement error in individual responses, this aggregation process may yield a more valid measure of the “objective” neighborhood construct of interest. This approach can be implemented by aggregating the responses of participants in a health study in order to characterize a given neighborhood represented in the study, or by conducting a separate survey co-located with health study participants in order to derive measures for areas which can then be linked to health study participants based on their place of residence. The rationale for conducting a separate survey is two-fold: (1) the focus of the survey is assessment of area or neighborhood characteristics and hence a more detailed assessment can be included than is possible in the health study itself (where neighborhoods are only one of several domains being assessed) (2) the separate survey allows for denser sampling in space which is likely to improve estimation of the area-level construct of interest.

In some cases it may be advantageous to combine the separate survey approach with a similar data collection approach targeted at the health study participants themselves. This would allow simultaneous investigation of the self-reported, individual-level perceived measure and the aggregate (potentially more “objective”) neighborhood-level measure. An alternative to conducting a separate survey is to employ trained raters to evaluate neighborhoods in systematic fashion on pre-specified dimensions. This approach, originally used in sociology has been termed systematic social observation [29]. It has the advantage that raters can be trained and assessments conducted in a systematic and quality controlled manner. A disadvantage is that some constructs (e.g. social cohesion) may not be measurable using this approach because their assessment necessitates the knowledge and perceptions of residents. The logistics and cost of systematic social observation also make it a difficult approach to implement across very broad geographic areas. The advantages of systematic social observation over survey and census measures in characterizing specific neighborhood conditions relevant to health are only beginning to be systematically evaluated [30,31].

A growing body of work has begun to focus on assessing the measurement properties of area measures constructed by aggregating the responses of survey participants or the observations of raters. This field has been referred to as ecometrics [28,32]. Traditionally psychometrics has evaluated the measurement properties of scales administered to individuals (for example the extent to which an individual’s reponses to different items of a scale are consistent with each other). Ecometrics moves beyond the individual-level to an assessment of the measurement properties at the area-level. If the construct of interest differs in a systematic fashion across areas (and if the scale used appropriately captures this variation), respondents or raters within a given area should be more likely to agree in their assessment than respondents or raters from different areas. Thus a key indicator of the measurement properties of the area-level measure is the within-neighborhood intraclass correlation coefficient for the scale of interest, which quantifies the extent to which respondents or rates agree in their assessment of a given neighborhood. The assessment of the measurement properties of neighborhood-level measures can be assessed using three-level multilevel models (sale items nested within person nested within neighborhoods). Another issue is the construction of the aggregate measures itself especially when the number of observations differs substantially by neighborhoods and some neighborhoods have few observations. In the case of neighborhoods with small numbers of observations, measures based simply on aggregating the observed data may have important measurement error. The use of shrinkage estimates such as empirical Bayes estimates (which address this problem) as well as the potential use other area level covariates to improve the estimate for a given area (as in conditional empirical bayes estimates) is beginning to be evaluated in health research [28,33].

Area-level measures constructed using surveys or raters are usually estimated for predefined (and often somewhat arbitrary) geographic areas such as census tracts. However, it may be unreasonable to think that these attributes change dramatically across these arbitrary geographic borders. More novel approaches have begun to use geostatistical methods and point data (e.g. from surveys or rater observations) to model and estimate smooth surfaces of the distribution of these attributes over space [34]. This modeling takes advantage of the spatial patterning in the data and may also make use of co-located covariate information to improve predictions. For example, data on the location of supermarkets can be used to improve survey-derived estimates of the availability of healthy foods. These surfaces can be used to obtain estimates for unobserved locations and also to obtain summary measures for areas of varying size (e.g. for a given radius around each participant’s home) which can then be examined in relation to health outcomes.

SPATIAL SCALE

Early work on areas or neighborhoods and health used administrative areas as proxies for neighborhoods or, more generally, for the areas potentially relevant to health. The use of these area definitions was largely driven by data availability and feasibility issues: it was relatively

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easy to link health study participants to routinely available data (such as census data) that could be used to characterize their place of residence. These administrative areas are obviously poor proxies for what participants may think of as their “neighborhood”; nevertheless their use is not totally unjustified. Census tracts in the US, for example, were originally developed to be relatively homogeneous in socioeconomic characteristics and may capture differences in social and physical area attributes relevant to health. Even if the geographic definition of tracts does not coincide with what residents may think of as their “neighborhood” it is plausible that in many cases the characteristics of these census areas would be highly correlated with those of the “neighborhood”, if it could be precisely defined.

A more fundamental problem is that there is still relatively little theory on the spatial scale likely to be relevant to a specific health outcome. It is very plausible that areas of different size (some of which may not be thought of as “neighborhoods” at all) could be relevant for different processes and different health outcomes. In fact, the area that a person thinks of as his or her “neighborhood” may not even be the relevant area for the outcome being studied. A priori theorizing on the links between spatial scale, mediating processes, and health outcomes is therefore key. Measuring the relevant attributes of these areas (many of which may not coincide with administrative areas at all) is a major challenge but is likely to be facilitated by the growing availability of spatial and GIS methods and software. In the absence of strong theory on the spatial scale relevant to a particular health-related process, exploratory analyses will continue to be important. At minimum, whenever possible, work should test the sensitivity of results to different spatial scales.

The vast majority of existing work has assumed that only the local area or immediate area around a person’s residence is relevant to health, ignoring the possible impact of features or resources of more distant areas. However it is unlikely that only features of the local area are relevant to a person’s health. For example, poor areas spatially isolated from resource rich wealthy areas may be substantially worse for health than poor areas near resource rich areas. Failure to investigate these spatial effects could result in substantial under estimation of the real effects of area effects on health. A growing body of work has begun to investigate these spatial effects much more broadly through the incorporation of distance measures and through spatial methods that allow the simultaneous investigation of the effects of both distal and proximal areas [35–38].

CUMULATE EFFECTS AND LAGS

As in any emerging field, early work on neighborhoods and health was mostly cross-sectional, relating neighborhood characteristics to the presence of risk factors or diseases at a given point in time. Subsequent work has also used cohort studies to examine the relationship between exposure to specific neighborhood characteristics at baseline and mortality or incident disease over a follow-up period [12,14,39,40].

These studies have provided useful information, but to date relatively little attention has been paid to the time frame necessary for neighborhood conditions to affect health. For some health-related processes, exposures, including neighborhood exposures, may need to accumulate over time to affect health, or they may only manifest themselves on health outcomes after a lag period. Just as the relevant spatial scale may differ depending on the health outcome and the process through which neighborhood conditions are hypothesized to affect health, the relevant time frame may differ for different health outcomes. For example, effects of neighborhood conditions on cardiovascular disease may require exposure to adverse neighborhood conditions over long periods, even over the lifecourse. In contrast, the effects of features of the built environment on physical activity may occur much more rapidly because of the ability of behavior to change rapidly in response to exposures. Studies have only recently begun to examine the role of lifecourse processes in neighborhood health effects [41].

Investigating the presence of cumulative and lagged health effects of neighborhoods is no easy task. It implies tracking changes in neighborhoods over long periods as well as characterizing the many different neighborhoods that persons may live in over a given period. Measuring specific attributes of neighborhoods is complex enough at a given point in time; tracking changes in neighborhood conditions is likely to be even more challenging from the point of view of data availability. For this reason, initial studies of the cumulative and lagged effects of neighborhood conditions may need to rely on secondary data and proxies. Ultimately it may not be possible to characterize the specific features of the neighborhoods a given person has lived in over his or her lifecourse in a rigorous fashion. As in any scientific endeavor, it is important to evaluate when a simplification imposed by the realities of data collection is likely to lead to a wrong answer and when it may result in an (approximately) right answer. For example, even studies that relate neighborhood conditions at one point in time (for example baseline of a cohort study) to subsequent incidence of disease are likely to yield an (approximately) correct estimate of neighborhood health effects if the baseline measure is highly correlated with the exposures during the much longer previous period relevant to the development of the outcome. Thus, if persons tend to live in generally similar neighborhoods over the period of interest (as some data suggests may be true) then a single measure may appropriately capture the relevant exposure. Even much-maligned cross-sectional studies may give the (approximately) right answer for outcomes likely to change rapidly in response to exposures close in time (e.g. behaviors). It is however important for researchers to (a) develop a priori theory (and hypotheses) regarding the time frames relevant for different health outcomes, (b) attempt to measure exposure over the relevant time frame whenever possible; and (c) evaluate the extent to which measurement limitations affect the interpretation of the results obtained.

STUDY DESIGN

The vast majority of work on neighborhood health effects has been observational. As in all observational work, the fundamental critique of these types of analyses has been that persons exposed and unexposed to the neighborhood characteristic of interest differ in other factors related to the health outcome, which will confound any associations of neighborhood characteristics with health outcomes. This issue (which is traditional confounding in epidemiologic terms) has also been referred to as “the selection problem” (because persons are selected or select themselves into neighborhoods based on individual characteristics related to the outcome) and non-exchangeability of exposed and unexposed. This non-exchangeability implies that the observational comparison does a poor job of approximating the counterfactual contrast necessary for drawing causal inferences. The traditional approach to this problem in epidemiology is to estimate associations after adjusting for individual-level confounders using stratification or regression approaches such as multilevel models. Critics have argued that this approach often relies on extrapolations beyond the range observed in the data due to limited overlap in individual-level characteristics for persons living in different types of neighborhoods, and hence that associations estimated using this approach are necessarily always biased [22].

The extent to which persons living in “exposed” and “unexposed” neighborhoods are comparable in individual-level characteristics, as well as the extent to which distributions overlap, can be (and should be) empirically examined in the data before any adjustment is performed. The amount of overlap in the distributions necessary for the adjusted estimate to be “valid” ultimately depends on the assumptions one is willing to make. Even when distributions do not exactly overlap, the potential for bias (because of limited overlap and consequent off-support inference) does not imply that bias is always present. Reporting the actual distributions, and therefore making the assumptions explicit, is important and likely to be more productive and informative than blanket critiques of all analyses because of the "non-exchangeability" problem. The extent to which non-exchangeability and non-overlapping distributions are a problem may also differ substantially depending on the sample and on the specific neighborhood characteristic being examined. For example, non overlapping distributions in individual-level socioeconomic indicators may be a problem when extreme categories of neighborhoods categorized based on aggregate SEP measures are compared. But it may be less of a problem when specific neighborhood features are examined. Propensity score approaches[42] have increasingly been used as an alternative to regression adjustment in studies of neighborhood effects with most studies to date confirming the results obtained using regression adjustment [43–45]. An advantage of propensity score matching is that it allows estimates to be derived from subgroups of the sample which are directly comparable. A limitation is that propensity score matching estimates the association of interest using a selected subgroup, hence it may not be generalizable to the full sample of interest [45]. In addition, propensity score approaches obviously do not solve the problem of mismeasured or unmeasured confounders. Another challenge in estimating neighborhood effects pertains to identifying which variables are true confounders (and hence should be adjusted for) and which are mediators (and hence should not). Some variables could conceivably be both confounders and mediators. Although statistical methods to deal with these situations have been developed [46], their data requirements have precluded their application in neighborhood health effects research to date.

The limitations necessarily inherent in traditional observational studies have highlighted the need for alternative and complementary approaches. One potentially useful approach is the use of instrumental variables [47]. In the context of neighborhood effects research a useful instrument would be a variable that is (a) causally related to the neighborhood characteristic of interest; (b) affects the health outcome only through the neighborhood characteristic; and (c) does not share common causes with the outcome. Unfortunately finding instrumental variables of use in neighborhood health effects research is a major challenge, and results may be highly sensitive to violations of often unverifiable assumptions [48]. A related approach is to capitalize on naturally occurring changes in neighborhoods and quasi-experiments [whenever available) in order to evaluate their health effects. This approach will often require researchers to work closely with policy makers, urban planners, and communities in order to conduct health assessments in a manner which will allow estimation of these effects. A third, and to some "ideal", approach is to conduct randomized trials. Randomized trial approaches to the study of neighborhood health effects are virtually non-existent. The one often cited example (Moving to Opportunity in the United States) [49,50] randomized poor individuals to moving or not moving to non-poor areas, and hence did not directly examine a neighborhood –level intervention. Randomized trials for the study of neighborhood health effects have two important challenges: (a) the need to randomize large numbers of distinct and unrelated "neighborhoods" (which may be infeasible in many settings) ; and (b) the need to have a clear understanding of what the "intervention" should be. Current state of knowledge regarding the specific features of neighborhoods that are relevant suggests that more work is needed to identify the interventions or treatments which it would be most useful to test in a randomized trial if it were possible. The difficulties in conducting a randomized trial of neighborhoods (and the necessarily selected sample of neighborhoods likely to participate) could also raise issues related to the generalizability of results obtained in a perfectly controlled but necessarily selected setting to the larger population of neighborhoods. Thus reliance on observational and quasi-experimental evidence is likely to continue.

CONCLUSION

Clearly, documenting causal effects of neighborhood contexts on health would have important policy implications. Differences across areas or neighborhoods are not "natural" but rather result from specific policies (or from the absence of policies). Neighborhood contexts are eminently changeable and responsive to economic and social policy broadly defined. In fact, as virtually everyone has observed, neighborhoods change constantly in response to external factors as well as to the collective actions of residents. Harnessing and influencing these changes so that they are beneficial to the health of residents could have enormous public health impact. Ultimately the evidence needed to support policies targeted at neighborhoods to improve health will come from multiple sources including large scale quantitative observational studies, qualitative studies of the ways in which persons relate to and are affected by neighborhoods, the evaluation of natural experiments or quasi experiments, and (when feasible) experimental studies. As is usually the case with complex research questions, conclusive evidence will not necessarily flow from increasing methodological sophistication within a single type of study, important as this methodological sophistication may be. Rather, consensus will emerge from the work of multiple disciplines, often with diverse methodological approaches, each with its strengths and its limitations. Partnership across disciplines, and also between health researchers, communities, urban planners, and policy experts interested in neighborhoods (often for reasons unrelated to health), will be key.

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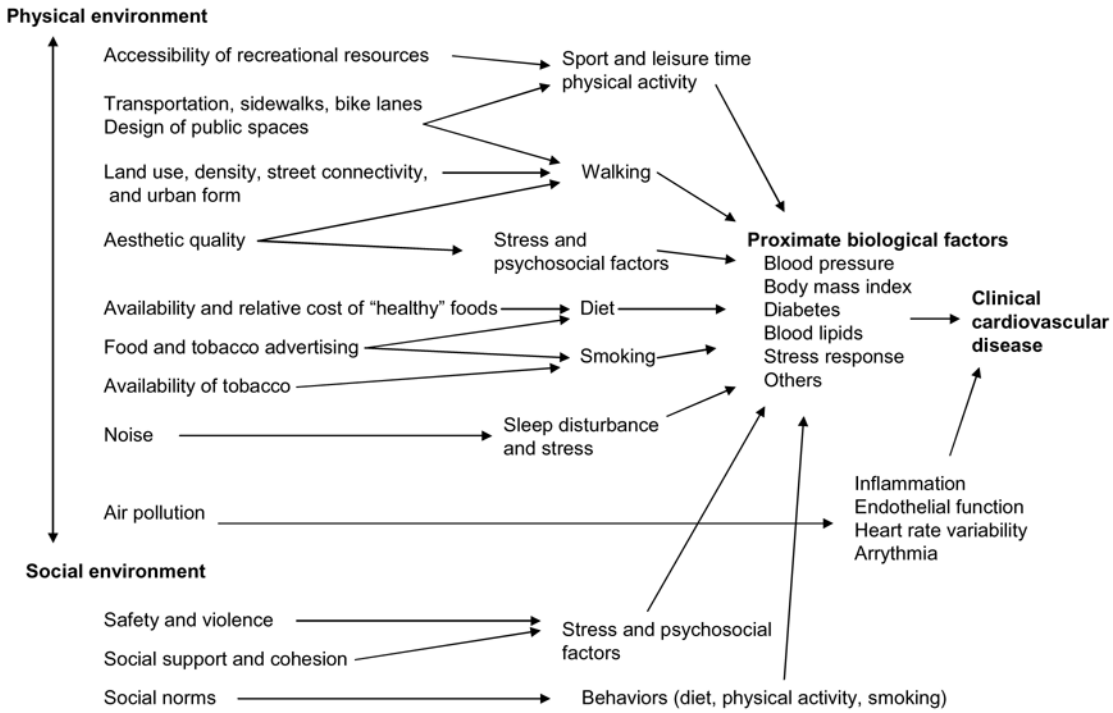

Figure 1.

Schematic representation of possible pathways linking residential environments to cardiovascular risk (previously published in [17]).