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NEIGHBORHOOD-LEVEL FACTORS: BARRIERS AND ASSETS TO CARDIOVASCULAR DISEASE

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In memory of Yoshie Kawakami, my grandmother, and
James Edward Ritchie, my American father

ABSTRACT

Aims To examine whether the availability of goods, services, and resources differs by level of neighborhood deprivation (*study I*). To examine whether there are associations between neighborhood availability of potentially health-damaging (fast food restaurants and bars/pubs) and health-promoting (physical activity facilities and health care facilities) goods, services, and resources and CHD incidence (*study II*). To examine the associations between objective neighborhood walkability and walking for active transportation, walking for leisure and MVPA, and random effects in a multilevel fashion (*study III*). To examine the concordance between objective and perceived neighborhood walkability, their associations with walking and objective physical activity, and sociodemographic characteristics of individuals in neighborhoods with objectively assessed high walkability who misperceive it as low (*study IV*).
Methods In *study I* geocoded data from all businesses in Sweden were used to examine the distribution of 12 main categories of goods, services, and resources in 6,986 neighborhoods, categorized as low, moderate, and high neighborhood deprivation. In *study II* multilevel logistic regression models were employed for the follow-up of 1,065,000 men and 1,100,000 women (aged 35–80 years) between December 1, 2005, and December 31, 2007, for individual-level CHD events. In *study III* an index consisting of residential density, street connectivity, and land use mix was constructed to define 32 highly and less walkable neighborhoods in Stockholm City. MVPA was measured objectively with an accelerometer and walking was assessed using IPAQ. Multilevel models were used in the analysis. In *study IV* objective neighborhood walkability was assessed within a 1,000 m radius of each individual's residential address. Perceived walkability was based on the NEWS. Walking was assessed using IPAQ, and total physical activity and MVPA by an accelerometer.
Results In *study I* the availability of all types of goods, services, and resources was better in moderate and high-deprivation neighborhoods than in low-deprivation ones. In *study II* the associations between neighborhood availability of potentially health-damaging and health-promoting goods, services, and resources and CHD incidence were relatively weak and non-significant after adjustment for neighborhood-level deprivation and individual-level age and income. In *study III* there were positive associations between living in highly walkable neighborhoods, compared to those living in less walkable neighborhoods, and walking for active transportation, walking for leisure, and MVPA. The proportion of the total variance at the neighborhood level was low. In *study IV* one-third of individuals in neighborhoods with objective high walkability misperceived it as low. This non-concordance was more common among older and married/cohabiting individuals. High perceived neighborhood walkability was associated with more minutes of walking for transportation, walking for leisure and objectively measured physical activity compared to low perceived neighborhood walkability.
Conclusions Our findings are noteworthy, given the necessity to ensure that current policies are based on context-specific empirical findings so that actions do not reach beyond available evidence. Further follow-up studies are needed to disentangle causal pathways and to provide more robust evidence for use in formulating efficient neighborhood policy agendas for reducing social inequalities in health.

CONTENTS

LIST OF PUBLICATIONS

This thesis is based on the following original articles, which will be referred to in the text by their Roman numbers.

I KAWAKAMI N, Winkleby M, Skog L, Szulkin R, Sundquist K. Differences in neighborhood accessibility to health-related resources: A nationwide comparison between deprived and affluent neighborhoods in Sweden. Health Place. 2010 Sep 21. [Epub ahead of print]

II KAWAKAMI N, Li X, Sundquist K. Health-promoting and health-damaging neighbourhood resources and coronary heart disease: a follow-up study of 2 165 000 people. J Epidemiol Community Health. 2011 Oct;65(10):866–72.

III Sundquist K, Eriksson U, KAWAKAMI N, Skog L, Ohlsson H, Arvidsson D. Neighborhood walkability, physical activity, and walking behavior: The Swedish Neighborhood and Physical Activity (SNAP) study. Soc Sci Med. 2011 Apr;72(8):1266–73.

IV Daniel Arvidsson, NAOMI KAWAKAMI, Henrik Ohlsson, Kristina Sundquist. Physical activity and concordance between objective and perceived walkability. Med Sci Sports Exerc. 2011 Jun 23. [Epub ahead of print]

ABBREVIATIONS AND DEFINITIONS

BEPAS	The Belgian Environmental Physical Activity Study
CHD	Coronary Heart Disease
CI	Confidence Interval
CNI	Care Need Index
CVD	Cardiovascular Disease
GIS	Geographic Information Systems
ICC	Intraclass Correlation
ICD	International Classification of Diseases
IPAQ	International Physical Activity Questionnaire
IR	Incidence Rates
MVPA	Moderate-to-Vigorous Physical Activity
NEWS	Neighborhood Environment Walkability Scale
NQLS	The Neighborhood Quality of Life Study
OR	Odds Ratio
PA	Physical Activity
PLACE study	The Physical Activity in Localities and Community Environments study
PR	Prevalence rate Ratio
SAMS	Small Area Market Statistics
SD	Standard Deviation
SES	Socioeconomic Status
SNAP study	Swedish Neighborhood and Physical Activity study
UPA score	Underprivileged Area score
WHO	World Health Organization

PREFACE

Coronary heart disease (CHD) is one of the main causes of morbidity and mortality in many countries worldwide. Established CHD risk factors are metabolic (diabetes, hypertension, hyperlipidemia), behavioral (smoking, physical inactivity, obesity) and genetic risk factors. Social epidemiological studies have also established that individual-level socioeconomic status (SES) is associated with CHD and that neighborhood-level SES predicts CHD incidence, after taking individual-level SES into account. However, the possible mechanisms behind the neighborhood "effect" on CHD remain to be established. During the last 10–15 years efforts have been made to determine which neighborhood factors mediate the associations between neighborhood socioeconomic characteristics and CHD. Some of these neighborhood factors include features in the physical/built environment. This thesis aims to shed new light on: (1) the association between neighborhood socioeconomic characteristics and neighborhood physical/built characteristics, (2) the association between neighborhood physical/built characteristics and CHD, and (3) the association between neighborhood physical/built characteristics and physical activity, an important behavioral risk factor for CHD.

INTRODUCTION

CARDIOVASCULAR DISEASE (CVD) AND CORONARY HEART DISEASE (CHD)

Cardiovascular disease (CVD) involves diseases in the heart and/or blood vessels (arteries as well as veins) but it is normally used to refer to those diseases related to atherosclerosis. Common examples of CVD are ischemic stroke and coronary heart disease (CHD). Although CHD is a preventable disease, it was reported as the world's number one cause of death in 2004 by the World Health Organization (WHO) (World Health Organization, Accessed April 19, 2011). In addition, according to the WHO, approximately 17.1 million people died of CVDs in 2004. Among these deaths, 7.2 million were caused by CHD. The WHO has also predicted that 23.6 million people will die from CVDs by 2030 and the majority will be due to stroke and CHD.

Although the mechanisms behind CHD have not been fully explained, several CHD risk factors have been established. These are metabolic (diabetes, hypertension, hyperlipidemia, obesity) (Mancia et al., 1997, Shirai, 2004), behavioral (smoking, physical inactivity, poor diet, excessive alcohol drinking) (Bhasin et al., 2011), demographic (high age, male sex, some racial/ethnic groups), socioeconomic (low socioeconomic status) (Lynch et al., 1996) and familial/genetic (Sundquist et al., 2011).

Demographic and familial/genetic risk factors represent non-modifiable risk factors. In contrast, behavioral and partly metabolic risk factors could be regarded as modifiable. It is possible to reduce the risk of CHD by targeting modifiable risk factors through lifestyle interventions and pharmacological treatment for diabetes, hypertension, and hyperlipidemia.

SOCIOECONOMIC STATUS (SES)

Socioeconomic status (SES) indicates the social position of individuals, societal groups or populations. It is conceptualized by social and economic characteristics, and examples of other terms for SES are socioeconomic position, social class, social status, social stratification, and social inequalities. Measures of SES have been used as strong and consistent determinants or predictors of health, and higher SES has in general been associated with better health (Marmot, 2004). SES can be measured in many different ways, such as occupation, income, and educational attainment.

Individual-level SES

Occupation, income, and educational attainment are key components that describe SES of individuals. These socioeconomic variables reflect the individual's knowledge, skills, and resources. They are also good markers of the "life chances" of each individual (Lynch and Kaplan, 2000). Nevertheless, as these variables partly reflect different concepts they may not be interchangeable and they may reflect different pathways to health outcomes. For example, income is strongly correlated to an individual's material circumstances, whereas education may be more correlated to an individual's knowledge and skills. For example, a high income may result in better opportunities to buy healthy food, whereas a high education may result in better knowledge about healthy food. Therefore, no socioeconomic variable could be regarded as “better” than the other; rather, they represent different opportunities or lack thereof for people.

Neighborhood-level SES

The different measures of individual SES can also be aggregated and used to characterize neighborhoods on the basis of the social and economic attributes of residents. For example, a high proportion of individuals with low income in the neighborhood would indicate that the neighborhood has a low SES. However, neighborhood-level SES is more often characterized by composite indices of deprivation. The choice of variables for the creation of the different indices is most often based on the availability of socioeconomic census data in different countries and over time.

For example, the *Townsend Deprivation Index/Score* and the *Carstairs Score* are widely used area-based indices of material deprivation (University of Southampton, Accessed April 5, 2011). The *Townsend Score* consists of the unweighted variables unemployment, no car, no home ownership, and overcrowding. Each of these census variables is divided by the total count of households or individuals living in a geographic area in which census variables are aggregated to calculate a percentage score. The *Carstairs Score* consists of the unweighted variables unemployment, no car, low social class, and overcrowding. The *Underprivileged Area (UPA) score* or the *Jarman Index* is somewhat differently constructed from the other social deprivation indices. It also takes into consideration the general practitioner’s (GP’s) ranking of the impact on their workload of the following indicators: elderly people living alone, children under five, unemployed people, single parents, overcrowding, manual workers, highly mobile people, and foreign-born people from the New Commonwealth or Pakistan. The *UPA score* is used to allocate an extra deprivation payment to the five percent most deprived neighborhood. All three scores originate from the UK. The *UPA score* or the *Jarman Index* has been revised on a regular basis as the content of census data has changed over time.

The Jarman Index

i. Unemployment – unemployed residents aged 16+ as a proportion of all economically active residents aged 16+.
ii. Overcrowding – persons in households with 1 or more persons per room as a proportion of all residents in households.
iii. Lone pensioners – lone pensioner households as a proportion of all residents in households.
iv. Single parents – lone “parents” as a proportion of all residents in households.
v. Born in New Commonwealth – residents born in the New Commonwealth as a proportion of all residents.
vi. Children aged under 5 – children aged 0–4 years as a proportion of all residents.
vii. Low social class – persons in households with economically active head of household in socio-economic group 11 (unskilled manual workers) as a proportion of all persons in households.

viii. One-year migrants – residents with a different address one year before the Census as a proportion of all residents.

Care Need Index (CNI) is a Swedish adaptation of the *Jarman Index* and is currently being used in most Swedish counties for allocation of primary health care resources (Sundquist et al., 2003). Neighborhood deprivation indices have also been developed in the US, based on the UK indices, and applied to examine their relationship to health-related outcomes (Eibner and Sturm, 2006).

In studies I and II, we used a neighborhood deprivation index that was developed previously to characterize Swedish neighborhoods. It is composed of the following four census variables: low educational status; low income; unemployment; and social welfare (Winkleby et al., 2007). The index is constructed as the higher the score means, the more deprived the neighborhoods and vice versa.

INDIVIDUAL-LEVEL SES AND CHD

Individuals with low socioeconomic status (SES) have a higher risk of CHD (Weber and Lehnert, 1997). These individuals may have limited resources and opportunities to achieve a healthy lifestyle and/or attain good health. For example, individuals with less years of educational attainment may have less knowledge of how to achieve a healthy lifestyle, including physical activity and a healthy diet. In addition, a lower educational attainment may lead to poorer job opportunities and, subsequently, a low income. Low individual income could hinder people from living in a clean and safe neighborhood with access to health-promoting resources.

NEIGHBORHOOD-LEVEL SES AND CHD

An extensive number of studies have shown strong and consistent associations between neighborhood-level SES (e.g., neighborhood deprivation) and CHD, independently of individual-level socioeconomic characteristics (Sundquist et al., 2004b, Sundquist et al., 1999, Diez Roux et al., 2001, LeClere et al., 1998, Pickett and Pearl, 2001, Smith et al., 1998, Sundquist et al., 2004a, Woodward, 1996).

For example, Diez Roux et al. found that neighborhood SES was inversely associated with incidence rates of CHD (Diez Roux et al., 2001) and concluded that the socioeconomic environment of neighborhoods affects individual cardiovascular health over and above individual socioeconomic characteristics. Swedish studies of coronary heart disease incidence and case fatality have confirmed these findings (Sundquist et al., 2006a, Sundquist et al., 2004a, Sundquist et al., 2006b, Sundquist et al., 2004b).

Recent neighborhood studies have mainly used multi-level modeling. Advantages of multi-level modeling are: (1) it allows both individual- and neighborhood-level variables to be included in a study so that the fixed neighborhood effects on various health outcomes can be examined in a more robust way; (2) it allows for the examination of random effects, i.e., how much of the total variance is at the neighborhood level.

Swedish multilevel studies have shown significant associations between neighborhood SES and CHD incidence, after taking individual-level sociodemographic characteristics into account (Sundquist et al., 2006a, Sundquist et al., 2004a, Sundquist et al., 2004b, Winkleby et al., 2007). In addition, the case fatality in CHD was higher in neighborhoods with low SES than in neighborhoods with high SES, after adjustment for individual-level sociodemographic characteristics such as age, sex, income, and/or education (Winkleby et al., 2007) .

Previous studies have also shown associations between living in a socially deprived neighborhood and having a poor health profile, e.g., high body mass index, smoking, and physical inactivity (Sundquist et al., 1999, Cubbin et al., 2006, Ohlander et al., 2006). Authors from those studies have hypothesized that a poor lifestyle lies in the causal pathway between neighborhood deprivation and CHD (Sundquist et al., 1999, Cubbin et al., 2006).

NEIGHBORHOOD CONTEXTUAL AND COMPOSITIONAL EXPLANATIONS FOR POOR HEALTH

Findings of previous research have led to the conclusion that the associations between neighborhood-level socioeconomic characteristics and health are caused by a contextual effect on health (which is explained by neighborhood characteristics) rather than a merely compositional effect (which is explained by individual characteristics of the residents).

A compositional explanation is that the individuals in an area or group (e.g., a neighborhood) possess similar characteristics. Thus, neighborhood effects on health are regarded as simply due to the aggregate individual characteristics of the residents.

A contextual explanation, on the other hand, is that the characteristics of the neighborhood have an independent influence on health, over and above the individual characteristics of the residents. For example, deprived neighborhoods may have high crime rates, few or no sidewalks, missing/broken street lights, and heavy traffic, which may lead to psychosocial stress and fear/reluctance to go outside, which in turn may have a negative impact on social and physical activity.

THEORIES OF NEIGHBORHOOD EFFECTS ON HEALTH

It has been hypothesized that neighborhoods with low SES or high deprivation level may have less access to health-promoting neighborhood resources and more access to health-damaging neighborhood resources. This hypothesis ties in with the theory of "deprivation amplification" (Macintyre, 2007). It is based on the assumptions that people living in deprived neighborhoods have lower availability of health-promoting goods, services, and resources (e.g., physical activity facilities, parks, health care centers) and higher availability of potentially health-damaging goods, services, and resources (e.g., fast food restaurants, alcohol outlets, bars) than people living in affluent neighborhoods.

During the past decade, the association between neighborhood SES/deprivation and availability of potentially health-promoting and/or health-damaging goods, services, and resources has been explored but findings have been inconsistent (Zenk et al., 2005, Morland et al., 2002, Ellaway et al., 2010, Macintyre, 2007).

It has become a challenge among public health professionals and epidemiologists to conceptualize and measure which features of neighborhood (social and physical) environments may influence health and health-related behaviors among affected residents (Diez Roux, 2007). In the meantime, theories such as "deprivation amplification" and "food deserts" have emerged in an effort to explain neighborhood effects on individual health. Deprivation amplification is the concept suggested by Macintyre and her colleagues, based on their earlier work. It is described as "a process, applying across the whole range of environmental influences on health, by which disadvantages arising from poorer quality environments (for example, lack of good public transport) amplify individual disadvantages (for example, lack of private transport) in ways which are detrimental to health" (Macintyre, 2007). Along the same line of theories, "food deserts" is the theory that neighborhood physical accessibility of different food services and resources (e.g., grocery stores/supermarkets vs. fast food) may contribute to healthy vs. unhealthy diets and, subsequently, to health problems (Cummins and Macintyre, 2006). The theory of food deserts assumes that individuals behave in rather similar ways and extend over their local environments (i.e., neighborhoods) only in a limited manner for, e.g., purchasing food items. Therefore, it can be argued that differences in the physical density of opportunities to consume a healthy diet are translated into actual differences in diet and, finally, into health disparities (Cummins et al., 2007).

Macintyre and her colleagues have also suggested five types of neighborhood features that might influence individual health and health-related behaviors based on a framework of human needs. The five types are: (1) physical features of the environment shared by all residents in a locality, (2) availability of healthy environments at home, work and play, (3) services provided, publicly or privately, to support people in their daily lives, (4) socio-cultural features of a neighborhood; and (5) the reputation of an area (Macintyre et al., 2002).

GEOGRAPHIC INFORMATION SYSTEMS (GIS)

GIS were used in studies I and II to measure neighborhood availability of goods, services, and resources. GIS were also used to assess neighborhood walkability in studies III and IV (see methods section below).

In general, GIS can aid in the design, implementation, analysis, and dissemination of public health and epidemiologic research studies. GIS are "computer-based ... systems composed of hardware, software, and data used to create, store, manage, display (in map form), and analyze spatial and attribute data in an integrated environment" (Melnick, 2002, Mullner et al., 2004).

Today, GIS are being increasingly used in public health activities and research (Rushton, 2003, Vaidyanathan et al., 2009, Hwang and Jaakkola, 2008, Whicker et al., 2008) and epidemiological applications that include monitoring health and illness (Centers for Disease Control and Prevention), mortality/disease atlases (National Cancer Institute, Accessed December 13, 2006, Pickle et al., 1996, Pickle et al., 1987a, Devine et al., 1990a), needs assessments (Faruque et al., 2003), resource planning and allocation (McLafferty, 2003, Porter et al., 2004), environmental health research (Vine et al., 1997, Cromley, 2003), spatial analyses (Pearce et al., 2006, Robinson, 2000, Rytkonen, 2004, Chung et al., 2004), identification of "hot spots" (Glass et al., 1992) and hypothesis generation (Wieczorek and Hanson, 1997).

Below, we will use unpublished data from the Stanford Heart Disease Prevention Program (Winkleby et al., 2006, Chuang et al., 2005, Cubbin and Winkleby, 2005) to apply GIS tools. We will show maps from individual- and neighborhood-level data to illustrate examples of how to: (1) define geographic boundaries for a study; (2) determine geographic representation of study participants; (3) calculate density and distance measures for analyses; (4) visualize change over time in neighborhood physical and demographic environments; and (5) disseminate findings to study communities.

The five examples based on data from the Stanford Heart Disease Prevention Program will illustrate the usefulness of displaying spatially-referenced data to define a study area, evaluate a sample, determine measures for analyses, assess changes in environments and populations over time, and disseminate findings. When defining neighborhood geographic boundaries, GIS can be an effective tool to assess the accuracy of boundaries used as proxies for neighborhoods. GIS tools can also help evaluate whether participants reflect the study's geographic catchment area; for example, one can examine the representation of recruited, screened, and retained participants and modify strategies as needed. A further application of GIS is to visualize changes over time in neighborhood physical and demographic environments, such as whether a community has experienced increasing exposure to fast food restaurants over time, thus possibly contributing to changes in dietary habits and levels of obesity. Finally, GIS tools offer an opportunity to disseminate study findings via website applications, such as information about neighborhood goods and services that can enhance health.

Maps were created using ArcView GIS 3.3, ArcGIS 8.x or ArcGIS 9.x (Environmental Systems Research Institute [ESRI], Redlands, CA). To define the geographic boundaries, we used two layers in the creation of Figure 1, based on data provided from US Postal Service 2000–2001 ZIP Code Areas and 2000 US Census Bureau ZIP Code Tabulation Areas. This allowed for an assessment of the discrepancies between the two different data sources. For Figure 2, we used geocoded information about individual locations that were displayed over the choropleth map by neighborhood poverty level. All individuals fell into one of the poverty levels (low, moderate, or high) and their approximate location is displayed on the map as a point. Density measures were calculated in two ways (Figure 3). The first density measure was based on a half mile (0.805 km) buffer zone around the participant's home. This represents a walking distance of 10–15 minutes, which is considered a maximum walking distance for most people (Pollack et al., 2005).

The second density measure was based on census tract boundaries (see below) and was calculated in each participant's neighborhood. Both measures were based on a count of features that completely fell into the buffer zone or neighborhood boundary. In ArcGIS, counts are provided through a built-in tool. Distance measures were also calculated in two ways. The first distance measure represented the street network distance (based on The Census 2000 TIGER/Line files) from the participants' home to the nearest alcohol outlet and was calculated using the extension program *Network Analyst* in ArcView GIS version 3.3. This extension program provides specialized tools for analysis of network-related data such as streets, bus routes or railroads. The second distance measure represented the straight-line distance ("as the crow flies" or Euclidean) to the nearest alcohol outlet. The straight-line distance can be obtained by spatially joining two point data sets (participant's home location and alcohol outlet location) based on projected data with geographic coordinates, which represent the origin point and destination point. This procedure can be performed in ArcGIS, using a built-in GIS tool, *Spatial Join*. For the creation of Figure 4, we used the same methodology as in Figure 2. Finally, Figure 5 was prepared compiling various geographic data (e.g. streets and physical activity related facilities). ArcGIS built-in graphic tools were applied to complete the figure.

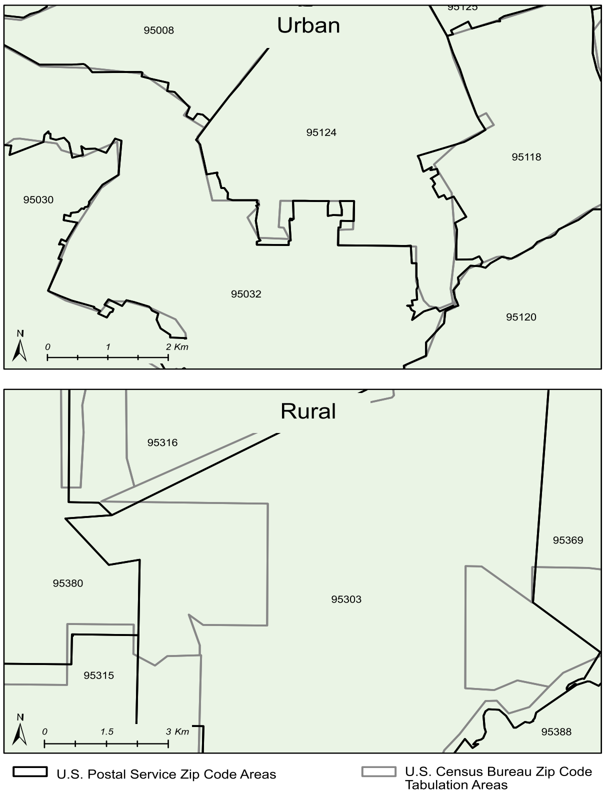

Figure 1. Urban/rural comparison of US Postal Service zip code area boundaries, 2000–2001, with US Census Bureau zip code tabulation area boundaries, 2000.

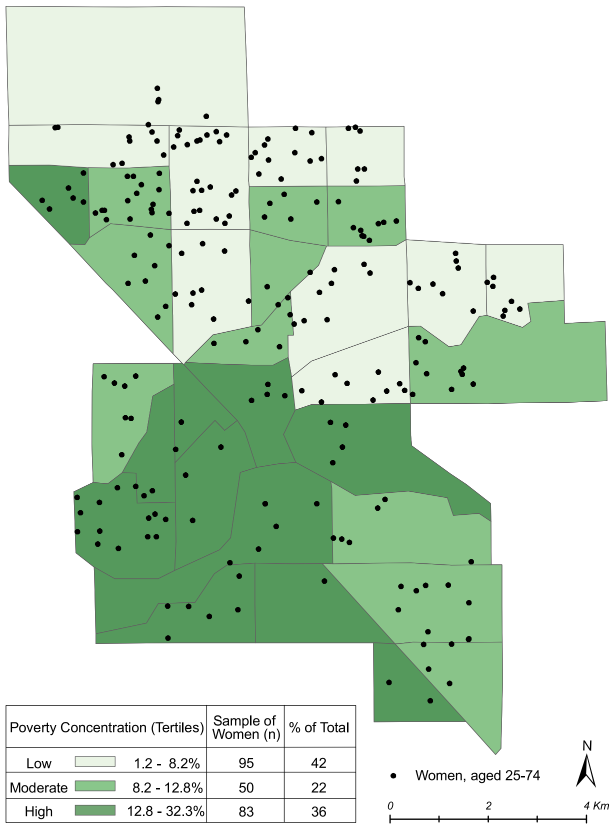

Figure 2. Residential location of participants by neighborhood-level poverty concentration, women aged 25–74, Modesto, CA, 1979–1980.

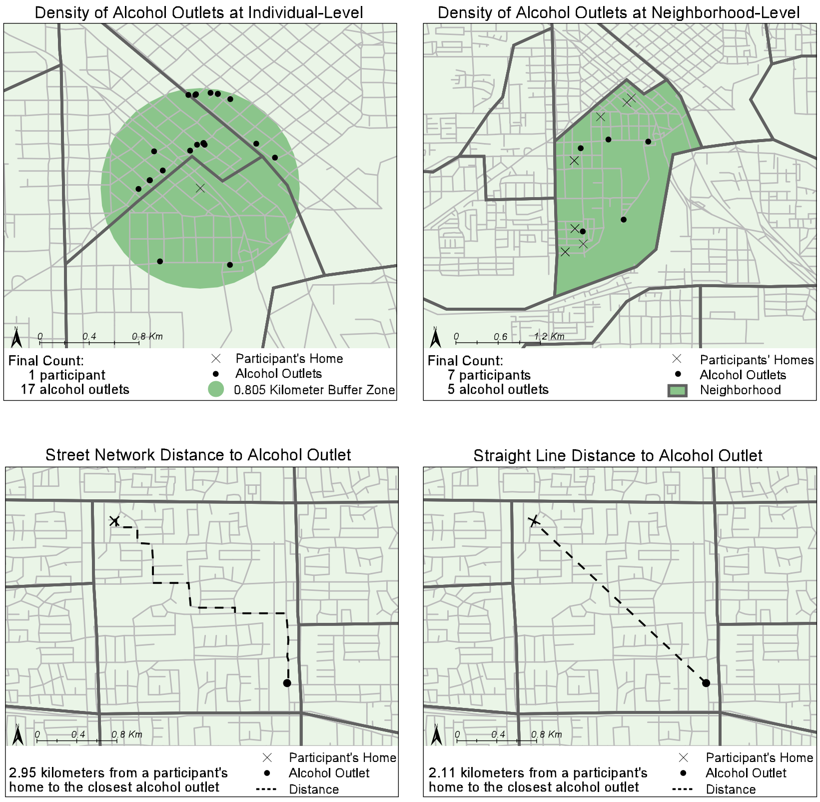

Figure 3. Methodologies for calculating density of and distance to alcohol outlets in neighborhoods.

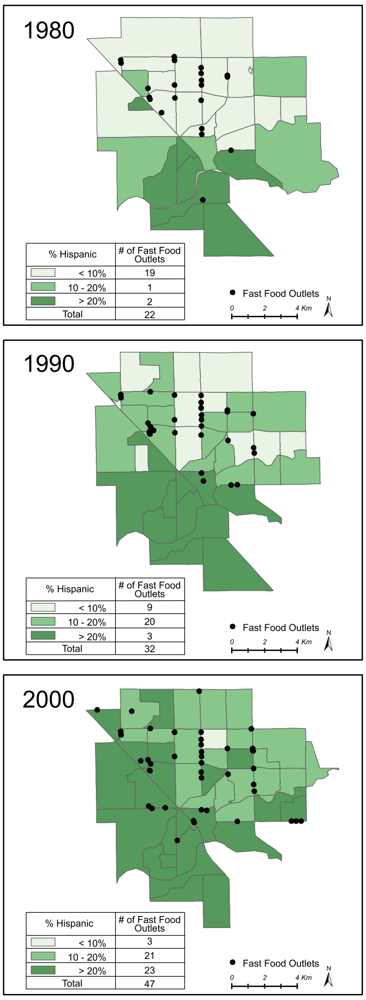

Figure 4. Change over time in number of fast food outlets and percentage of Hispanic Concentration at the census tract level, Modesto, CA, 1980, 1990, 2000.

Figure 5. Example of web-based dissemination of information about neighborhood physical activity resources.

Results based on data from the Stanford Heart Disease Prevention Program
(1) *Defining geographic boundaries for a study.* Figure 1 presents an urban and rural comparison of US Postal Service 2000–2001 ZIP Code Area boundaries with 2000 US Census Bureau ZIP Code Tabulation Area boundaries, for two different areas in Northern California. In the top map of the urban area, the two sets of boundaries are nearly identical, while in the bottom map of the more rural area this is not the case.

(2) *Determining geographic representation of study participants.* Figure 2 shows the approximate residential location of women participants at the baseline survey in one of the SHDPP cities according to neighborhood-level poverty concentration, measured in tertiles. In the actual study, beginning in the 1970s, women were randomly sampled within each city of the SHDPP by census tracts. However, application of GIS tools shows that response rates were differential, resulting in different participation rates among women from the 3 different census tract poverty concentration levels (i.e., women from the moderate poverty concentration census tracts had the lowest response rates). Use of GIS during the recruitment phase of the SHDPP would have allowed the investigators to identify this problem, determine reasons for differential response, and develop new protocols to reach women from the moderate poverty concentration census tracts. GIS has an added advantage over simply tabulating response rate frequencies as it provides a visual representation of where women are underrepresented (areas that may need more intense recruitment efforts) and potential barriers that may

influence response rates (e.g., lack of bus stops for transportation to a clinic, high crime rates close to a woman's home).

(3) *Calculating density and distance measures for analyses.* Figure 3 illustrates various methodologies to calculate density- and distance-based measures for analyses. The top left frame displays the number of alcohol outlets for an individual participant in a buffer zone (a proxy for the participants' immediate neighborhood). All outlets within a half mile (0.805 Km) buffer zone of the participant's home were included, and could then be standardized by population for a density measure. In contrast, the top right frame examines alcohol outlets at the neighborhood level, including all outlets that are within the census tract boundary, creating another density measure. The bottom two frames display two different ways of calculating distance-based measures; on the left is the street network-based distance from a participant's home to the nearest alcohol outlet (2.95 km) and on the right is the straight line distance ("as the crow flies") from a participant's home to the same outlet (2.11 km).

(4) *Visualizing change over time in neighborhood physical and demographic environments.*
Figure 4 presents change over time in the number of fast food outlets and percentage of Hispanic concentration at the census tract level in one SHDPP city in 1980, 1990, and 2000. Figure 4 also displays changes in neighborhood (census tract level) boundaries over time. These boundaries largely correspond to the main roads in the city. Overall, Modesto's population grew 68% between 1980 and 2000 and the proportion of Hispanics more than doubled (15% to 32%). The growth of Hispanics across the city, however, was uneven, with large increases in the number of neighborhoods falling into the >20% Hispanic category over the two decades. During the same time period, fast food restaurants more than doubled in number overall (from 22 to 47), mirroring the Hispanic population growth, and residents of neighborhoods with the highest Hispanic concentrations were exposed to the greatest number of such restaurants, whereas an opposite pattern was observed in 1980.

(5) *Disseminating findings to study communities.* Figure 5 presents a hypothetical example of disseminating findings to the public, i.e., through a web-based GIS application. Pictured here is an easy-to-understand application for finding resources to promote physical activity near one's home. A person is instructed to enter her/his postal code (ZIP Code) to find a map with physical activity resources. If the person clicks on a particular resource, she/he then finds a description of the resource and information regarding hours, amenities, and programs for youths and seniors. Much of this information can be found in online databases, which can then be linked with data collected in the study.

Note: all maps and figures based on unpublished data from the Stanford Heart Disease Prevention Program were created by Naomi Kawakami in collaboration with Professor Marilyn Winkleby at Stanford University School of Medicine and Associate Professor Catherine Cubbin at University of Texas at Austin.

PHYSICAL ACTIVITY

Physical activity is any bodily movement that contributes to energy expenditure. Examples of regular moderate intensity physical activity include various sport and recreation activities, housework, gardening, occupational activities, and active transport (e.g., walking to/from work; cycling to train station or school). Regular moderate-intensity physical activity such as walking can decrease the risk of hypertension, coronary heart disease, stroke, diabetes, breast and colon cancer, depression and falls. Exercise is a subcategory of physical activity that is planned, structured, repetitive, and purposeful in the sense that the improvement or maintenance of physical fitness is the objective (World Health Organization, Accessed September 1, 2011, Eyler et al., 2003). The WHO has reported that approximately 31% of adults (aged 15 and over) were physically inactive in 2008 (men: 28% and women: 34%). An estimated 3.2 million deaths globally are attributable to physical inactivity (World Health Organization, Accessed September 1, 2011).

The WHO explains that this global public health problem may be partly due to insufficient participation in physical activity during leisure time as well as the increased time in sedentary behaviors such as sitting, lying down, and watching television during occupational and domestic activities (World Health Organization, Accessed September 1, 2011). Furthermore, the WHO suggests that physical inactivity may be caused by several environmental factors that are barriers to participating in physical activity. Such factors are crime/violence, high-volume traffic, low air quality/pollution, lack of sidewalks and sport/recreation facilities. The WHO urges that "Population-based, multi-sectorial, multi-disciplinary, and culturally relevant policies need to be implemented to increase physical activity levels globally" (World Health Organization, Accessed September 1, 2011).

PHYSICAL ACTIVITY MEASURES

There are several different methods available to measure physical activity (and/or energy expenditure) (Tudor-Locke and Myers, 2001). Calorimetry, doubly labeled water, motion sensors, observation, diaries, logs, and records are *direct* measures of physical activity. Fitness measures, anthropometric measures, metabolic measures, heart rate telemetry, self-report questionnaires, and surveys are referred to as *indirect* PA measures. Among these direct/indirect measures, self-report methods (questionnaires/surveys) and motion sensors are potentially the most practical approaches to quantify physical activity behaviors for population-level surveillance studies as well as clinical and program applications (Tudor-Locke and Myers, 2001).

Self-reported measures

There are 30 or more self-reported instruments for measuring physical activity (Pereira et al., 1997). The *International Physical Activity Questionnaires* (IPAQ) is a self-administered 7-day recall physical activity questionnaire. IPAQ was developed for physical activity surveillance and monitoring that can be used internationally in order to obtain comparable physical activity measures. IPAQ was used in studies III and IV.

IPAQ has been translated into different languages and adopted by different cultural contexts (see list at weblink 2 below). In addition, it has been tested (see list at weblink

1 below) for validity and reliability in various countries (Craig et al., 2003). It is available in a short and a long version. The short version is designed for the use in surveillance systems at the national and regional level while the long version can derive more detailed information in research studies or for evaluation purposes (see list at weblink 3 below). The short form includes questions regarding frequency, duration of time spent on different physical activity levels (walking, vigorous, moderate-intensity, sedentary activity). The long form assesses specific domains of physical activity such as household work/gardening, occupational, self-powered transport, leisure-time related physical activity, sedentary activity (sitting on a weekend/weekend day), and pace of walking/cycling.

1-Validity, in use: https://sites.google.com/site/theipaq/references#TOC-IPAQ-in-use
2-Language, culture: https://sites.google.com/site/theipaq/questionnaires
3-Background: https://sites.google.com/site/theipaq/background

Objective measures
Motion sensors are alternative methods (to self-report methods), which can objectively measure physical activity in one or more planes of movement. A pedometer is the simplest instrument of motion sensors, recording steps as physical activity measures. Accelerometers are more complex motion sensors that record movement as "activity counts". They measure the intensity and frequency of movement, and also record the time. Thus, they can be used, for example, to characterize the total volume of activity and estimate the energy expenditure as the number of minutes per day multiplied by the intensity of the activities (Welk, 2002).

Actigraph GT1M (ActiGraph, Pensacola, Florida, USA) is a uniaxial accelerometer-based physical activity monitor that can objectively measure levels of physical activity in adults under free-living conditions. Actigraph GT1M was tested for validity in a study conducted by Abel et al. (Abel et al., 2008) and the authors concluded that it provides a valid measure of physical activity. Actigraphs were used in studies III and IV.

WALKING

Walking is considered as a light to moderate intensity physical activity behavior, depending on the intensity. It is one of the simplest and cheapest physical activity behaviors that most people can perform in their local environments (i.e., neighborhoods) with a minimum of time and resources.

Even though walking is "only" a light to moderate intensity physical activity behavior, it carries some of the health benefits that are obtained from more vigorous types of physical activity (Eyler et al., 2003). It has been repeatedly reported as the most common physical activity behavior in the United States and Australia (Siegel et al., 1995, Owen et al., 2004, Leslie et al., 2005). Walking is also the most affordable physical activity behavior, especially for the lower socioeconomic groups (Siegel et al., 1995).

WALKABILITY

There has been a growing interest in assessing neighborhood walkability and to examine its association with various measures of physical activity among residents living in high- and low-walkability neighborhoods.

Walkability, history and current definitions
Better neighborhood walkability has been suggested to be able to promote healthier lifestyles. It has also a potential to offer more "sustainable" living environments. Walkability can simply be put as a measurement of how inviting an area is to potential walkers. However, its definition and measurement has involved social and physical environmental attributes of neighborhoods. The concept of walkability may have been introduced already in 1929 when Clarence Perry proposed how an ideal neighborhood unit should be composed as a part of *The Regional Plan of New York and Its Environments*. He suggested that a city should be composed of small neighborhood units that are about 160 acres or within a range of five minutes walking distance (¼ mile radius) from one of several city centers such as a community center or other "neighborhood institutions". His plan proposed a pedestrian-oriented neighborhood environment (i.e., walkable neighborhoods) where children and adults could safely walk from their homes to schools, playgrounds, work, and local amenities (Perry, 1998).

Recent movements such as *New Urbanism* (New Urbanism, Accessed October 3, 2011) in the 1980's and *Smart Growth* (Smart Growth America, Accessed October 3, 2011) in the 1990's have adapted Perry's "neighborhood unit" concept. It has also been revitalized in modern planning principles such as *Transit Oriented Developments* (*TOD*) and *Traditional Neighborhood Developments* (*TND*).

Building on this sense of walkable neighborhoods originated by Perry, the current definition includes factors such as safety (e.g., traffic volumes; crime rates), aesthetics, local availability/accessibility of various goods and services, and social cohesiveness/social capital.

Moudon et al. have stated that "Defining the walkable neighborhood extends beyond pedestrian concerns (double meaning intended), the ability to walk in a neighborhood indicates not only a type of mobility and means of travel, but also a type of sociability between neighborhoods, which together affect the physical, mental, and spiritual health of people in the community" (Moudon et al., 2006).

Walkable Communities, Inc. (Walkable Communities Inc, Accessed May 5, 2011b) suggests a 12-step checklist that may help to define, achieve or strengthen a walkable neighborhood such as the existence of a town center with various shops and stores for both children and adults. Those shops and stores would be open for at least 8 hours a day and be located within a quarter -mile walk (5 minutes) from the center of the neighborhood. Public space is also a factor that contributes to a walkable neighborhood. A walkable neighborhood has public space that can be accessed by all homes within an eighth of a mile (Walkable Communities Inc, Accessed May 5, 2011a).

Walk Score (Walk Score, Accessed October 18, 2011a) has listed 7 factors that make a neighborhood walkable. A walkable neighborhood has a center that is located on a main street or at a junction with a public space. It has an adequate population density that generates enough customers for local businesses and a mixed land use. It supports public transit to run frequently, bicyclists, and residents with mixed incomes. Moreover, accessibility to parks, public spaces, schools, and workplaces near the residents' homes makes a neighborhood walkable (Walk Score, Accessed October 18, 2011b).

Walkable Neighborhoods (Walkable Neighborhoods, Accessed May 5, 2011) has a long list of various definitions of a walkable neighborhood. Their definitions are similar to those definitions mentioned above. For example, a walkable neighborhood is defined as a neighborhood where people live within walking distance of a variety of amenities, which they want to visit. Another definition characterizes a walkable neighborhood as a place with means of transportation such as walking, biking, and mass transit rather than motorized vehicles within the neighborhood.

Proximity and connectivity
There are two fundamental aspects of the way land is used that may influence physical activity or walking behaviors at the neighborhood level: *proximity* (distance) and *connectivity* (directness of travel) (Saelens et al., 2003b). These aspects are considered to affect individuals' choices to use motorized or non-motorized transport and they have been used as a basis for the conceptualization and measurement of neighborhood walkability.

Proximity has mostly been defined by two land use related variables: density (compactness of land use) and land use mix (the degree of heterogeneity or diversity of functionally different land uses that share the same space) (Leslie et al., 2007). In theory, the more compact and mixed a neighborhood environment is, the shorter are the distances between origins and destinations. The choice of walking over other travel modes is highly dependent on the travel distance. Desirable distances between origins (such as an individual's home) and destinations (such as shops, workplaces, and regional transit services) for walking to be a competitive travel mode are less than 1/2 mile (O'Sullivan and Morall, 1966). Proximity by density and land use mix can facilitate and support more walking in the local environment, i.e., neighborhoods. *Connectivity* is defined as the directness of the path between origins and destinations over the street network (Leslie et al., 2007). High connectivity is characterized by less physical barriers (e.g., less highways/freeways, walls; physical obstacles) and by streets making a grid pattern that facilitates direct paths and routes between origins and destinations (Saelens et al., 2003b).

WALKABILITY MEASURES

Today, the importance of measuring neighborhood walkability subjectively (i.e., perceived) as well as objectively has been recognized. Many previous studies have, however, commonly used only perceived characteristics of neighborhood environments (or perceived walkability) to examine their potential associations with physical activity in the health research field. An article from 2002 reviewed 19 studies on the association between environmental factors and adults' participation in physical activity (Humpel et al., 2002). The authors found that 16 studies used perceived measures of environments and only one study used both perceived and objective measures to study the association between environmental factors and physical activity.

However, previous literature about the influence of neighborhood environments on walking and cycling suggests that it may be useful to employ both perceived and objective measures of neighborhood environments (Saelens et al., 2003b). This is partly because it has not yet been identified whether the perceived neighborhood environment has “an independent, synergistic, or shared association” with walking and cycling (Saelens et al., 2003b). In addition, “Perceptions of neighborhoods may be especially important in evaluating the reasons for residents’ choice of community in which to live, as this could better inform the nature and directionality of the relation between neighborhood environments and walking/cycling” (Saelens et al., 2003b).

Self-reported walkability

A self-reported survey instrument, *Neighborhood Environment Walkability Survey* (NEWS), was composed for the population in the US and tested in US cities/towns. Nevertheless, it has been translated into different languages and used in different countries and cultural contexts. It was also used in study IV in this thesis. The instrument assesses an individual’s perception of neighborhood environmental attributes that are hypothetically related to physical activity. NEWS is largely based on empirical literature from the urban planning and transportation planning research and was composed by Saelens and Sallis (Saelens et al., 2003b).

NEWS asks several questions about neighborhood environments and focuses on: residential density, land use mix diversity and access, street connectivity, walking/cycling facilities, aesthetics, traffic safety, and crime safety (Saelens et al., 2003a).

The instrument has been evaluated for its reliability and validity in the above study. The authors of that study found that the instrument had moderate to high test-retest reliability with evidence of construct validity, in which the residents in high walkable neighborhoods reported higher residential density, land use mix and street connectivity, compared to the residents in low walkable neighborhoods (Saelens et al., 2003a).

Objective walkability

GIS can assess neighborhood environments in an objective matter. GIS can link various spatial data and “enables the integration of measures of proximity, connectivity, density and other environmental factors with systematic assessments of household or individual behavior” (Saelens et al., 2003b).

A spatial index of walkability, the *Walkability Index*, objectively assesses neighborhood environments such as density, evenness, and connectivity using GIS methods. The different measures of environmental attributes used in this index were based on empirical literature from the urban planning and transportation planning research. The Walkability Index was originally developed for the Neighborhood Quality of Life Study (NQLS) conducted in the US (Frank et al., 2010) and later adapted for use in the Australian study, Physical Activity in Localities and Community Environments (PLACE) study (Leslie et al., 2007).

The Walkability Index can be calculated in spatial units (e.g., census block groups in the United States; Census Collection Districts (CCDs) in Australia) and was originally composed of four GIS derived measures of environmental attributes: (1) residential density, (2) intersection density, (3) land use mix, and (4) retail floor area ratio. Each measure is calculated in GIS separately. The final index is the sum of the z-scores of these four measures.

Data from the Swedish Neighborhood and Physical Activity (SNAP) study were included in studies III and IV in this thesis. For the SNAP study, three measures from the original index measures were adapted (because data on retail floor area ratio are not available in Sweden): (1) residential density, (2) intersection density, and (3) land use mix. See below for details.

MULTILEVEL MODELING

Multilevel modeling has relatively recently become a popular analytic approach in neighborhood studies, although they have been used earlier in other fields such as geography, education, and sociology. This is partly because of the advancement of statistical methods and accompanying software, which can offer tools for analyzing data in nested data structures (Diez-Roux, 2000). More importantly, it has been suggested that variables of neighborhoods or other contexts may influence individual health apart from individual characteristics (Diez-Roux et al., 1997).

More or less traditional approaches to the examination of neighborhood effects typically involve analyzing effects either at the individual or neighborhood level (Duncan et al., 1998). Such approaches, however, have been criticized as problematic because there is a need to simultaneously investigate both neighborhood-level and individual-level health determinants and explain their independent and heterogeneous effects (Diez-Roux et al., 1997, Duncan et al., 1998) Ana Diez Roux has summarized four highlights of multilevel models, which differ from traditional analytical approaches (Diez-Roux, 2000). Firstly, multilevel models can simultaneously investigate the effects of both individual-level and neighborhood-level predictors on individual-level outcomes. Secondly, the non-independence of observations (individuals) within neighborhoods is accounted for. Thirdly, neighborhoods (contexts) are not treated as being unrelated, and lastly, variations between individuals and between and within neighborhoods can be examined.

In studies II, III, and IV, we used the nested data structure (individuals nested in neighborhoods) and conducted multilevel analysis to investigate neighborhood effects on individual health outcomes.

AIMS

Study I
The aim of study I was to examine whether the availability of 12 main categories of goods, services, and resources differs between deprived and affluent neighborhoods in all urban neighborhoods in Sweden.

Study II
The first aim of study II was to examine whether neighborhood availability of fast food restaurants, bars/pubs, physical activity facilities, and health care resources was associated with individual-level CHD risk. The second aim was to test whether these possible associations remained after adjustment for neighborhood-level deprivation and individual-level sociodemographic characteristics.

Study III
The first aim of study III was to examine the associations between objective neighborhood walkability and walking for active transportation, walking for leisure, and accelerometer-measured moderate-to-vigorous physical activity, and whether these hypothesized associations are moderated by individual-level sociodemographic factors and neighborhood-level SES. The second aim was to examine random effects in a multilevel fashion, to quantify how much of the total variance of the walking and physical activity outcomes could be due to differences at the neighborhood level.

Study IV
The first aim of study IV was to investigate the concordance between objective and perceived neighborhood walkability in a large Swedish sample of adults. The second aim was to investigate the associations between objective and perceived neighborhood walkability and self-reported walking as well as objective physical activity. The third aim was to investigate the sociodemographic characteristics of individuals who live in neighborhoods with objectively assessed high walkability but who misperceive it as low.

MATERIAL AND METHODS

GEOGRAPHIC INFORMATION SYSTEMS (GIS)

Geographic information systems (GIS) were used in the spatial analysis and database management. A GIS is a computer-aided system that can capture, store, manipulate, analyze, model, and visualize spatial and non-spatial data (e.g., demographic data and disease rates) in the form of maps. We applied the ArcGIS/ArcInfo 9.2 software from ESRI (*ESRI* Environmental Systems Research Institute, Inc., Redlands, CA, United States), which offers various ready-to-use spatial analysis tools. Key GIS procedures applied in study I were: selection of study neighborhoods; estimation of land areas; calculation of absolute counts of neighborhood goods, services, and resources; and preparation of maps. Additional GIS procedures applied in study II were: calculation of individual-centered buffer zones/distances. Key GIS procedures used in studies III and IV will be listed and described below.

Various GIS data (in polygons, lines, and points) were used throughout studies I–IV in this thesis. They were collected at the national (studies I and II) as well as the local level (studies III and IV). Table A summarizes the GIS data used in this thesis.

SMALL AREA MARKET STATISTICS (SAMS)

Small area market statistics (SAMS) cover all Sweden and are small geographic units, which are used for administrative purposes. These units were provided to us by Statistics Sweden, the Swedish government-owned statistics bureau. Each SAMS has an average of about 1000 residents and they were used as proxies for neighborhoods, as has been done previously (Sundquist et al., 2004a, Sundquist et al., 2006a, Sundquist et al., 2006b, Sundquist et al., 2004b, Winkleby et al., 2007).

Studies I and II examined only those SAMS, which overlap with “localities” (in Swedish: “tätorter”). The “localities” in Sweden are defined by Statistics Sweden for every five-year period and represent any village, town, or city with a minimum of 200 residents and adjacent areas where the houses are no more than 200 meters apart (Statistics Sweden, Accessed August 8, 2009).

We chose to include only SAMS overlapping with localities because more rural types of SAMS have very few goods, services, and resources. In 2005, 1,940 Swedish localities were recorded by Statistics Sweden. ArcGIS was used to overlay the SAMS boundaries with the locality boundaries. Selected SAMS that overlapped with localities for inclusion in studies I and II represented 7,945 SAMS out of a total of 9,617 SAMS in Sweden. The selected SAMS included 84% of the Swedish population. Furthermore, SAMS with fewer than 50 people were excluded on the basis that they might yield unreliable statistical estimates in the calculation of the neighborhood deprivation index. A final number of 6,986 and 7, 033 SAMS were included in studies I and II, respectively.

Table A. An overview of the GIS data used in this thesis.

GIS data	Data source, year	Study number	Application
Polygon data of predefined geographic boundaries (SAMS; administrative areas)	Statistics Sweden, 2003 and 2000	Studies I–IV	Used as an approximation of neighborhoods or base of neighborhoods: SAMS (studies I–II); administrative areas (studies III–IV).
Polygon data of localities or “tätorter”	Statistics Sweden, 2005	Studies I–II	Overlapped with SAMS to select study neighborhoods.
Polygon data of buildings with land use types	Stockholm City Planning Administration (SBK), 2007	Studies III–IV	Creating building (dwelling) points for the walkability index.
Line data of centerlines, bicycle and foot paths	Stockholm City Planning Administration (SBK), 2007	Studies III–IV	Creating intersection points for assessing street connectivity for the walkability index.
Point data of registered residential addresses	Stockholm Office of Research and Statistics (USK), 2008	Studies III–IV	Selecting the SNAP study individuals. Creating 1,000 m buffer zones around individuals’ homes (study IV).
Point data of individuals’ approximate residential locations	Statistics Sweden, 2005	Study II	Creating 500 & 1,000 m buffer zones around individuals’ approximate homes. Calculating nearest distances to goods, services; resources.
Point data of goods, services, and resources	Teleadress, Sweden, 2005 and 2008	Studies I–IV	Measuring neighborhood availability as counts and distance measures (studies I–II). Measuring the diversity of land use types or land use mix in neighborhoods for the walkability index (study III–IV).

NEIGHBORHOOD DEPRIVATION INDEX (STUDIES I AND II)

Previous research has shown that neighborhood deprivation is associated with an increased risk of CHD (Sundquist et al., 2004a, Diez Roux et al., 2001, Sundquist et al., 2006b, Sundquist et al., 2004b, Winkleby et al., 2007) and therefore, a neighborhood deprivation index was included in studies I and II. The neighborhood deprivation index was constructed using the 2005 census data provided by Statistics Sweden. A summary index was used to determine neighborhood-level deprivation (Winkleby et al., 2007), which included the following four deprivation indicators for residents aged 25 to 64 (the socioeconomically active part of the population): low income (income from all sources, including that from interest and dividends, defined as less than 50% of the individual median income); unemployment (not employed, excluding full-time students, those completing compulsory military service, and early retirees); low educational status (< 10 years of formal education); and social welfare recipient status. A z score was calculated for each SAMS. The z scores were then summed to create the index. The index was categorized into the following three groups, where higher scores reflect more deprived neighborhoods and lower scores more affluent neighborhoods:

(1) Low neighborhood deprivation (most affluent): below one standard deviation (SD) from the mean.

(2) Moderate neighborhood deprivation: within one SD of the mean.

(3) High neighborhood deprivation (most deprived): above one SD from the mean.

NEIGHBORHOOD AVAILABILITY OF GOODS, SERVICES, AND RESOURCES (STUDIES I AND II)

The Swedish company *Teleadress* (Teleadress, Accessed August 8, 2009) provided the nationwide ready-to-use geocoded business contact information (i.e., goods, services, and resources). *Teleadress* was created when the former government-owned Telecom Company was divided into several subcompanies. It is a leading information aggregator, processor, and provider of Swedish contact information, which delivers all available telephone numbers, addresses, and geographical coordinates in Sweden. The data include all the information in the Swedish Telephone Book, i.e. the Yellow Pages, which is in accord with previous research (Pollack et al., 2005, Chuang et al., 2005).

The data are, however, much more complete than the data in an ordinary telephone book. Having cooperation agreements with all Swedish telephone operators, the company provides information on practically all businesses in Sweden. This includes all businesses and services that have a registered telephone number and/or businesses that have provided information about their existence to the company. Inclusion in the database is free of charge and the company also purchases additional information about businesses from Statistics Sweden to create a comprehensive business listing. These procedures are maintained to ensure a high level of completeness of the data. Accuracy is maintained through an average of 30,000 database updates a day (Teleadress, Accessed August 8, 2009).

In addition, all listed or registered businesses are geocoded in order to provide the business locater via online interactive maps as well as other GIS applications. The ready-to-use nationwide GIS dataset of business contacts was provided to us for November 2005. There were 64 different main industry or business types, by which 83,776 business contacts with their geographic coordinates were sorted. This included a selection of common goods, services, and resources which have been examined in previous studies as potentially health-promoting or health-damaging (Morland et al., 2002, Pollack et al., 2005, Gordon-Larsen et al., 2006, Pearce et al., 2007b).

For study I, we created 12 main categories of goods, services, and resources:

Goods

1. Food/grocery stores (further subdivided into chain food/grocery stores, non-chain food/grocery stores, convenience stores, and gas station food/grocery stores)

2. Shops/stores (e.g., hardware stores, home appliance stores, furniture stores, department stores, sports stores)
3. Liquor stores (the Swedish government-owned liquor stores)

Services and resources

4. Cultural resources (e.g., museums, concert halls, motion-picture theaters, libraries, theaters)
5. Restaurants (e.g. full-service eateries, bakeries, cafés)
6. Fast food restaurants (e.g., pizzerias and hamburger joints)
7. Auto services (e.g., auto parts shops, auto electronic shops, auto body shops)
8. Monetary services (e.g., banks and post offices)
9. Other services (e.g., hair dressers, key services, shoemakers, dry cleaners)
10. Sport facilities (e.g., swimming pools, gyms, ski facilities)
11. Health care resources (e.g., pharmacies/drug stores, public hospitals, health care centers, dentists)
12. Bars and taverns

For study II, the predictor variables were four categories of neighborhood goods, services, and resources that could be regarded as either health-damaging (fast food restaurants and bars/pubs) or health-promoting (physical activity facilities and health care facilities). The categories were:

1. Fast food restaurants (e.g., pizzerias and hamburger joints)
2. Bars/pubs
3. Physical activity facilities (e.g., swimming pools, gyms, ski facilities)
4. Health care facilities (e.g., health care centers, public hospitals, dentists, pharmacies)

The 12 main categories were used as indicators of availability but will be referred to below as only availability. Although the term "accessibility" is consistent with existing literature (Macintyre et al., 2008, Abercrombie et al., 2008, Ball et al., 2009), this growing body of research may need to develop a more accurate terminology. We therefore prefer the term "availability". In studies I and II, neighborhood availability was measured as: (1) counts by pre-defined administrative areas or SAMS. In study II, neighborhood availability was also measured in two additional ways: (2) counts by individual buffer zones and (3) distance measures (see below).

COUNTS BY PRE-DEFINED NEIGHBORHOODS OR SAMS (STUDIES I AND II)

Numbers of goods, services, and resources in each SAMS unit that fell into each of the chosen categories were calculated separately using the GIS. Availability was defined as the presence within the SAMS unit of at least one feature for the category in question.

COUNTS BY INDIVIDUAL BUFFER ZONES (STUDY II)

Buffer zones around each individual's approximate residential location were created in the GIS as proxies for each individual's immediate neighborhood. For each individual, we applied buffer zones whose radii were 500 meters and 1,000 meters in order to examine possible differences in associations according to the size of the buffer zone. The sizes of the buffer zones were estimates of how far people are willing to walk in order to reach certain locations (Lee and Moudon, 2006).

Number of goods, services, and resources within the buffer zones were calculated separately for each of the four categories using the GIS. Availability was defined as the presence within the buffer zone of at least one feature for the category in question.

DISTANCE MEASURES (STUDY II)

This measure of neighborhood availability was used only as a control in order to examine any possible incongruence between the results of the analysis of the individual buffer zones and the distance measures. Nearest distances "as the crow flies" from the residential locations of the individuals were calculated separately for goods, services, and resources in each of the four categories using the GIS. Availability was defined as a distance of less than 1,000 meters between the residential location of the individual and the nearest feature in question.

STUDY POPULATION (STUDY II)

The study population comprised a large, nationwide random sample of men and women aged 35–80 years on December 1, 2005 (the start of the follow-up). All individuals were identified from a national Swedish research database, managed at the Center for Primary Health Care Research at Lund University. This database contains nationwide individual-level medical diagnoses from the Swedish Hospital Discharge Register (obtained from the National Board of Health and Welfare) and the Cause of Death Register. These data are linked to Population Register (census) data obtained from Statistics Sweden, the Swedish Government-owned statistics bureau. The Population Register includes remarkably complete individual-level data on sociodemographic factors such as age and income. Our extensive dataset, covering the entire Swedish population (aged 35–80 years), was too large to analyze using the software available to us. Therefore, we randomly selected approximately 50% of the men and women aged 35–80 years. We used the SAS program random seed to select the half random sample. The study population comprised 1,065,000 men and 1,100,000 women. The men and women were followed between December 1, 2005, and December 31, 2007, for the outcome variable (see below). To address the aims of the study, all individuals in the study population were geocoded to their approximate residential locations. Each individual's actual residential location or street address was assigned to a 100 x 100 meter grid cell. This approximation meant that nobody's "true" location was revealed, thereby protecting the anonymity of the study subjects. A personal identification number was used for data linkage and to track all individuals during the study period. Thus, there was no loss to follow-up. The personal identification numbers took the form of unidentified serial numbers, provided to us by Statistics Sweden, which guaranteed anonymity to all individuals.

OUTCOME VARIABLE (STUDY II)

The outcome was defined as first hospitalization during the study period for individual-level CHD (both morbidity and mortality). The disease codes were based on the tenth version of the International Classification of Diseases (ICD-10) and included the following diagnoses: I20, angina pectoris; I21, acute cardiac infarction; I22, reinfarction (within 4 weeks); I23, complications due to acute cardiac infarction; I24, other acute forms of CHD; and I25, chronic CHD. Men and women with pre-existing CHD, defined as hospitalization for CHD ≤5 years before the start of the study, were excluded. In total, 39,749 men and 29,545 women died from all causes during the study period.

INDIVIDUAL-LEVEL COVARIATES (STUDY II)

Gender: analyses for men and women were conducted separately. Age was categorized as 35–44, 45–54, 55–64, 65–74 and 75–80 years. Family income was categorized as empirical quartiles based on the distribution. The family income variable took the number of people in the family into account as well as the ages of the family members (children were given lower consumption weights than adults).

DATA ANALYSIS (STUDY I)

The 12 main categories were used as outcome variables to examine availability of various goods, services, and resources by level of neighborhood deprivation. They were expressed as absolute counts of goods, services, and resources per SAMS neighborhood, after adjustment for population density (number of persons/km^2). This approach is in line with previous research (Macintyre et al., 2008).

Poisson regression was initially considered in the data analysis but was not suitable because nearly all the outcome variables (except liquor stores) had overdispersed data. Overdispersed data means that the observed variance is higher than the expected variance (the variance of a theoretical model). Poisson regression analysis is often used to analyze count data such as ours. However, it does not allow for the variance to be adjusted independently of the mean because it has only one free parameter. When the data are overdispersed, the negative binomial distribution is especially useful, i.e. for data whose sample variance exceeds the sample mean the negative binomial distribution can be used instead of the Poisson distribution because it has an additional free parameter. Therefore, we used a negative binomial regression model that allows the data to have extra-Poisson variation (Pawitan, 2001, Stata, 2007). This model was used to assess the association between neighborhood deprivation and the outcome variables, adjusting for possible confounding by population density (included in the model as a linear term). The lowest level of neighborhood deprivation was used as the reference. For each of the three levels of deprivation we present the absolute counts of goods, services, and resources, estimated prevalence rates (absolute counts of goods, services, resources/SAMS) and the prevalence rate ratios with 95% confidence intervals. The software used was Stata 10.1 (e.g., the NBREG function) (Stata, 2007).

DATA ANALYSIS (STUDY II)

Age-standardized incidence proportions (proportions of subjects who became cases among those who entered the study time interval) were calculated separately for men and women by direct age standardization using ten-year age groups, with the entire Swedish population of men or women aged 35–80 as the standard population. Multi-level (hierarchical) logistic regression models were created with incidence proportions as the outcome variables. The analyses were performed using MLwiN (Rasbash et al., 2000).

Multi-level logistic regression models were used in the computing process to help our large multi-level models to converge. These models are a good approximation of multi-level Cox proportional hazards models under conditions such as ours (large sample size, relatively low incidence, risk ratios of moderate size, and relatively short follow-up) (Callas et al., 1998).

First, we created models that only included the neighborhood availability of each of the four categories of neighborhood goods, services, and resources in order to determine the crude odds ratios (ORs) of CHD with 95% confidence intervals (CIs). Next, we created a model that also included neighborhood-level deprivation. The third and final model included neighborhood availability, neighborhood-level deprivation and individual-level age and income. There were statistically significant associations between neighborhood-level deprivation and neighborhood availability of each of the four categories of neighborhood goods, services, and resources. High- and moderate-deprivation neighborhoods had a significantly higher prevalence of both “health-damaging” and “health-promoting” goods, services, and resources (data not shown in tables).

Cross-level interaction tests were performed. No interactions between the individual-level sociodemographic variables and the neighborhood-level variables were found.

OBJECTIVE NEIGHBORHOOD WALKABILITY (STUDIES III AND IV)

Studies III and IV were based on data from the Swedish Neighborhood and Physical Activity (SNAP) study, performed in Stockholm in Sweden. The city of Stockholm is divided into 408 small administrative areas with homogeneous types of buildings. They contain approximately 2,000 individuals per unit. The geographic boundaries of the administrative areas follow the road/street network and they are also well-known geographic units that could be used for future health interventions. They constituted a basis for the creation of the 32 neighborhoods included in the SNAP study.

The selection of the 32 neighborhoods for the SNAP study was based on neighborhood walkability (high or low) and neighborhood income (high or low). Figure 6 shows the administrative areas in Stockholm, by high/low neighborhood walkability and high/low neighborhood income. This resulted in four types of neighborhoods: high walkability/high income, high walkability/low income, low walkability/high income, and low walkability/low income, i.e., 8 neighborhoods in each category. Figure 7 shows the final 32 neighborhoods in the SNAP study. The walkability in each administrative area in Stockholm was established by calculating a walkability index using GIS. The index was partly based on a previously described walkability index (Frank et al., 2006) including four components: (1) residential density, (2) street connectivity, (3) land use mix, and (4) retail floor area ratio. In the SNAP study, the walkability index included the first three components, i.e. residential density, street connectivity, and land use mix. The retail floor area ratio was not included because data on retail building floor area are not available in Sweden. Data on residential density were delivered by Statistics Sweden, and calculated as the ratio of the number of residential units per square kilometer (excluding water bodies). Street connectivity was based on data provided by the City Planning Administration in Stockholm and was calculated as the number of "true" intersections (three or more "legs") per square kilometer. Two or more intersections closer to each other than 10 meters were counted as one using a buffering function. Highways were not included in the calculations. Bicycle and foot paths were included if they had an intersection with a street. A higher connectivity corresponds to a higher density of intersections allowing for a more direct path between destinations. Figure 8 illustrates how the intersections were created for the calculation of connectivity in the walkability index. Land use mix was calculated as the evenness of the distribution of the five categories (see below) included in the land use mix and indicates the degree to which a diversity of land use types occurs in a certain geographic area. The calculations of the evenness in the land use mix were based on geocoded point data. We created five categories of residential, commercial, and office developments for the calculation of land use mix: (1) Retail/service, (2) Entertainment/physical activity, (3) Institutional/health care, (4) Office/workplace, and (5) Dwellings. The Herfindahl-Hirschman Index (HHI index) was used to assess the level of land use mix. The higher the value of the HHI index, the lower the level of land use mix (Forsyth, 2007).

Figure 6. Administrative areas in Stockholm, by high/low neighborhood walkability and high/low neighborhood income.

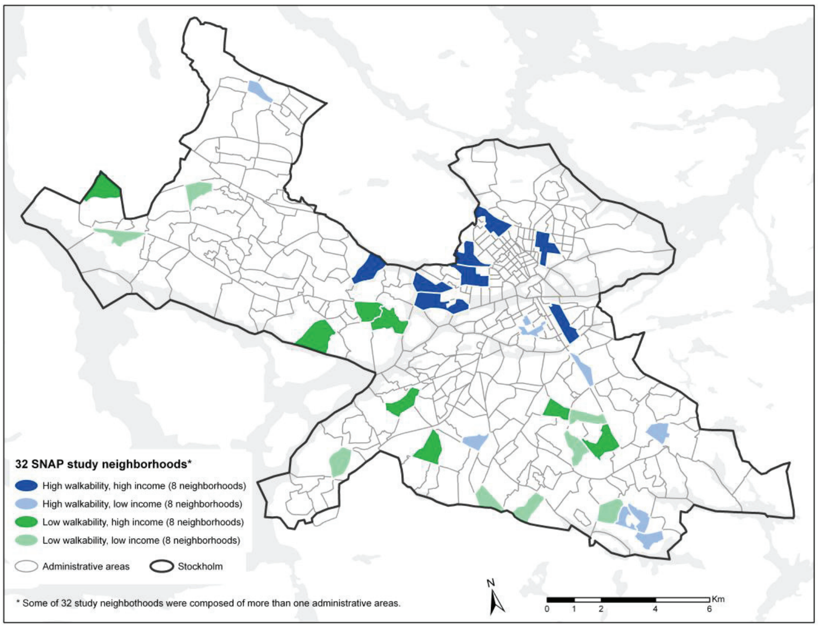

Figure 7. The final 32 neighborhoods in the SNAP study.

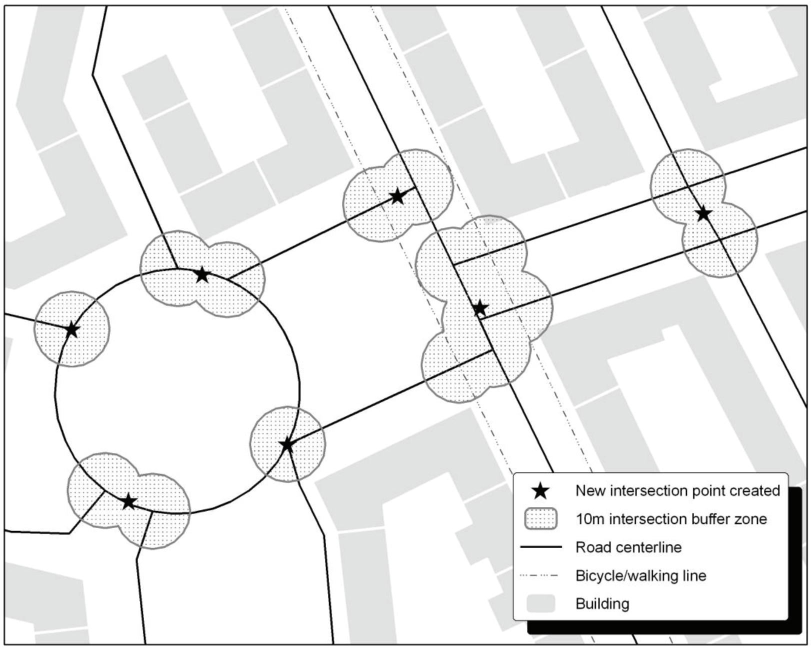

Figure 8. Intersections for the calculation of connectivity in the walkability index.

The data for the first four categories in the land use mix were delivered by the private company *Teleadress* (see above).

Previous studies have mostly weighted connectivity x 2 (Frank et al., 2006). We chose, however, to use the weight 1.5 instead because our walkability index was based on three items instead of four.

The following formula was used:

Walkability index = $Z_{\text{Residential density}} + 1.5{*}Z_{\text{Street connectivity}} + Z_{\text{Land use mix}}$

The walkability index for each neighborhood was calculated as the sum of the z-scores for the three components included in the index, i.e. residential density, street connectivity, and land use mix. Next, the walkability index scores were divided into deciles. Administrative areas within the first, second, third, and fourth deciles were considered less walkable areas and those within the seventh, eighth, ninth, and tenth deciles were considered highly walkable areas. This approach is in line with previous research (Owen et al., 2007, Sallis et al., 2009, Van Dyck et al., 2010).

Neighborhood income was included in the selection process in order to account for possible neighborhood differences in physical activity that could be explained by the socioeconomic structure of the neighborhood, which is also in accord with previous studies (Owen et al., 2007, Sallis et al., 2009, Van Dyck et al., 2010).

Data on neighborhood income was delivered by Statistics Sweden. Neighborhood income was based on the disposable median family income, which took into account the number and age of the family members. For example, children and adolescents were given lower consumption weights than adults. The median neighborhood family income for each administrative area was calculated and the administrative areas were divided into deciles. The second, third, and fourth deciles constituted low neighborhood income and the seventh, eighth, and ninth deciles represented high neighborhood income.

One hundred and twenty-seven of the 408 small administrative areas in Stockholm were assigned to one of the following four categories: high walkability/high income, high walkability/low income, low walkability/high income, and low walkability/low income. The size of these 127 administrative areas ranged between 0.03 and 2.73 square kilometers. We selected the administrative areas that were as close as possible in size to the area 0.65 square kilometers. This area corresponds to the size of the neighborhoods created in the Twin Cities Walking Study (Forsyth, 2007).

We partly used a clustering process to create the study neighborhoods in the category high walkability/high income because the administrative areas in that category were rather small. Practically all administrative areas in the category high walkability/high income were, however, located in the inner city, where the administrative areas are well connected to each other. Clustering of administrative geographic units to create study neighborhoods has also been used in previous research (Leslie et al., 2007, Frank et al., 2006). This procedure yielded 8 study neighborhoods in each category, i.e., in total, 32 neighborhoods with at least 500 households.

In study IV, objective walkability was recalculated for each participant to define a neighborhood on the basis of a 1,000 m circular buffer zone around each participant's residential address. The residential address of each study participant was geocoded using GIS and a 1,000 m circular buffer zone was drawn around it. This radius was based on an estimate of how far people are willing to walk in order to reach a certain location (Lee and Moudon, 2006).

Z-scores were calculated for study participants for each of the three walkability components (for residential density and street connectivity as z = (x-mean)/SD; and for land use mix as z = (mean-x)/SD). Objective neighborhood walkability was then calculated from the z-scores for the three walkability components using the formula presented above.

PERCEIVED NEIGHBORHOOD WALKABILITY (STUDY IV)

The Neighborhood Environment Walkability Scale (NEWS) was used to assess perceived residential density, land use mix and street connectivity (Saelens et al., 2003a). Residential density was scored according to the original scoring protocol for the NEWS (Saelens et al., 2003a). The items in NEWS that were used to create the land use mix diversity subscale assessed perceived distance to a variety of facilities. To better match to the 1,000 m buffer zone, the items included in the land use mix subscale were rescored in the following way: 1–5 min (score 3); 6–10 min (score 2); 11–20 min (score 1); and 20+ min (score 0). The mean of the scores was calculated as a measure of land use mix. With a normal walking pace in adults of about 4 km/h (Srinivasan, 2009). Fifteen minutes of walking corresponds to a distance of 1,000 m. Hence, a cut-off at 20 minutes when scoring the NEWS items would match the 1,000 m buffer zone more appropriately. The first item of the street connectivity scale, assessing the number of cul-de-sacs, was excluded from the scoring because such streets are not included in the objective walkability. The mean score of the included items was used as a measure of street connectivity. Z-scores for each of the three walkability components were calculated as z = (x-mean)/SD and summed into the overall perceived neighborhood walkability using the same formula that was used for objective neighborhood walkability.

STUDY SAMPLES IN THE SNAP STUDY (STUDIES III AND IV)

Our goal was to assess 75 individuals from each neighborhood, i.e., in total, 2,400 participants, aged 20–65. The power calculations were partly based on previous research (Owen et al., 2007) and on an assumed mean difference of 5 minutes/day of MVPA between individuals from highly walkable neighborhoods and those from less walkable ones, an assumed standard deviation of 24, and a response rate of 40%. In order to reject the null hypothesis with a power (probability) of 0.8 and a type I error probability of 0.01, we needed to study 585 individuals in each of the two types of neighborhoods (high walkability versus low walkability), i.e. 1,170 in total. We chose, however, an approach of oversampling because our assumptions were based on information from very few previous studies. The Stockholm Office of Research and Statistics performed the simple random sampling of 250 individuals from each neighborhood (a total of 8,000 individuals) without including immigrants who had arrived in Sweden later than 2003 (i.e. five years before the start of the study) as our questionnaire was provided only in Swedish. This is in accord with previous studies from the US and Australia, where only English-speaking individuals have been included. Of the 8,000 individuals, 6,089 had a listed landline or mobile phone number and were included in the recruitment procedure. An information letter was sent to their home address one week before a telemarketing company (Markör AB, Örebro, Sweden) contacted the individuals by phone. Inclusion criteria at this stage were the following: (1) being able to read and write Swedish, (2) having lived in the neighborhood for at least three months, and (3) having no serious impaired ability to walk. Of the 4,747 individuals who were reached, 4,369 met the inclusion criteria and 3,226 agreed to participate in the study.

After exclusion of participants due to dropouts, lost accelerometers, technical errors in the accelerometers, and incomplete wearing time of the accelerometer (see definition below), the final study population for analyses consisted of 2,269 individuals, which gave a response rate of 52% (2,269/4,369) in study III.

In study IV, complete data were received from 1,925 individuals, including objective and perceived walkability, valid accelerometer data (see criteria below), and complete self-reported physical activity data and sociodemographic characteristics from the study questionnaire. This corresponds to a response rate of 44.1% (1,925/4,369).

The telemarketing company (see above) had previous experience in recruiting study participants for research purposes, and one of the co-authors of study III (UE) provided detailed written and oral information to all personnel involved in the recruitment process. Individuals from all of the 32 neighborhoods were recruited between November 2008 and November 2009. Every week a list of recruited individuals was sent to us from the company. Then, an accelerometer, a logbook, a questionnaire, and a prepaid return envelope were sent to the individuals. No data were collected during the Christmas and summer vacation periods, which, in Sweden, correspond to weeks 50 to 2 and weeks 25 to 33, respectively.

NON-RESPONSE ANALYSIS

A non-response analysis of 205 randomly selected non-respondents (interviewed by phone) revealed that there were slightly more women among the respondents than among the non-respondents. Respondents were also slightly older than non-respondents. There were no statistically significant differences in socioeconomic characteristics between respondents and non-respondents.

OBJECTIVE MEASURES OF PHYSICAL ACTIVITY (STUDIES III AND IV)

The uniaxial accelerometer Actigraph GT1M (ActiGraph, Pensacola, Florida, USA) was used to objectively assess the individuals' level of physical activity. It gives a valid and reliable measure of physical activity in adults under free-living conditions (Abel et al., 2008).

The individuals were asked to wear the accelerometer on the hip or the lower back during all waking hours for seven consecutive days, except when engaging in water activities. The ActiGraph was set to add up physical activity data in 60-second epochs, which represents the predominantly used period to integrate and analyze accelerometer data in adults (Owen et al., 2007, Trost et al., 2005, Sallis et al., 2009, Van Dyck et al., 2010). In study III, non-wearing time was defined as ≥60 consecutive minutes of no registered physical activity (zero counts), which is in line with previous research (Van Dyck et al., 2010). In study IV, non-wearing time was defined as ≥30 min of no registered physical activity (zero counts). Time spent on MVPA was identified using Freedson's cut points for accelerometer data, which for MVPA amount to ≥1952 counts per minute (Freedson et al., 1998). Ten-minute bouts of MVPA were defined as at least 10 consecutive minutes (≥ 1952 counts per minute) allowing for 1–2-minute drops below this threshold. The mean daily time accumulated in ten-minute bouts of MVPA is shown in Table 6. A variance analysis of our data for MVPA was performed to determine the required number of days for inclusion (Matthews et al., 2002).

The final inclusion criteria for valid days were set at ≥ 10 hours of wearing time per day for ≥ 6 days, including at least one weekend day. Time spent on MVPA was calculated as the mean of all valid days. Around 3.2% of the accelerometers were lost in the mailing process.

SELF-REPORTED MEASURES OF PHYSICAL ACTIVITY (STUDIES III AND IV)

Walking for active transportation and walking for leisure were assessed using questions from the long version of the International Physical Activity Questionnaire (IPAQ). The IPAQ is a self-administered 7-day recall physical activity questionnaire that has been tested for validity and reliability (Meeus et al., 2010; Papathanasiou et al., 2009). The IPAQ has shown good reliability and fair-to-moderate validity when compared to accelerometers (Craig et al., 2003). It has been used in population-based studies in Sweden (Sodergren et al., 2010).

The two questions used to assess walking for active transportation were the following: (1) “On how many days during the last 7 days did you walk for at least 10 minutes at a time to go from place to place?” and (2) “How much time did you usually spend on one of those days walking from place to place?” Walking for leisure was assessed with the questions: (1) “Not counting any walking you have already mentioned, on how many days during the last 7 days did you walk for at least 10 minutes at a time during your leisure time?” and (2) “How much time did you usually spend on one of those days walking during your leisure time?” Cleaning and scoring procedures were performed in accordance with the IPAQ guidelines (www.ipaq.ki.se/scoring.htm).

INDIVIDUAL-LEVEL SOCIODEMOGRAPHIC VARIABLES (STUDY III)

Age, gender, marital status, and family income were based on self-reports. Age was categorized into four groups: 20–30 years (reference), 31–40 years, 41–50 years, and 51–66 years. Marital status was categorized into two groups: married/cohabiting with a partner and single (reference). Family income was categorized into three groups: low (<300,000 SEK/year, reference), middle (300,000–800,000 SEK/year), and high (> 800,000 SEK/year).

INDIVIDUAL-LEVEL SOCIODEMOGRAPHIC VARIABLES (STUDY IV)

Sociodemographic characteristics were assessed using the study questionnaire. Sex, age, educational level, and marital status were included in the analysis. Age was categorized as 20–29, 30–49 and 50–66 years. Educational level was dichotomized as university education or no university education. Marital status was categorized as being single or married/cohabiting.

DATA ANALYSIS (STUDY III)

The association between neighborhood walkability and individual MVPA was analyzed using multilevel linear regression models (Goldstein, 2003) with individuals at the first level and neighborhoods at the second level. We developed two consecutive models. Model A (crude) only included *neighborhood walkability.* Model B also included the individual covariates *age, gender, marital status, and family income,* as well as *neighborhood-level income,* which is in line with previous studies on the association between neighborhood walkability and physical activity outcomes (Owen et al., 2007, Sallis et al., 2009, Van Dyck et al., 2010). This allowed us to investigate whether these characteristics moderated the association between neighborhood walkability and individual MVPA. The model was estimated by MLwiN using non-parametric bootstrap estimates (1,000 replicates and five sets) in order to test for the possible effects of non-normal distributions and the accuracy of inferences about the parameter values (Rasbash et al., 2000). Beta coefficients and 95% confidence intervals are presented as measures of association. The beta coefficients represent minutes/day.

Individual *Walking for active transportation* and individual *Walking for leisure* were analyzed using a mixed-effects, mixed-distribution model due to the excessive number of zeros in the outcome variables (Tooze et al., 2002).

In total, 431 individuals (20%) reported zero regarding *Walking for active transportation* while 657 (30%) reported zero regarding *Walking for leisure*. The model is made up of two parts: the first is a logistic part for occurrence of the outcome, which estimates the probability of a positive value versus zero. The second is a linear part that models the intensity (i.e. amount in minutes/week) of the response, given that the response is greater than zero. The second (linear) part of the model did not include those individuals who reported zeros regarding *Walking for active transportation* or *Walking for leisure*. In the second part of the mixed-effects, mixed-distribution model we assumed a normal distribution. In order to justify this assumption, we performed an ancillary analysis using bootstrap estimates in the linear part. This yielded almost identical results to those in the second part in the mixed-effects, mixed-distribution model, supporting our assumption of a normal distribution. The mixed-effects, mixed-distribution model allowed us to interpret the occurrence of the outcome presented as an odds ratio with a 95% confidence interval, as well as the amount of the response presented as a beta coefficient (minutes/week) with a 95% confidence interval. A random effect for the occurrence and a random effect for the amount were included in the model to account for clustering of individuals within neighborhoods. We developed two consecutive models for each outcome. Model A included *Neighborhood walkability* and Model B also included the individual covariates *age, gender, income, and marital status,* as well as *neighborhood-level income*. This allowed us to investigate whether inclusion of these characteristics attenuated the association between *Neighborhood walkability* and *Walking for active transportation* or *Walking for leisure*. The model was estimated using SAS v. 9.2 (SAS Institute, Cary, NC, USA), with the MIXCORR macro developed by Tooze et al. (Tooze et al., 2002).

To facilitate the interpretation of the variance at the neighborhood level, we calculated the intraclass correlation (ICC) (Snijders and Bosker, 1999). A large ICC would indicate that differences between the neighborhoods account for a considerable part of the individual differences in our studied outcomes. On the other hand, an ICC close to zero would indicate that the neighborhoods exert only a small influence on the total variance between individuals (Snijders and Bosker, 1999). The ICC is the percentage of the total variance of the individual outcome attributable to the neighborhood level.

ICC was calculated according to the following formula:

$$V_2 / (V_1 + V_2) \qquad (\textit{Equation 1})$$

where V_1 = variance between individuals (first-level variance) and V_2 = variance between neighborhoods (second-level variance). However, in the logistic part of the mixed-effects, mixed-distribution model, the neighborhood-level variance is measured on a different scale than the individual-level variance and hence they are not comparable. We used the latent variable method to convert the individual-level variance from the probability scale to the logistic scale (Goldstein et al., 2002).

This method assumes that the unobserved individual variable follows a logistic distribution with the individual variance equal to 3.29 ($\Pi^2/3$). The ICC is then calculated according to equation 1.

DATA ANALYSIS (STUDY IV)

Z-scores were calculated for objective and perceived neighborhood walkability. Z-scores for neighborhood walkability and for the subcomponents residential density, land use mix and street connectivity were dichotomized using median splits and four concordance categories were created: high objective/high perceived, high objective/low perceived, low objective/high perceived, and low objective/low perceived. The distribution into the four categories and kappa statistics were used to assess concordance between objective and perceived neighborhood walkability. Additionally, the difference between individual objective and perceived neighborhood walkability was calculated and the participants were divided into quartiles depending on the size and direction of the difference. Two of the quartiles represented a small difference between the methods, while the other two represented a large difference. The proportions of individuals with a small difference were determined for each concordance category.

To investigate the associations between neighborhood walkability and self-reported walking or objective physical activity, three consecutive regression models were developed for each specific outcome (walking for transportation, walking for leisure, total physical activity and MVPA). Model A included objective neighborhood walkability. Model B also included perceived neighborhood walkability and in Model C, the individual covariates sex, age, educational level, and marital status were included. However, initial analyses showed that the variable marital status was not associated with the outcomes and did not alter the estimates. It was therefore excluded from the models. As the outcome variables were not normally distributed, we estimated the models with parametric bootstrap (1,000 replicates and 50 sets) using MLwiN software (Center for Multilevel Modeling, University of Bristol, Bristol, UK) in order to improve the inferences about parameter values. β-coefficients and 95% confidence intervals are presented as measures of association. The β-coefficients represent minutes per week (walking for transportation, walking for leisure), counts per minute (total physical activity), or minutes per day (MVPA). We tested for possible interactions, but none were found.

Logistic regression analyses (OR, 95% confidence interval) were used to investigate whether sociodemographic characteristics were associated with non-concordance between objective and perceived neighborhood walkability among individuals in neighborhoods with objectively assessed high walkability. Both univariate and multivariate analyses were performed, with sex, age, and educational level as covariates.

RESULTS

STUDY I

Table 1 shows population sizes and neighborhood characteristics in 2005 by level of neighborhood deprivation. Most neighborhoods or SAMS fell into the moderate level of neighborhood deprivation (about 60% of the total number). The proportions of low and high neighborhood deprivation among the total SAMS were about 20% at each level. Table 1 also shows the proportion of people with low income, unemployed, people with less than 10 years of education, and social welfare recipients for each level of neighborhood deprivation (low, moderate, and high). Compared to low-deprivation neighborhoods, high-deprivation neighborhoods had more than twice as many people with low income and around three times as many unemployed persons or people with low educational level. The largest difference between low and high-deprivation neighborhoods was found for social welfare recipients: 1.11% versus 13.09%.

Table 1. Descriptive data of the three levels of neighborhood deprivation.

	Level of neighborhood deprivation		
	Low	Moderate	High
Number of people	1,846,338	4,938,121	1,667,965
Number of neighborhoods	1,647	4,160	1,179
Neighborhood deprivation index by range	–3.06 to < –1	–1 to 1	> 1 to 10.8
Items of neighborhood deprivation index			
Low income (%)	6.53	9.05	16.01
Unemployed (%)	1.73	2.98	5.32
<10 years education (%)	10.50	17.50	27.09
Social welfare recipient (%)	1.11	3.24	13.09

Table 2 shows the prevalence rates (Ps) and prevalence rate ratios (PRs) with 95% confidence intervals (CIs). Low-deprivation neighborhoods were used as the reference group in the models. Each category was analyzed separately. For each of the 12 main categories of goods, services, and resources, there were significant differences between the reference group (low deprivation) and the two other levels of neighborhood deprivation, i.e. moderate and high levels. All types of goods, services, and resources

Table 2. Prevalence ratios (PRs) with 95% confidence intervals (CIs) for the three levels of neighborhood deprivation with low neighborhood deprivation as reference category.

	Level of neighborhood deprivation										
	Low (n=1647)			Moderate (n=4160)				High (n=1179)			
Category	n	P*	PR	n	P*	PR	95% CI	n	P*	PR	95% CI
Goods											
Food stores and grocery stores	664	0.39	1.0	3623	0.83	2.16	1.96, 2.38	1185	0.92	2.49	2.22, 2.80
chain food stores	314	0.19	1.0	1692	0.41	2.14	1.89, 2.41	520	0.44	2.32	2.01, 2.69
non-chain food stores	252	0.14	1.0	1469	0.32	2.23	1.91, 2.61	532	0.37	2.59	2.17, 3.10
convenience stores	29	0.01	1.0	173	0.03	2.52	1.61, 3.95	47	0.02	2.12	1.25, 3.62
gas station food stores	69	0.05	1.0	289	0.08	1.69	1.29, 2.20	86	0.10	2.29	1.67, 3.15
Shops	668	0.39	1.0	3753	0.87	2.21	1.84, 2.65	839	0.68	1.72	1.37, 2.16
Liquor stores	37	0.02	1.0	576	0.15	6.30	4.54, 8.75	151	0.16	6.83	4.74, 9.83
Services and resources											
Cultural resources	239	0.14	1.0	1599	0.37	2.63	2.24, 3.09	399	0.32	2.27	1.88, 2.75
Restaurants	2115	1.06	1.0	12055	2.39	2.26	2.00, 2.55	2671	1.78	1.68	1.45, 1.95
Fast food restaurants	510	0.29	1.0	2626	0.59	1.99	1.77, 2.24	829	0.62	2.10	1.83, 2.42
Auto services	1933	1.25	1.0	9199	2.34	1.88	1.65, 2.14	1981	1.90	1.52	1.30, 1.78
Monetary services	367	0.23	1.0	3020	0.73	3.26	2.75, 3.86	879	0.75	3.36	2.77, 4.09
Other services	1244	0.61	1.0	7073	1.38	2.25	2.01, 2.52	1738	1.10	1.78	1.56, 2.05
Sports facilities	623	0.39	1.0	2758	0.71	1.79	1.60, 2.00	636	0.61	1.53	1.30, 1.79
Health care resources	505	0.27	1.0	3300	0.68	2.53	2.19, 2.91	933	0.64	2.39	2.02, 2.82
Bars and taverns	123	0.05	1.0	975	0.15	3.33	2.42, 4.59	151	0.08	1.64	1.10, 2.46

* Prevalence for a median population density area (median =808 pers/km^2)

n = total count

PR = prevalence ratio, CI = confidence interval were more prevalent in moderate and high-deprivation neighborhoods. The significantly increased PRs in moderate and high-deprivation neighborhoods ranged between a minimum of 1.52 (high deprivation, auto services) and a maximum of 6.83 (high deprivation, liquor stores). The PRs for all types of food and grocery stores were 2.16 and 2.49 in moderate and high-deprivation neighborhoods, respectively, and varied between 1.69 (gas station food stores, moderate deprivation neighborhoods) and 2.59 (non-chain food stores, high deprivation neighborhoods) for the different subtypes of food and grocery stores. For fast food restaurants, the PRs were 1.99 and 2.10 in moderate and high-deprivation neighborhoods, respectively. The corresponding PRs for sports facilities were 1.79 and 1.53 and, for health care resources, 2.53 and 2.39.

PRs higher than 3 were found for the category "monetary services" in moderate and high-deprivation neighborhoods (PRs were 3.26 and 3.36, respectively) and for the category "bars and taverns" in moderately deprived neighborhoods (PR = 3.33).

Figure 9 displays two maps from the city of Stockholm, each showing the distribution, by level of neighborhood deprivation, of the following two categories of goods, services, and resources: (1) all types of "food/grocery stores" and (2) "fast food restaurants". The figure displays neighborhoods with no access, neighborhoods with access to one, and neighborhood with access to two or more of the items in question. Although no statistical tests were performed for these maps, the figure suggests that the prevalence of both categories was higher in more deprived neighborhoods in Stockholm.

STUDY II

Table 3 shows the distribution of the study population, number of CHD events and age-standardized incidence (%) by neighborhood deprivation and neighborhood availability of potentially health-damaging and health-promoting goods, services, and resources (based on the SAMS neighborhoods). Around 40% of study subjects lived in neighborhoods with availability to health care facilities or physical activity facilities. Almost half (45.5%) of the study population had at least one fast food restaurant in their neighborhood. Most people lived in neighborhoods with no bars/pubs. The age-standardized incidence of CHD increased with increasing neighborhood deprivation. For the total study population, the incidence for women was 0.6% in low-deprivation neighborhoods and 1.0% and 1.2%, respectively, in moderate- and high-deprivation neighborhoods. The corresponding incidences for men were 1.5%, 2.0%, and 2.4%, respectively.

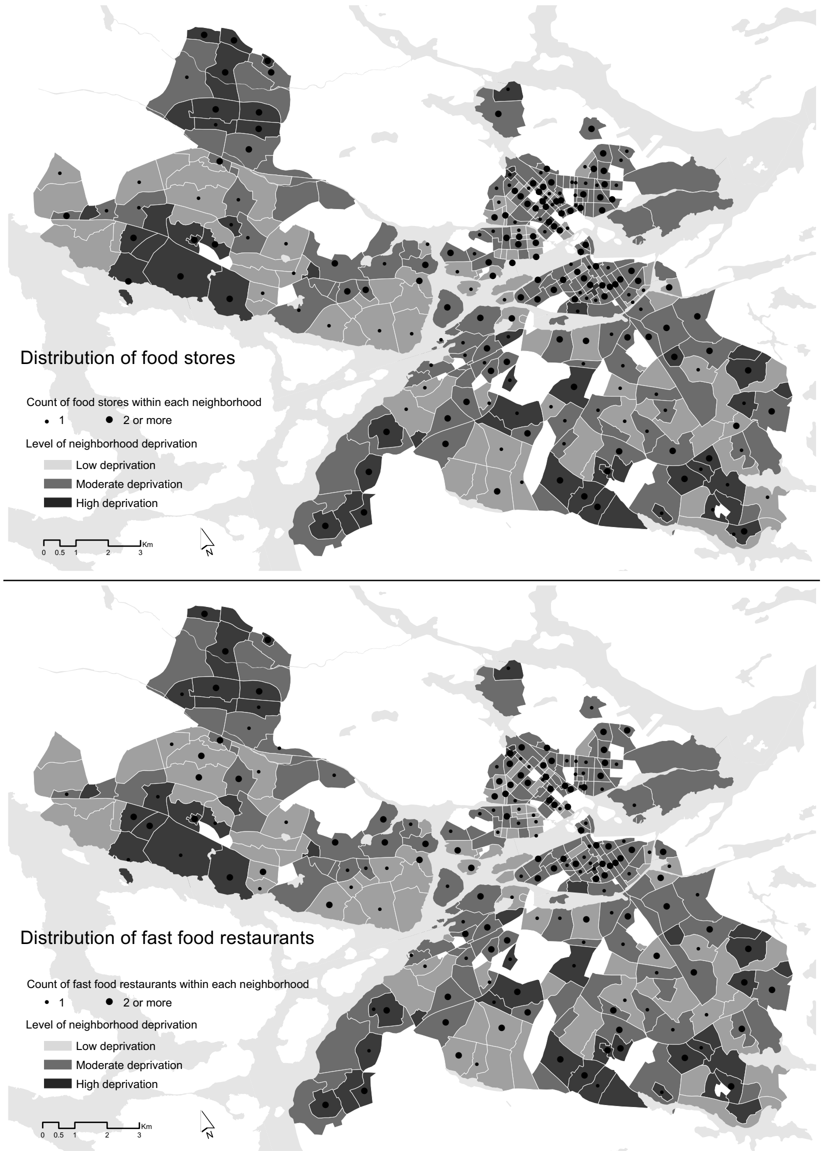

Figure 9. The distribution of food/grocery stores and fast food restaurants by level of neighborhood deprivation. Stockholm, Stockholm County, Sweden.

Table 3. Distribution of the study population, number of CHD events, and age-standardized incidence proportions (%) by level of neighborhood deprivation and neighborhood availability of potentially health-damaging and health-promoting goods, services, and resources.

	Men (n=1,065,000)					Women (n=1,100,000)				
	Distribution (%)	Number of CHD events	Incidence proportions by level of neighborhood deprivation (%)			Distribution (%)	Number of CHD events	Incidence proportions by level of neighborhood deprivation (%)		
			Low	Moderate	High			Low	Moderate	High
Neighborhood availability by category		20,800	1.5	2.0	2.4		10,484	0.6	1.0	1.2
Fast food restaurants										
No access	54.5	11,117	1.5	2.0	2.4	53.3	5,246	0.6	1.0	1.2
Access	45.5	9,683	1.5	2.0	2.3	46.7	5,238	0.6	1.0	1.3
Bars/pubs										
No access	87.3	18,052	1.5	2.0	2.4	86.6	8,923	0.6	1.0	1.3
Access	12.7	2,748	1.5	2.0	2.2	13.4	1,561	0.7	1.0	1.2
Physical activity facilities										
No access	59.0	12,115	1.5	2.0	2.4	58.8	5,952	0.6	1.0	1.2
Access	41.0	8,685	1.5	2.0	2.4	41.2	4,532	0.6	1.0	1.3
Health care facilities										
No access	61.3	12,245	1.5	2.0	2.4	59.8	5,812	0.6	1.0	1.3
Access	38.7	8,555	1.5	2.0	2.3	40.2	4,672	0.6	1.0	1.2

Table 4. Models showing associations between coronary heart disease and neighborhood availability of potentially health-damaging and health-promoting goods, services, and resources. Neighborhoods are defined by predefined geographic units (small area market statistics, SAMS).

	Men (n=1,065,000)									Women (n=1,100,000)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Neighborhood availability by category																		
Fast food restaurants																		
Access	**1.04**	**1.01**	**1.08**	1.00	0.97	1.03	1.00	0.97	1.02	**1.14**	**1.09**	**1.19**	**1.08**	**1.03**	**1.12**	1.00	0.96	1.04
No access	1			1			1			1			1			1		
Bars/pubs																		
Access	1.04	0.99	1.09	1.01	0.97	1.06	0.99	0.95	1.04	**1.12**	**1.05**	**1.20**	**1.07**	**1.01**	**1.14**	1.02	0.96	1.08
No access	1			1			1			1			1			1		
Physical activity facilities																		
Access	1.03	0.99	1.06	1.02	0.99	1.05	1.00	0.97	1.03	**1.08**	**1.03**	**1.13**	**1.07**	**1.02**	**1.12**	1.03	0.99	1.08
No access	1			1			1			1			1			1		
Health care facilities																		
Access	**1.12**	**1.08**	**1.15**	**1.07**	**1.03**	**1.10**	1.02	0.99	1.05	**1.20**	**1.15**	**1.25**	**1.13**	**1.08**	**1.18**	1.01	0.97	1.05
No access	1			1			1			1			1			1		

Model 1 is unadjusted; model 2 is adjusted for neighborhood-level deprivation; and model 3 is adjusted for neighborhood-level deprivation and individual-level age and income. Bold type: confidence interval does not include 1.

Table 5. Models showing associations between coronary heart disease and neighborhood availability of potentially health-damaging and health-promoting goods, services, and resources. Neighborhoods are defined by buffer zones (radius 1,000 meters) surrounding each person.

	Men (*n*=1,065,000)									Women (*n*=1,100,000)								
	Model 1			Model 2			Model 3			Model 1			Model 2			Model 3		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Neighborhood availability by category																		
Fast food restaurants																		
Access	**1.07**	**1.04**	**1.11**	**1.05**	**1.01**	**1.08**	1.00	0.99	1.05	**1.21**	**1.15**	**1.26**	**1.16**	**1.11**	**1.22**	0.99	0.95	1.04
No access	1			1			1			1			1			1		
Bars/pubs																		
Access	**1.04**	**1.01**	**1.08**	1.01	0.98	1.05	1.00	0.96	1.03	**1.15**	**1.10**	**1.21**	**1.11**	**1.06**	**1.16**	0.98	0.94	1.03
No access	1			1			1			1			1			1		
Physical activity facilities																		
Access	**1.04**	**1.01**	**1.07**	1.01	0.98	1.04	1.00	0.97	1.03	**1.14**	**1.09**	**1.19**	**1.10**	**1.05**	**1.15**	0.98	0.94	1.02
No access	1			1			1			1			1			1		
Health care facilities																		
Access	**1.10**	**1.07**	**1.14**	**1.06**	**1.03**	**1.10**	1.02	0.99	1.05	**1.29**	**1.23**	**1.34**	**1.22**	**1.17**	**1.28**	1.03	0.99	1.08
No access	1			1			1			1			1			1		

Model 1 is unadjusted; model 2 is adjusted for neighborhood-level deprivation; and model 3 is adjusted for neighborhood-level deprivation and individual-level age and income. Bold type: confidence interval does not include 1.

Table 4 shows the models for the associations between the four categories of neighborhood availability and CHD. Model 1 is unadjusted; model 2 is adjusted for neighborhood deprivation; and model 3 is adjusted for neighborhood deprivation and the individual-level variables age and income. Reference groups are men and women living in neighborhoods with no access to the category of goods, services, and resources in question. For men, there were slightly, but statistically significantly, higher risks of CHD for those living in neighborhoods with access to fast food restaurants, physical activity facilities or health care facilities (model 1). The significantly increased risks were reduced or disappeared on adjustment for neighborhood deprivation (model 2). In model 3, no increased risks remained after adjustment also for age and income. For women, a similar pattern was observed, with a significantly higher CHD risk for those living in neighborhoods with access to fast food restaurants, bars/pubs, physical activity facilities, or health care facilities (model 1). The significantly increased risks were reduced on inclusion of neighborhood deprivation (model 2) and disappeared on inclusion also of age and income (model 3).

Similar models were created using buffer zones (radius 1,000 meters) as proxies for each individual's immediate neighborhood (Table 5). The results were almost identical to those obtained using models based on the SAMS neighborhoods (Table 4). This was also the case when smaller buffer zones (radius 500 meters) were used as proxies for each individual's immediate neighborhood (data not shown in tables) and when availability was defined as the presence of at least one feature within 1,000 meters of an individual's residential location (distance measure) (data not shown in tables).

STUDY III

Descriptive statistics on the 2,269 individuals

Table 6 shows that the median objectively measured MVPA of SNAP participants amounted to 41 min/day (SD = 23 min). The participants reported a median of 125 min/week of walking for active transportation (SD = 275 min) and a median of 60 min/week of walking for leisure (SD = 222). The proportion of female participants was 55% and the proportion of married/cohabiting participants was 74% of the entire study sample. Forty percent were over 50 years old and 42% were found among those with middle income. Differences in the income distribution between individuals living in the four types of neighborhoods also appeared, which justifies the inclusion of, for example, individual income as a covariate.

Models

Interaction tests included, for example, testing for possible neighborhood-level SES interactions, but none were found. Table 7 shows the multilevel linear regression analysis for models including MVPA as the outcome variable. Model A shows that individuals living in highly walkable neighborhoods had 3.4 more minutes of MVPA/day than individuals living in less walkable neighborhoods, and this difference was statistically significant. After the inclusion of neighborhood-level SES and the individual-level variables, the difference between highly walkable neighborhoods and less walkable ones remained significant and decreased only slightly to 3.1 minutes of MVPA/day. The calculation of ICC showed that 0.9% of the total variance was at the neighborhood level (both Model A and B).

Table 6. Descriptive statistics on the 2,269 individuals included in the study.

			Type of neighborhood							
	All		**High Walkability High Income**		**High Walkability Low Income**		**Low Walkability High Income**		**Low Walkability Low Income**	
	Median	**St dev**	**Median**	**St dev**	**Median**	**St dev**	**Median**	**St dev**	**Median**	**St dev**
Moderate-to-vigorous physical activity (min/day)	41	23	47	23	39	25	39	23	40	23
Time in 10-minute bouts of moderate-to-vigorous physical activity (min/day)	14	18	17	18	12	18	14	18	13	19
Walking for active transportation (min/week)	125	275	180	287	150	300	100	254	100	267
Walking for leisure (min/week)	60	222	90	225	68	248	60	216	60	208
Gender	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
• Male	1014	45%	201	42%	162	39%	378	48%	273	47%
• Female	1255	55%	278	58%	252	61%	411	52%	314	53%
Age (years)										
• 20–30	251	11%	82	17%	68	16%	42	5%	59	10%
• 31–40	461	20%	115	24%	88	21%	139	18%	119	20%
• 41–50	645	28%	104	22%	111	27%	242	31%	188	32%
• 51–66	912	40%	178	37%	147	36%	366	46%	221	38%
Family income										
• Low	766	34%	205	43%	220	53%	152	19%	189	32%
• Middle	959	42%	179	37%	173	42%	325	41%	282	48%
• High	544	24%	95	20%	21	5%	312	40%	116	20%
Marital status										
• Single	590	26%	186	39%	154	37%	106	13%	144	25%
• Married/Cohabiting	1679	74%	293	61%	260	63%	683	87%	443	75%

Table 7. Multilevel linear regression for predictors of moderate-to-vigorous physical activity. Numbers represent β-coefficients (with 95% confidence intervals) in minutes/day (n=2,269).

	Model A[1]	**Model B**[2]
Walkability (High vs. Low)	3.4 (0.8–5.8)	3.1 (0.4–5.6)
Neighborhood SES (High vs. Low)		1.8 (–0.7–4.4)
Male vs. Female		3.2 (1.2–5.1)
Age (years)		
• 20–30		Reference
• 31–40		–5.1 (–8.5 – –1.6)
• 41–50		–5.2 (–8.4 – –1.9)
• 51–66		–6.7 (–10.0 – –3.5)
Family income		
• Low		Reference
• Middle		0.9 (–1.1–2.9)
• High		3.4 (0.6–6.3)
Married/cohabiting vs. Single		3.3 (1.1–5.8)
Random effects		
Variance $_{individual}$	537 (506–566)	529 (498–556)
Variance $_{neighborhood}$	4.7 (0.0–8.6)	4.7 (0.0–8.7)
Intraclass correlation	0.9%	0.9%
[1] Model A only includes walkability, [2] Model B also includes all other variables.		

Table 8 shows the mixed-effects, mixed-distribution model for occurrence (logistic) and amount in minutes/week (linear), including walking for active transportation as the outcome variable. The logistic part shows that the odds for walking for active transportation were 92% higher (reference = 1; CI = 1.40–2.63) among individuals who lived in highly walkable neighborhoods than among those living in less walkable neighborhoods (Model A). After the inclusion of neighborhood-level SES and the individual-level variables (Model B), the odds decreased to 1.77 (i.e. 77% higher odds) but remained significant (CI = 1.30–2.41). The ICC was 2.1% in Model B in the logistic part of the analysis.

Model A in the linear part of the analysis shows that individuals who lived in highly walkable neighborhoods had 57 more minutes/week of walking for active transportation than individuals who lived in less walkable neighborhoods. In the adjusted model (Model B), the difference between highly and less walkable neighborhoods decreased to 50 minutes/week but remained significant. The ICC was 0.4% in Model B in the linear part of the analysis.

Table 8. Mixed-effects, mixed-distribution models for predictors of walking for active transportation (n=2,269).

	Model A[3]	**Model B**[4]
Occurrence (Logistic)[1]		
Walkability (High vs. Low)	1.92 (1.40–2.63)	1.77 (1.30–2.41)
Neighborhood SES (High vs. Low)		1.30 (0.96–1.76)
Male vs Female		0.67 (0.53–0.83)
Age (years)		
• 20–30		1 (Reference)
• 31–40		0.95 (0.60–1.50)
• 41–50		0.72 (0.47–1.11)
• 51–66		0.74 (0.49–1.12)
Family income		
• Low		1 (Reference)
• Middle		0.83 (0.62–1.09)
• High		0.97 (0.69–1.37)
Married/cohabiting vs. Single		0.89 (0.65–1.20)
Random effects		
Variance $_{\text{neighborhood}}$	0.09 (0.00–0.18)	0.07 (0.00–0.15)
Intraclass correlation	2.6%	2.1%
Amount (Linear)[2]		
Walkability (High vs. Low)	57 (26–88)	50 (20–81)
Neighborhood SES (High vs. Low)		–5 (–35–25)
Male vs. Female		–18 (–45–8)
Age (years)		
• 20–30		Reference
• 31–40		–14 (–62–35)
• 41–50		17 (–29–63)
• 51–66		52 (8–96)
Family income		
• Low		Reference
• Middle		–36 (–69 – –3)
• High		–84 (–124 – –44)
Married/cohabiting vs. Single		39 (4–74)
Random effects		
Variance $_{\text{individual}}$	78,573 (73,278–83,867)	76,567 (71,436–81,697)
Variance $_{\text{neighborhood}}$	507 (0–1,499)	297 (0–1,198)
Intraclass correlation	0.6%	0.4%

[1] Numbers in the fixed part of the regression are odds ratios (95% confidence intervals).
[2] Numbers in the linear part of the regression are β-coefficients (95% confidence intervals) in minutes per week.
[3] Model A only includes walkability.
[4] Model B also includes all other variables.

Table 9. Mixed-effects, mixed-distribution models for predictors of walking for leisure (n=2,269).

Table		
	Model A[3]	**Model B**[4]
Occurrence (Logistic) [1]		
Walkability (High vs. Low)	1.22 (1.01–1.48)	1.28 (1.04–1.56)
Neighborhood SES (High vs. Low)		1.22 (0.96–1.76)
Male vs. Female		0.67 (0.56–0.81)
Age (years)		
• 20–30		1 (Reference)
• 31–40		0.92 (0.65–1.30)
• 41–50		1.11 (0.80–1.54)
• 51–66		1.71 (1.24–2.36)
Family income		
• Low		1 (Reference)
• Middle		1.14 (0.90–1.44)
• High		1.02 (0.77–1.35)
Married/cohabiting vs. Single		1.00 (0.78–1.29)
Random effects		
Variance $_{\text{neighborhood}}$	0.00 (0.00–0.00)	0.00 (0.00–0.00)
Intraclass correlation	0.0%	0.0%
Amount (Linear) [2]		
Walkability (High vs. Low)	18 (–8–45)	18 (–9–43)
Neighborhood SES (High vs. Low)		–3 (–28–22)
Male vs. Female		–29 (–54 – –5)
Age (years)		
• 20–30		Reference
• 31–40		–7 (–53–40)
• 41–50		33 (–11–77)
• 51–66		63 (21–104)
Income		
• Low		Reference
• Middle		–40 (–10 – –71)
• High		–58 (–22 – –95)
Married vs. Single		33 (1–64)
Random effects		
Variance $_{\text{individual}}$	56,171 (52,118–60,225)	54,681 (50,743–58,618)
Variance $_{\text{neighborhood}}$	352 (0–922)	44 (0–612)
Intraclass correlation	0.4%	0.1%

[1]Numbers in the fixed part of the regression are odds ratios (95% confidence intervals).
[2]Numbers in the linear part of the regression are β–coefficients (95% confidence intervals) in minutes per week.
[3]Model A only includes walkability; [4]Model B also includes all other variables.

Table 9 shows the results of the analysis of the association between neighborhood walkability and walking for leisure, using the mixed-effects, mixed-distribution model for occurrence (logistic) and amount in minutes/week (linear). The logistic part shows that the odds for walking for leisure were 22% higher (reference = 1; CI = 1.01–1.48) among individuals who lived in highly walkable neighborhoods than among those living in less walkable neighborhoods (Model A). After including neighborhood-level SES and the individual-level variables (Model B), the odds remained significant and changed only slightly from 1.22 to 1.28 (CI = 1.04–1.56). The ICC in the logistic part was 0%.

Model A and Model B in the linear part of the analysis show that individuals who lived in highly walkable neighborhoods had 18 more minutes/week of walking for leisure than individuals who lived in less walkable neighborhoods, but this difference was non-significant. The ICC was 0.1% in Model B in the linear part of the analysis.

STUDY IV

Concordance between objective and perceived neighborhood walkability

Table 10 shows the concordance and non-concordance between objective and perceived neighborhood walkability and their components. There was an agreement between objective and perceived neighborhood walkability categorization in 67.0% (33.5% + 33.5%) of the participants. A higher proportion in the two concordance groups (high objective/high perceived and low objective/low perceived) seemed to have a small difference between objective and perceived neighborhood walkability values compared to the two non-concordance groups (high objective/low perceived and low objective/high perceived). The percentages were 53.3% and 73.2% versus 33.5% and 10.9%, respectively (Table 10). We also calculated kappa values (data not shown in tables) as a measure of concordance between pairs (objective and perceived). For neighborhood walkability the kappa was 0.34 (95% CI: 0.30–0.38). Of the three walkability subcomponents, residential density displayed the strongest agreement (76.2%, kappa=0.48, 95% CI: 0.44–0.52), followed by land use mix (69.3%, kappa=0.39, 95% CI: 0.34–0.43), and street connectivity (60.9%, kappa=0.22, 95% CI: 0.17–0.26).

Table 10. Distribution of concordance and non-concordance between objective and perceived neighborhood walkability and their components (n=1,925).

	Neighborhood walkability			
	High objective/ high perceived %	High objective/ low perceived %	Low objective/ high perceived %	Low objective/ low perceived %
Walkability	33.5	16.5	16.5	33.5
*Small difference**	*53.3*	*33.5*	*10.9*	*73.2*
Residential density	36.9	13.1	12.7	37.3
Land use mix	33.4	16.6	14.1	35.9
Street connectivity	29.0	20.7	18.4	31.9

*Proportion (%) of participants within each category of objective and perceived neighborhood walkability where the difference between individual objective and perceived neighborhood walkability values was considered small (see definition in Methods/Data analysis).

Table 11. Sociodemographic characteristics of the neighborhood walkability concordance and non-concordance groups (N=1,925).

			Neighborhood walkability				
			High objective/ high perceived	High objective/ low perceived	Low objective/ high perceived	Low objective/ Low perceived	Total concordance*
		n	%	%	%	%	%
Sex	Female	1042	34.5	16.5	16.2	32.8	67.3
	Male	872	32.5	16.6	16.6	34.3	66.8
Age	20–29	200	44.0	12.0	15.5	28.5	72.5
	30–49	1034	34.2	15.3	17.2	33.3	67.5
	50–66	680	29.4	19.9	15.4	35.3	64.7
Educational level	University education	1072	34.1	15.7	17.5	32.7	66.8
	No university education	839	32.8	17.6	15.0	34.6	67.4
Marital status	Single	462	41.8	15.5	11.5	31.2	73.0
	Married/ cohabiting	1443	30.7	17.0	17.9	34.4	65.1

*Total concordance = High objective/high perceived + Low objective/low perceived.

Table 11 presents the sociodemographic characteristics of participants in the four concordance categories. It seemed to be more common for younger and/or single people to live in neighborhoods with objectively assessed high walkability.

Associations of objective and perceived neighborhood walkability with self-reported walking and objective physical activity

Individuals who lived in neighborhoods with objectively assessed high walkability and who also perceived it as high had the highest median values for the walking and objective physical activity variables. An exception was for total physical activity, where they had similar median values to those of individuals who lived in neighborhoods with objectively assessed low walkability but who perceived it as high (Table 12).

Table 12. Self-reported walking and objective physical activity in the neighborhood walkability concordance and non-concordance groups (n=1,925).

	Neighborhood walkability			
	High objective/ high perceived	High objective/ low perceived	Low objective/ high perceived	Low objective/ low perceived
	Median (IR)	Median (IR)	Median (IR)	Median (IR)
Walking for transportation (min/week)	150 (60–360)	140 (20–250)	120 (25–270)	90 (0–210)
Walking for leisure (min/week)	75 (0–180)	60 (0–180)	60 (0–195)	60 (0–180)
Total physical activity (counts/min)	375 (308–477)	352 (277–445)	377 (291–457)	367 (285–453)
Moderate-to-vigorous physical activity (min/day)	46 (31–61)	40 (28–56)	42 (30–56)	41 (27–57)

IR, Interquartile Range (25th–75th percentile).

Tables 13 and 14 present the results of the regression analyses. The β-coefficients represent differences in the outcome variables in relation to the reference category. Individuals in neighborhoods with objectively assessed high walkability engaged in 50.9 more minutes of walking for transportation per week (95% CI: 25.8–72.8) than individuals in neighborhoods with low walkability (Table 13, Model A1). This difference was attenuated when perceived neighborhood walkability (Model B1) and the sociodemographic characteristics (Model C1) were added to the model. In the full model (Model C1), living in neighborhoods with objectively assessed high walkability was associated with 35.0 more minutes of walking for transportation per week (95% CI: 14.6–64.6) compared to living in neighborhoods with low walkability. Those who perceived the neighborhood walkability as high (Model C1) had 41.5 more minutes of walking for transportation per week than those who perceived it as low (95% CI: 15.8–

62.9). Individuals in neighborhoods with objectively assessed high walkability also had 19.6 more minutes of walking for leisure per week (95% CI: 1.7–36.8) than individuals in neighborhoods with low walkability (Model A2). The association was attenuated by the inclusion of perceived neighborhood walkability (Model B2) and the sociodemographic characteristics (Model C1). The difference in the full model (Model C2) was 10.5 minutes per week (95% CI: –5.2–28.5). Perceiving neighborhood walkability as high was associated with 21.8 more minutes of walking for leisure per week (95% CI: 2.8–40.0) than perceiving it as low (Model C2).

Table 13. Linear regression, where values (β-coefficients) represent differences in self-reported walking (minutes/week) compared to the reference category (n=1,925).

1. Walking for transportation, minutes per week (95% CI)			
		Models	
	A1	**B1**	**C1**
High objective walkability[a]	50.9 (25.8–72.8)	40.0 (12.8–69.7)	35.0 (14.6–64.6)
High perceived walkability[b]		36.3 (20.4–55.9)	41.5 (15.8–62.9)
Male[c]			–32.0 (–50.8 – –12.4)
Age 30–49[d]			–3.8 (–71.7–42.7)
Age 50–66[d]			–0.2 (–3.1– 4.2)
No university education[e]			33.4 (15.8– 49.3)
2. Walking for leisure, minutes per week (95% CI)			
		Models	
	A2	**B2**	**C2**
High objective walkability[a]	19.6 (1.7–36.8)	14.7 (–11.4–35.4)	10.5 (–5.2–28.5)
High perceived walkability[b]		16.8 (0.7–35.4)	21.8 (2.8–40.0)
Male[c]			–34.6 (–48.3 – –16.9)
Age 30–49[d]			–40.8 (–84.3 – –7.5)
Age 50–66[d]			–39.2 (–58.3 – –20.1)
No university education[e]			20.6 (2.7–36.8)
References: [a]low objective walkability; [b]low perceived walkability; [c]women; [d]age 20–29; [e]university education.			

For total objective physical activity (counts/min), high objective and high perceived neighborhood walkability increased the number of counts per minute by 9.4 (95% CI: –11.7–27.4) and 8.6 (95% CI: –9.1–21.5), respectively, in the full model (Table 14, Model C1). Individuals in neighborhoods with objectively assessed high walkability had 3.6 more minutes of MVPA per day (95% CI: 1.6–5.9) than those in neighborhoods with low walkability (Table 14, Model A2). This result was attenuated when perceived neighborhood walkability (Model B2) and the sociodemographic characteristics (Model C2) were added. The difference in the full model (Model C2) was 2.8 minutes per day (95% CI: 0.9–5.0) for MVPA. In this model, perceiving the neighborhood walkability as high was associated with 1.7 more minutes of MVPA per day (95% CI: –0.3–3.7) than perceiving it as low.

Table 14. Linear regression, where values (β-coefficients) represent differences in objective physical activity compared to the reference category (n =1,925).

1. Total physical activity, counts per minute (95% CI)			
	Models		
	A1	**B1**	**C1**
High objective walkability[a]	10.7 (–2.0–20.0)	7.2 (–8.8–20.1)	9.4 (–11.7–27.4)
High perceived walkability[b]		11.0 (–0.9–22.7)	8.6 (–9.1–21.5)
Male[c]			9.1 (–2.9–17.4)
Age 30–49[d]			47.4 (27.7–66.8)
Age 50–66[d]			18.2 (5.8–34.1)
No university education[e]			–5.9 (–19.2–9.9)

2. Moderate-to-vigorous physical activity, minutes per day (95% CI)			
	Model		
	A2	**B2**	**C2**
High objective walkability[a]	3.6 (1.6–5.9)	2.6 (0.5–4.9)	2.8 (0.9–5.0)
High perceived walkability[b]		2.2 (0.4–4.9)	1.7 (–0.3–3.7)
Male[c]			3.5 (1.7–5.9)
Age 30–49[d]			7.8 (3.2–11.8)
Age 50–66[d]			0.7 (–4.3–5.2)
No university education[e]			–2.8 (–4.5—0.8)

References: [a]low objective walkability; [b]low perceived walkability; [c]women; [d]age 20–29; [e]university education.

Sociodemographic characteristics and perception of neighborhood walkability
Among individuals in neighborhoods with objectively assessed high walkability, 33.0% misperceived it as low and these individuals were further examined through multivariate logistic regression analysis (Table 15). It was more common in individuals who were older and married/cohabiting to misperceive the neighborhood walkability and the subcomponents residential density and land use mix as low. It was also more common in individuals with no university education to misperceive the residential density as low. Perception of street connectivity was not associated with the sociodemographic characteristics.

Table 15. Neighborhoods with objectively assessed high walkability: odds ratios (OR)[#] for misperceiving neighborhood walkability and its subcomponents as low according to the sociodemographic characteristics.

		Neighborhood walkability OR (95% CI)	Residential density OR (95% CI)	Land use mix OR (95% CI)	Street connectivity OR (95% CI)
Sex	Female	1.00 (ref)	1.00 (ref)	1.00 (ref)	1.00 (ref)
	Male	1.03 (0.78–1.36)	1.15 (0.87–1.53)	0.88 (0.67–1.15)	0.91 (0.70–1.18)
Age	20–29	1.00 (ref)	1.00 (ref)	1.00 (ref)	1.00 (ref)
	30–49	1.47 (0.89–2.43)	2.80 (1.56–5.04)***	1.76 (1.08–2.87)*	0.85 (0.55–1.31)
	50–66	2.19 (1.32–3.65)**	3.09 (1.70–5.62)***	2.56 (1.46–4.22)***	0.81 (0.52–1.26)
Educational level	University education	1.00 (ref)	1.00 (ref)	1.00 (ref)	1.00 (ref)
	No university education	1.18 (0.89–1.55)	1.36 (1.03–1.80)*	1.06 (0.81–1.38)	1.27 (0.98–1.65)
Marital status	Single	1.00 (ref)	1.00 (ref)	1.00 (ref)	1.00 (ref)
	Married/cohabiting	1.41 (1.02–1.94)*	2.02 (1.43–2.84)***	1.89 (1.38–2.60)***	1.03 (0.77–1.38)

[#]Results of the multivariate analyses are presented with sex, age, educational level and marital status as covariates.

*P<0.05 **P<0.01 ***P<0.001

DISCUSSION

Study I examined whether the availability of 12 main categories of goods, services, and resources differed by level of neighborhood deprivation. The results showed that availability of all types of goods, services, and resources is better in moderate and high-deprivation neighborhoods than in low-deprivation ones. Important examples included goods, services, and resources that are potentially health-promoting as well as health-damaging.

The interpretation of the health consequences of various types of neighborhood goods, services, and resources for the residents is not straightforward. Health-promoting services and resources may include sports facilities that offer opportunities for people to be physically active and achieve better health. Health care resources are also potentially health-promoting because they offer better opportunities to obtain health care and preventive measures for chronic diseases, such as hypertension and diabetes.

Allocation of health care resources to deprived neighborhoods has the potential to reduce health inequalities between people living in deprived and affluent neighborhoods. Neighborhood access to health care resources was examined in a study from New Zealand and the findings showed that more deprived neighborhoods had higher access to health care resources (Pearce et al., 2007a), which is in agreement with the results of study I. These findings contradict theories that inequalities in health between people living in deprived neighborhoods and people living in affluent neighborhoods are caused by a lack of health care resources. Another study from New Zealand examined the association between health care utilization and neighborhood access to health care providers and found that access was associated with more blood pressure tests, doctors' consultations and pharmacy visits (Hiscock et al., 2008).

Grocery stores and supermarkets are assumed to be health-promoting, although they also include many health-damaging "junk" foods and beverages. In addition, fast food restaurants are considered to be health-damaging with their access to high-caloric foods and beverages, although some have menus that include salads, fresh fruit, vegetarian dishes, and other "healthy choices."

Bars and taverns could have negative effects (promotion of alcohol consumption) as well as positive effects (social support). One study from the US showed that the most deprived neighborhoods had a substantially higher alcohol outlet density than the least deprived neighborhoods (45.5% versus 14.8%), whereas the least deprived neighborhoods were associated with the heaviest alcohol consumption (Pollack et al., 2005). The authors of that study concluded that the mismatch between supply and demand may cause people in the most deprived neighborhoods to suffer disproportionately the negative health consequences of living near alcohol outlets. Examples of negative health consequences of living near alcohol outlets (in addition to the negative health consequences of the alcohol itself) are that presence of alcohol outlets may be associated with noise and other types of disturbances. It could be argued that the sometimes higher access to alcohol outlets in deprived neighborhoods exists because residents in affluent neighborhoods have more empowerment than residents in deprived neighborhoods to counteract the licensing of alcohol outlets in their immediate vicinity.

The results from study I do not support the hypothesis of "deprivation amplification", suggesting that the consistent differences in health between individuals in deprived neighborhoods and those in affluent neighborhoods are not explained by poorer access to health-promoting goods, services, and resources in deprived neighborhoods. However, the sum of the negative impact of health-damaging goods, services, and resources might be larger than the sum of the benefits accrued from health-promoting ones. In addition, residents in more deprived neighborhoods might have a higher utilization of health-damaging than health-promoting goods, services, and resources.

Study II examined whether there are associations between the neighborhood availability of potentially health-damaging (fast food restaurants and bars/pubs) and health-promoting (physical activity facilities and health care facilities) goods, services, and resources and CHD incidence. The associations were relatively weak and no longer remained significant after adjustment for neighborhood-level deprivation and individual-level age and income.

These findings contradict a theoretical framework used to explain previous observations of increased CHD incidence rates in socially deprived neighborhoods. This framework is based on the assumption that certain environmental factors in deprived neighborhoods, such as the presence of health-damaging fast food restaurants and a lack of health-promoting physical activity facilities, lead to increased rates of certain CHD risk factors, such as obesity and physical inactivity. The hypothesized increased rates of CHD risk factors ultimately cause CHD incidence rates to increase in deprived neighborhoods. Recent large-scale studies have shown, however, that there is no clear association between level of deprivation and neighborhood availability of different types of potentially health-damaging and health-promoting goods, services, and resources (Marmot, 2004, Pearce et al., 2007b).

This led Macintyre et al. to conclude that: "we need to ensure that theories and policies are based on up-to-date and context-specific empirical evidence" (Macintyre et al., 2008). A similar point of view was expressed by Pearce et al.: "…the evidence-base for such a deprivation gradient in service and amenity access is not strong, and in some cases the policy agenda has extended beyond the available evidence" (Pearce et al., 2007b).

Recent studies have also examined the cross-sectional associations between certain CHD risk factors and neighborhood availability of goods, services, and resources. For example, a study from the US investigated the association between obesity and availability of fast food restaurants (Mehta and Chang, 2008). The authors found that individuals living in counties with high availability of fast food restaurants were more likely to be obese and have a high BMI than individuals living in counties without high availability of fast food restaurants. A nationwide study in New Zealand examined the associations between dietary habits, weight status and neighborhood access to fast food restaurants (Pearce et al., 2009). This study, in contrast to the US study, was conducted in small geographic areas ("census meshblocks"). The authors also included distance measures to define neighborhood availability. They reported that individuals living near to fast food restaurants were not more likely to be obese (Pearce et al., 2009).

The contrasting findings of these two studies may be explained by differences in the size of the geographic areas (counties vs. smaller census meshblocks). Small geographic areas are more likely to reflect neighborhood availability than large geographic areas such as counties. Other studies have also provided inconsistent results. For example, a study from the US examined the cross-sectional association between obesity prevalence rates and the availability of fast food restaurants. The availability of fast food restaurant was defined in two ways: (1) density per census tract and (2) distance between the residential address and the nearest fast food restaurant (Morland and Evenson, 2009). The authors detected higher obesity prevalence rates in census tracts with more than one fast food restaurant, even after accounting for individual-level demographic factors. In complete contrast, the obesity prevalence rate was inversely correlated with the proximity of the nearest fast food restaurant.

Studies on the association between neighborhood availability of physical activity facilities and levels of physical activity are also inconsistent. One study from the US involving participants from three regions reported a positive association between the density of physical activity facilities and levels of physical activity (Diez Roux et al., 2007). However, the results of a second US study failed to confirm this association (Lee et al., 2007).

Study II is the first of its kind, and its findings must therefore be interpreted with caution and be confirmed in other settings before they can be used as the basis for drawing up evidence-based policy measures. In addition, a stronger research focus should be placed on other neighborhood factors that may cause CHD. Such neighborhood components could include complex sets of factors that may combine to cause atherosclerotic changes in blood vessels and subsequent ischemia in the heart, brain, and other vital organs. For example, socially deprived neighborhoods have higher crime rates than affluent ones, which could lead to fear of being exposed to violent crime among the residents. This could frighten people from going out and hinder them from taking part in physical activity, e.g. taking a walk or jogging in the evening. External signs of deprivation, such as vandalism and littering, and the presence of derelict buildings, broken windows, and abandoned cars, can also lead to feelings of alienation, stress and fear. The poor reputation of certain neighborhoods could contribute to feelings of inferiority among the residents that could amplify the negative effects of pre-existing individual-level social inequalities. All these factors, and their interactions, could lead to psychosocial stress and depression, which are associated with CHD (Sundquist et al., 2005).

Study III examined: (1) the associations between objective neighborhood walkability and walking for active transportation, walking for leisure and accelerometer-measured MVPA, and whether these hypothesized associations are moderated by individual-level sociodemographic factors and neighborhood-level SES, and (2) random effects in a multilevel fashion, which quantifies how much of the total variance of the walking and physical activity outcomes could be due to differences at the neighborhood level. The results showed the following statistically significant results among individuals living in highly walkable neighborhoods, compared to those living in less walkable neighborhoods: (1) 77% and 28% higher odds for walking for active transportation and walking for leisure, respectively, (2) 50 minutes more walking for active transportation/week, and (3) 3.1 minutes more MVPA/day. No significant differences in minutes/week of walking for leisure were found between highly walkable and less walkable neighborhoods. There were no significant interactions. The proportion of the total variance at the neighborhood level was low.

So far, objective results from only three countries have been presented and the results of study III are mainly in agreement with previous research from the US, Australia, and Belgium. However, there were also differences. The finding of more

MVPA in highly walkable neighborhoods was in agreement with the NQLS from the US (Sallis et al., 2009) and the BEPAS from Belgium (Van Dyck et al., 2010).

The finding of the association between neighborhood walkability and walking behavior was partly in agreement with previous studies. The NQLS (Sallis et al., 2009) and the BEPAS (Van Dyck et al., 2010) found positive associations between neighborhood walkability and walking for active transportation, as well as walking for leisure, whereas the PLACE study from Australia found an association with walking for active transportation, but not with walking for leisure (Owen et al., 2007). Our study found that neighborhood walkability was associated with walking for active transportation (yes vs. no) and time spent on walking for active transportation as well as walking for leisure (yes vs. no), but not with time spent on walking for leisure.

The similarities between countries are important to note, but the observed differences between countries are also important to keep in mind because every country's policy agenda should be based on available evidence from that country. For example, only Australia had a significant interaction between SES and neighborhood walkability (Owen et al., 2007), i.e., high-SES Australian adults may benefit more from living in highly walkable neighborhoods than low-SES adults. In contrast, residents living in low-SES neighborhoods in the US, Belgium, and Sweden seem to benefit to the same extent from a highly walkable environment as residents living in high-SES neighborhoods.

Study IV examined the concordance between objective and perceived neighborhood walkability, their associations with self-reported walking and objective physical activity, and sociodemographic characteristics of individuals in neighborhoods with objectively assessed high walkability who misperceive it as low. The results showed that one-third of individuals in neighborhoods with objectively assessed high walkability misperceived it as low and that this non-concordance was more common among older and married/cohabiting individuals. Also, high objective as well as high perceived neighborhood walkability was associated with more minutes of walking for transportation, walking for leisure and objectively measured physical activity compared to low objective and low perceived neighborhood walkability.

The findings of study IV correspond in part to previous studies investigating objective and perceived aspects of the built environment, where the concordance was poor to moderate (Adams et al., 2009, Ball et al., 2008, Boehmer et al., 2006, Frohlich et al., 2007, Gebel et al., 2009, Gebel et al., 2011, Kirtland et al., 2003, McCormack et al., 2008, McGinn et al., 2007). For example, Gebel et al. found a concordance between perceived and objective measures of walkability in two-thirds of the participants (Gebel et al., 2009). The authors also found that one-third of the individuals in neighborhoods with objectively assessed high walkability misperceived it as low, and that this non-concordance was more common in individuals with lower educational and income level. Study IV showed the same proportions of concordance between objective and perceived neighborhood walkability. However, individuals with low educational level in neighborhoods with objectively assessed high walkability were not more likely to misperceive the walkability as low than individuals with high educational level.

Adams et al. (Adams et al., 2009) and McCormack et al. (McCormack et al., 2008) focused on the land use mix component of neighborhood walkability and investigated the concordance between objective and perceived distances to a variety of facilities. Adams et al. found a stronger concordance between objective and perceived neighborhood measures among more physically active individuals, and McCormack et al. showed that the concordance differed depending on the amount of walking. From their perspective, the concordance between objective and perceived neighborhood land use mix would be influenced by the amount of physical activity. In addition, a recent follow-up study showed that individuals in neighborhoods with objectively assessed high walkability and who also perceived it to be high maintained their level of walking to a higher degree than those who perceived the walkability to be low (Gebel et al., 2011).

Most studies have shown poor to moderate concordance between objective assessments and perceptions of the built environment (Adams et al., 2009, Ball et al., 2008, Boehmer et al., 2006, Frohlich et al., 2007, Gebel et al., 2009, Gebel et al., 2011, Kirtland et al., 2003, McCormack et al., 2008, McGinn et al., 2007). Also, both objective and perceived neighborhood walkability contribute to the amount of physical activity, and positive changes in the perception of environmental attributes have been associated with increased physical activity (Humpel et al., 2004, Ries et al., 2009).

To sum up, the magnitude of the results in studies III and IV is in line with previous studies investigating the association between neighborhood walkability and walking for transportation as well as walking for leisure (Sallis et al., 2009, Van Dyck et al., 2010).

Neighborhood walkability may influence walking for transportation to a relatively high extent, but the influence on overall physical activity may be smaller (Giles-Corti et al., 2005).

LIMITATIONS AND STRENGTHS

There are limitations in the studies included in the present thesis. First, it is possible that residual confounding exists because socioeconomic status cannot be fully measured by socioeconomic indicators. Second, we did not include detailed aspects of neighborhood goods and services, such as the size of businesses, operational hours, and selections/qualities/price ranges. In addition, the availability of neighborhood goods and services does not necessarily translate into utilization by local residents. Third, there are several neighborhood characteristics, not measured here, that may influence the health status of residents, such as urban decay, graffiti, litter, and derelict buildings. Fourth, the follow-up period in study II was only two years. However, study II is the first of its kind to follow individuals for the “hard” outcome CHD, instead of merely examining cross-sectional associations between CHD risk factors and neighborhood availability of certain goods, services, and resources. Moreover, we were able to capture all hospitalized CHD events in a study population of 2,165,000 individuals during a two-year period and we found no evidence that variations in neighborhood availability of four types of goods, services, and resources would lead to a significant number of people crossing the threshold for manifest CHD. Fifth, the boundaries of the neighborhood (SAMS) units were based on administrative areas and may therefore not have corresponded perfectly with the residents’ definitions of their own neighborhood. Previous studies have suggested that neighborhoods are defined by patterns of social interaction, rather than by geographic boundaries (Diez Roux, 2004, Tienda, 1991, Bond Huie, 2001). We were partly able to overcome this issue, however, by assessing the neighborhood availability of goods, services, and resources in buffer zones (radius 1,000 or 500 meters) around an individual’s approximate residential location. Sixth, it is possible that a response bias exists in studies III and IV if those who are more physically active are also more prone to wear an accelerometer and fill out a questionnaire. However, it is unlikely that this bias would have a different magnitude across neighborhoods. Moreover, there were no differences in SES between respondents and non-respondents. Seventh, the association between neighborhood walkability, physical activity, and walking behavior could be an artifact due to self-selection bias, i.e., people who like to walk may have chosen to move to a neighborhood with high walkability. Eighth, the use of self-reported outcome measures for walking introduced some self-report bias. Ninth, the cross-sectional design of studies III and IV means that no inferences about causality could be drawn.

An important strength of study I is that we included detailed neighborhood data from neighborhoods covering the residential addresses of 84% of the entire population, i.e. those living in urban areas. Second, the validity of these data is likely to be high because of the procedures followed to compile the goods, services, and resources data. In addition, research conducted in the UK has shown that secondary data, such as publicly available lists of food/grocery stores, has a high validity (Cummins and Macintyre, 2009). Third, the use of small geographic units where the goods, services, and resources were likely within walking distance increases the probability of utilization by local residents. Fourth, the calculation of neighborhood availability to goods, services, and resources took the population density into account. In addition, we were able to distinguish chain food stores from non-chain food stores; chain food stores are more likely to offer a wider and healthier selection of produce. Fifth, we were able to conduct a follow-up study in which the exposure (neighborhood availability) was assessed before the outcome (study II). Excluding those hospitalized for CHD in the previous 5 years is also a strength in study II but it does not exclude all those with pre-existing diagnosed CHD. Sixth, the data on goods, services, and resources are much more complete than the data in an ordinary telephone book. Having co-operative agreements with all Swedish telephone operators, *Teleadress* provides information on practically all businesses in Sweden. This includes all businesses and services that have a registered telephone number and/or businesses that have provided information about their existence to the company. Inclusion in the database is free of charge and the company also purchases additional information about businesses from Statistics Sweden to create a comprehensive business listing. These procedures ensure that data completeness is maintained at a high level. Accuracy is maintained through an average of 30,000 database updates a day (Teleadress, Accessed August 8, 2009). Seventh, the assessment of neighborhood walkability was based on objective GIS-based measurements (Leslie et al., 2007) as well as perceived subjective measurements (Panter and Jones, 2008). This is a key strength because previous research has demonstrated correlates of non-concordance between perceived and objective measures of walkability (Gebel et al., 2009). The objective GIS-based measurements used in studies III and IV were the best available to us and largely similar to the data sources used in previous studies from the US, Australia, and Belgium. Eighth, the study sample in the SNAP study was randomly selected and included 2,269 persons, which puts it in the position of one of the largest studies to date. Ninth, the assessments of physical activity were based on both self-reported and objective measures. Accelerometers were used to provide objective measures of physical activity, although they do not discriminate between different domains, i.e. in what context or purpose the physical activity is performed. Finally, a major strength of study IV was that objective neighborhood walkability was assessed in buffer zones around each individual's home address and was therefore more comparable with perceived neighborhood walkability assessed with the NEWS questionnaire.

CONCLUSIONS

Despite some caveats, our findings are noteworthy, given the necessity to ensure that current policies are based on context-specific empirical findings so that actions do not reach beyond available evidence. Further follow-up studies are needed to disentangle causal pathways and to provide more robust evidence for use in formulating efficient neighborhood policy agendas for reducing social inequalities in health.

SVENSK SAMMANFATTNING/SWEDISH SUMMARY

Denna avhandling syftar till att undersöka:
om tillgången på varor, tjänster och resurser i bostadsområdet skiljer sig beroende på bostadsområdets socioekonomiska status (studie I);
om det finns samband mellan bostadsområdets tillgång på potentiellt hälsoskadliga (snabbmatsrestauranger och barer/ pubar) och hälsofrämjande (sportanläggningar och sjukvårdsinrättningar) resurser och kranskärlssjukdom (studie II);
om det finns samband mellan bostadsområdets ”promenadvänlighet” och promenerande i transportsyfte, promenerande i motionssyfte och objektivt uppmätt fysisk aktivitet med rörelsemätare (studie III);
om det finns en överensstämmelse mellan objektiv och upplevd ”promenadvänlighet”, om det föreligger samband mellan dessa mått och promenerande samt objektiv fysisk aktivitet och om sociodemografiska egenskaper hos individen påverkar den upplevda ”promenadvänligheten” (studie IV).

Metodik I studie I användes geokodade data från alla företag i Sverige för att undersöka fördelningen av 12 huvudkategorier av varor, tjänster och resurser i 6986 bostadsområden, klassade som välbärgade, medel och ekonomiskt utsatta bostadsområden. I studie II användes flernivå regressionsmodeller för uppföljning av 1 065 000 män och 1 100 000 kvinnor (i åldern 35–80 år) mellan den 1 december 2005 och 31 december 2007, för att på individnivå följa upp kranskärlssjukdom. I studie III skapades ett index för att definiera 32 bostadsområden med hög och låg ”promenadvänlighet” i Stockholms stad. Fysisk aktivitet mättes objektivt med en accelerometer och promenerande bedömdes med hjälp av enkäter. Flernivåmodeller användes i den statistiska analysen. I studie IV användes samma mått som i studie III men upplevd ”promenadvänlighet” baserades på en enkät.

Resultat I studie I var tillgången till alla typer av varor, tjänster och resurser bättre i medel och ekonomiskt utsatta bostadsområden än i välbärgade sådana. I studie II var sambandet mellan tillgången på potentiellt hälsoskadliga och hälsofrämjande resurser i bostadsområdet och kranskärlssjukdom relativt svag och icke-signifikant efter justering för bostadsområdets socioekonomiska status och individens ålder och inkomst. I studie III fanns positiva samband mellan att bo i promenadvänliga områden, jämfört med dem som bodde i mindre promenadvänliga bostadsområden, och promenerande i transportsyfte, promenerande i motionssyfte och objektivt uppmätt fysisk aktivitet med rörelsemätare. Andelen av den totala variationen på bostadsområdesnivå var dock låg. I studie IV missbedömde en tredjedel av individerna i bostadsområden med hög ”promenadvänlighet” den som låg. Denna icke-konkordans var vanligare bland äldre och gifta/sammanboende individer. Hög upplevd ”promenadvänlighet” var associerad med promenerande i transportsyfte, promenerande i motionssyfte och objektivt uppmätt fysisk aktivitet med rörelsemätare.

Slutsatser Våra resultat är viktiga, med tanke på nödvändigheten av att säkerställa att ett eventuellt förnyande av bostadsområden grundas på evidensbaserade resultat så att inte kostsamma åtgärdsprogram sätts in utan tillräckliga vetenskapliga bevis. Ytterligare uppföljande studier behövs för att belysa orsakssamband och ge mer hållbara belägg för att minska sociala ojämlikheter i hälsa.

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