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Effects of Built Environmental Factors on Perceived Health Status and Health Disparity

도시환경이 건강도 및 건강격차에 미치는 영향 연구

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Ⅰ. Introduction

The issue of regional inequalities, especially in income and job opportunities, has long been an important subject of research in welfare economics, sociology, and urban planning (Baer. 1964; Eckhaus. 1961; Lasuen. 1962; Preston and McLafferty. 1999). Health disparities have emerged as one of the most frequently considered research and policy agendas, especially in urban planning and public health. This is because they address two of the most important issues which affect every member and aspect of society: health and social equity. Several organizations have initiated research on health disparity, seeking to find the causes and to provide policy solutions(e.g. World Bank, Robert Wood Johnson Foundation, Pan American Health Organization, and US Department of Health and Human Services).

Increasing evidence suggests that the environment is a significant contributor to many public health challenges such as obesity, type II diabetes, cardiovascular and respiratory diseases, and depression(Hill. et al. 2003; Jackson and Kochtitzky. 2001; Poston and Foreyt. 1999). Further, disparities in health are believed to be associated with the unequal distribution of resources and opportunities in the environment such as access to health care, physical activity and exercise facilities, and healthy food(Gordon-Larsen. et al. 2006). However, empirical studies have been insufficient for understanding the extent and magnitude of health disparities in the United States. Furthermore, while it is believed that certain aspects of the built environment are associated with physical activity and health outcomes, the specific roles of the built environment in promoting health status and reducing health disparity are unclear at the moment.

1. Theoretical Framework

There are several theoretical frameworks used to explain the relationship between the built environment and health, physical activity, and dietary patterns: social learning theory(Bandura. 1977), social cognitive theory(Bandura. 1986), social marketing theory(Andreasen. 1995), diffusion of innovations theory(Rogers. 1995), trans-disciplinary paradigm(King. et al. 2002), ecological theory(Egger and Swinburn. 1997), and so forth. The theoretical underpinnings of this research are as follows. First, general systems theory offers an important framework for this study. It originated in biology and is now popular in almost every field of study(Ashby. 1956; Bertalanffy. 1968). Systems theory emphasizes the complexity and interdependence of relationships among systems. A system is a set of objects or elements in interaction to achieve a specific goal each system has subsystems which function as part of the larger system. All systems have five common elements: input, output, process, feedback, and goal(Gillies. 1982). According to the classification of elements of general systems theory, the components of this research can be arranged as follows. Inputs are the knowledge and understandings of health disparity, built environment, health status, physical activity, and dietary patterns. Through the understanding of the relationships and interactions among these different knowledge areas, decreasing or eliminating health disparity, which is the goal of the system, can be accomplished. Second, Egger and Swinburn(1997) proposed an ecological theory to understand and conceptualize health problems. In order to explain the relationship between the built environment and physical activity, the ecological theory offers ways to conceptualize multi-level determinants. Moreover, it considers environmental influences from micro to macro scales. McLeroy. et al.(1988) proposed a socio-ecological model for health promotion. The model suggests that patterned behavior is determined by intrapersonal, interpersonal, institutional, community, and public policy factors. King. et al.(2002) also suggested not only the consideration of the macro and micro scales of environments, but also the types of physical activity and extent of particular environmental conditions which have positive and negative influences on physical activity. In addition, this theory includes several relevant environmental influences such as physical, economic, political, and socio-cultural perspectives to identify the energy balance of a body and physical activity. Third, the behavioral model of environment(BME) helps the identification and conceptualization of the built environment for outdoor physical activity, especially for walking and biking(Moudon and Lee. 2003). It consists of three elements, including origin/destination(OD), route(R), and area(A). These three aspects influence an individual's travel decisions about walking and biking, and are useful for describing overall neighborhood characteristics related to physical activity. For example, one will likely consider distance(OD), attractiveness of route(R), and attractiveness of destination(A) when deciding to go out for a walk. This study uses ecological theory as the primary model to frame the research, general systems theory to guide the conceptualization of the research in general, and BME to guide the operationalization of the built environment.

2. Empirical Evidence

1) Indicator and Measurement

One of the traditional topics in health disparity research is finding the indicators and measurement indices that are best suited for testing inequalities. By measuring inequality, it is possible to understand how well programs or policies promote social justice in health and how these strategies might be further developed and improved in the future. Clear and measurable definitions of health disparity are essential to the creation of effective policies. Many studies have tried to find optimal indicators and measurements, but the results are inconclusive.

Perceived health status has been popularly used in previous research as a predictor of mortality and hospitalization(Idler and Benyamini. 1997; Kennedy. et al. 2001; Miilunpalo. et al. 1997). This indicator has been used for cross-country comparisons of health disparity levels because it is easy to capture and has only marginal variance among surveys(van Doorslaer and Koolman. 2004; van Doorslaer. et al. 1997; van Doorslaer. et al. 2000). Another advantage for perceived health status is that it is easy to understand; it does not rely on a medical conceptualization and employs individuals' evaluations of their own health(van Doorslaer. et al. 1997). The Gini coefficient has been used commonly as a measure of income disparity, and to a lesser degree, health disparity(Musgrove. 1986; Turrell and Mathers. 2001; Kerani, Handcock, Handsfield and Holmes. 2005). Several alternative disparity measures have also been used in health disparity literature, including the Concentration coefficient, odd ratio, and Atkinson index(Manor and Matthews. 1997; Wagstaff, Paci and van Doorslaer. 1991; Waters. 2000). The Gini coefficient has been considered the gold standard in regional science and urban economics, and it is easy to understand and interpret.

2) Environment, Health Status, and Health Disparity

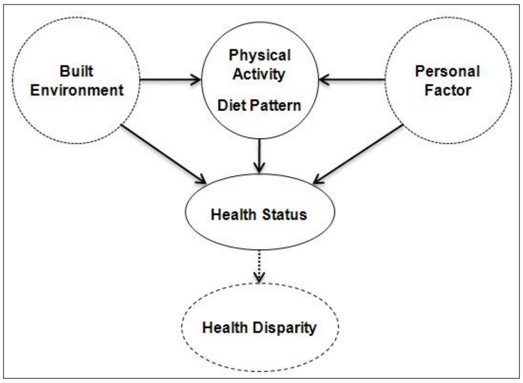
While a significant body of literature has revealed that the built environment was one of the most important key factors in the current obesity epidemic(Chisholm. et al. 1998; Frank. et al. 2004; Hill. et al. 2003; Mobley. et al. 2006; Morland. et al. 2006; Poston and Foreyt. 1999; Price and Gottesman. 1991; Weinsier. et al. 1998), the research examining the association between the built environment and perceived health status is unclear at the moment. However, many studies confirmed that perceived health status has been significantly associated with various health conditions such as obesity(Cornelisse- Vermaat. et al. 2006), mortality(Idler and Angel. 1990; Kaplan and Camacho. 1983), and psychological distress(Farmer and Ferraro. 1997; Tessler and Mechanic. 1978). Built environmental conditions may also be associated with perceived health status. A study by Doyle. et al.(2006) is a rare work where the relationship between the built environment and perceived health status has been examined. In addition to perceived health status, this study used other health conditions as outcome variables including frequency of walking, obesity, hypertension or diabetes, and physician rated health. Hierarchical regression models with county and individual levels were used. County level variables as built environmental conditions included walkability and crime rate, and individual variables included age, gender, race, income, education level, social support(i.e. how frequently subjects interacted with others), smoking habits, and years living in the area. The research hypothesis was that individuals who lived in the areas with high walkability and low crime rates tended to walk more, have lower BMIs, have lower diabetes or hypertension, and have high self-rated and physician-rated health conditions. The findings reported that all relationships were in the expected direction, although some of them were statistically insignificant. Individuals who lived in walkable and safe areas were significantly associated with higher walking and lower obesity rates, but had no significance with hypertension or diabetes, perceived health status, and physician-rated health. Doyle. et al.(2006) related these insignificant results to the hypothesized Active Community Environments(ACES) causal chain among the outcome variables. The hypothesized ACES concept was the sequential logic that walkable and safe areas promote greater physical activity, lower obesity, fewer chronic conditions, and better overall health. That is, the findings reflected the influences on walking and obesity only. From this it is reasonable to conclude that the built environment was strongly associated with health conditions, and healthy environments essentially promoted physical activity and healthy diets(Frank. et al. 2004; Hill and Peters. 1998; Morland. et al. 2006; Morland. et al. 2002). In addition to treating diseases and promoting health, one of the core objectives of the healthcare system is to reduce disparities in health. Increasing evidence indicates that the built environment may play a role in this objective. For example, lower-SES and higher-minority block groups have been associated with reduced physical activity-related facilities and this may eventually cause inequalities in physical activity and obesity levels by sub-population groups(Gordon-Larsen. et al. 2006).

II. Objectives

The aim of this study examines the built environmental correlates of health status and health disparity using a multiple regression model. Drawing from the theoretical framework and empirical evidence, this study considers two major forces(built environments and personal factors) potentially related to health status and health disparity.

The hypothesis is that areas with more supportive built environments(those with variables which increase physical activity and

Figure 1 _ Linked Relationship among Built Environment, Personal Factor, Health Status, and Health Disparity

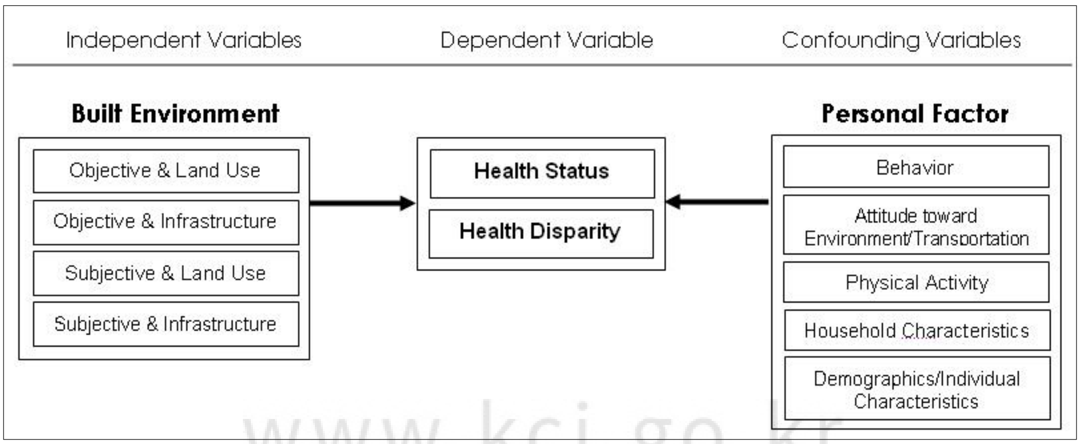


healthy diets) have a higher health status and/or a lower health disparity than areas with less supportive built environments. More supportive built environments will enhance perceived health status and alleviate health disparity.

<Figure 1> describes a linked relationship among built environment, health status, and health disparity. Literature review in the previous chapter confirms that the built environment is a significant factor contributing to increased levels of physical activity, healthy dietary habit, and perceived health status. These behavioral outcomes, perceived health status, physical activity, and diet are interconnected and the literature shows that the built environment plays an important role in affecting the levels of perceived health status and promoting more active lifestyles.

<Figure 2> describes the conceptual framework used to select variables for multiple regression analysis used in estimating the levels of perceived health status and health disparity. Specifically, the built environment is the key independent variable while personal factor is a confounding variable in this model. More specific information about variables will be refined in the next chapter.

Figure 2 _ Conceptual Framework: Built Environment and Personal Factors Associated with Health Status and Health Disparity



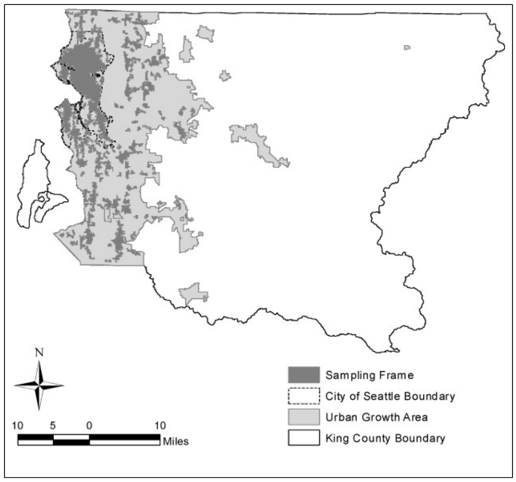
III. Methods

1. Study Area and Data Collection Methods

As described in <Figure 3>, this study uses the 436-respondent telephone survey and the Geographic Information System(GIS) data generated from the Walkable and Bikable Communities project(WBC project) in City of Seattle and its surrounding urbanized areas in Washington, from 2001 to 2004(Moudon. et al. 2007). The participants included adults of at least 18 years of age who were able to walk at least three city blocks.

The telephone survey captures demographic and household characteristics, recreational and travel behavior, neighborhood perception, and attitudes towards the environment. The objective measures of physical environments come from parcel and network GIS databases, and are captured using a custom-made GIS extension. The WBC project employs spatial sampling instead of traditional sampling strategies in order to ensure an appropriate distribution and variation in the environmental variables(Lee. et al. 2006). This study selects areas with a minimum level of support for walking and biking conducted by residential density(10 or more dwellings per acre) and proximity to neighborhood retail use(240 meters or less). More detailed information on this sampling strategy, such as the theoretical and methodological foundation and application process, is found in Lee. et al.(2006).

Figure 3 _ Study Area



source: Adapted from Lee, Moudon and Courbois. 2006.

2. Measurement and Variables

According to the empirical evidence of indicators and measurement in health disparity, self-reported health status is an easily obtained and valid indicator of health which can be used to measure disparity. The Gini coefficient is also commonly-used, valid, effective, and easy to compare and understand as a measurement. Therefore, this study uses perceived health status and the Gini coefficient as an indicator and a measurement of health conditions, respectively.

The dependent variables were perceived health status and the Gini coefficients in health status. Health status(self-reported health status recorded on a 5-point Likert scale, ranging from poor to excellent) comes

Table 1 _ Built Environmental Variables

Section	Variable	Measurements
Objectively measured land use	Household density	Dwelling units per acre within a 1km network buffer(logged count)
	Distance to downtown	Distance to downtown Seattle, Central Business District(ft)
	Land use mix	Land use mix within a 3km network buffer: 0(single use)~1(equal mix of single family, multi family, retail service, education, institution, office, and other)
	Destination	Number of each destination within a 1km network buffer
		Distance to the closest destination up to 3km network distance(ft)
Objectively measured infrastructure	Street length	Total length of streets within a 1km network buffer(ft)
	Street width	Average number of lanes per way on the streets within a 1km network buffer(count)
	Traffic speed	Average posted traffic speed of the streets within a 1km network buffer(miles/hr)
	Traffic volume	Average traffic volume of the streets within a 1km network buffer(vehicles per way/day)
	Bus service	Number of bus stops within a 1km network buffer(count)
	Signal	Number of traffic signals within a 1km network buffer(logged count)
	Sidewalk	Total sidewalk length within a 1km network buffer(ft)
	Intersection	Number of street intersections within a 1km network buffer(count)
	Slope	Mean slope within a 1km network buffer(%)
Subjectively measured land use	Neighborhood land use	Residential, Non-residential
	Predominant housing type	Single family homes, apartments or condominiums, and mix of single family homes and apartment(categorical)
Subjectively measured infrastructure	Neighborhood perception	Presence of auto-oriented facilities(latent factor)
		Presence of destinations(latent factor)
		Safety and maintenance(latent factor)
		Visual quality(latent factor)
		Presence of amenities for biking and jogging(latent factor)
		Social support for walking or biking(other people walking or biking in the neighborhood)(latent factor)
		Street amenities(latent factor)
		Problems related to automobiles(latent factor)

Source: Adapted from Kim and Lee. under review
note: 1) 24 Destinations were considered, including bank, bar, big-box retail, church, neighborhood/community shopping center, convenience store, day care center, fast food restaurant, fitness center, grocery store, hospital, library, mixed-use, museum, office, post office, regional shopping center, restaurant, retail store, school, sport facility, theater, park, and trail.
2) Due to the large number of variables, variable coding and descriptive statistics of significant variables were reported in <Table 3>.

directly from the survey. The perceived health status is transformed into a dichotomous scale lumping the 5-point Likert scale into two groups(e.g. zero, good; one, excellent). The Gini index can be biased if a sample size is very small(Deltas. 2003). A minimum number

Table 2 _ Personal Variables

Section	Variable	Measurements
Health status	Perceived health status	Perceived health status
Health disparity	Health status disparity	Gini coefficient in health status
Behavior	Total walking	Total weekly minutes of walking(categorical)
	Recreation walking	Weekly walking for recreation(yes/no)
	Transportation walking	Weekly walking for commuting and to retail services(yes/no)
	Biking	Weekly biking for recreation or commuting(yes/no)
	Transit use	Weekly transit use(yes/no)
Attitude	Attitude toward environment /transportation	Problems of traffic congestion and air pollution(latent factor)
		Knowledge of physical activity(latent factor)
		Preference of walking and biking to solve congestion(latent factor)
Physical activity	Physical activity at work	Level of physical activity at work(categorical)
	Vigorous activity	Total weekly minutes of vigorous activity(categorical)
	Moderate activity	Total weekly minutes of moderate activity(categorical)
	Exercise at home	Using exercise equipment at home(yes/no)
Household characteristics	Home ownership	Home ownership(yes/no)
	Car ownership	Number of cars per household
	Dog ownership	Having a dog(yes/no)
Demographics/ Individual characteristics	Age	Age(categorical)
	Gender	Male, female
	Race	White, nonwhite
	Education	Level of education(categorical)
	Marital status	Marital status(categorical)
	Income	Average yearly household income(categorical)
	Driving	Vehicle miles traveled(VMT) per month(categorical)
	Sedentary activity	Total weekly hours of sedentary activity at home(categorical)
	Eating out	Number of times eating out per week

Source: Adapted from Kim and Lee. under review
note: Due to the large number of variables, variable coding and descriptive statistics of significant variables were reported in <Table 3>.

of ten samples within each spatial unit was determined, based on a preliminary study(Kim. 2007) as necessary for the measurement of individual health disparity. Ten samples is a threshold which prevents any strong small—sample biases in the Gini statistic in this study. Increasing the buffer size increases the number of respondents with at least ten neighbors within a buffer; however, this also increases spatial correlation problems. Several attempts were made to determine an optimal buffer size that would maximize the respondent sample while minimizing overlap between buffers. The result was a 3km radius created around each respondent(N=436) for computing disparity measures assessing the variation in health status among the neighbors within each buffer.

All built environmental and personal variables were brought forward from a previous study(Kim. 2007; Kim and Lee. under review). The independent variables were those built environmental variables selected based on the literature review and conceptual framework presented in <Figure 2>. A large pool of variables was considered due to insufficient theory or empirical evidence available for guiding the selection of specific measurements. Built environmental factors were classified into objective and subjective variables, and they were further divided into land use and infrastructure variables <Table 1>. The objectively measured land use variables included spatial characteristics in terms of household density, distance to downtown, land use mix, and the number of each destination land use type. The objectively measured infrastructure variables covered the total street length, average street width, average traffic volume, average traffic speed, number of bus stops, number of traffic signals, total sidewalk length, number of street intersections, and mean slope. Subjectively measured variables in land use included neighborhood composition and predominance of housing types as drawn from the WBC survey. The infrastructure class variables included eight latent factor variables on neighborhood perception extracted from 32 survey items: ① presence of auto-oriented facilities, ② presence of destinations, ③ safety and maintenance, ④ visual quality, ⑤ presence of amenities for biking or jogging, ⑥ social support for walking and biking, ⑦ street amenities, and ⑧ problems related to automobiles.

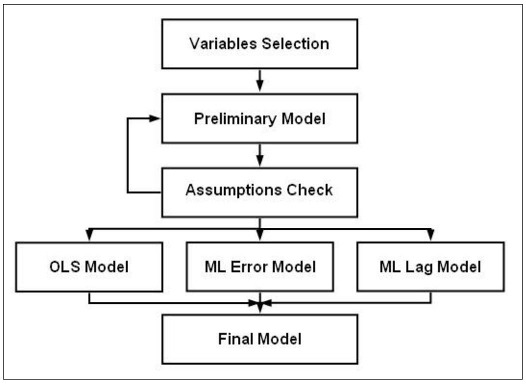
Confounding variables were the personal factors and they were classified into behavior, attitudes toward the environment and transportation, physical activity, household characteristics, and individual demographic characteristics<Table 2>. The behavior variables included total walking, recreation walking, transportation walking, biking, and transit use. The attitude variables were latent factor variables extracted from 11 survey items including problems of traffic congestion and air pollution, knowledge of physical activity, and preference for walking and biking to solve congestion. The physical activity variables include physical activity at work, vigorous and moderate activity, and if the respondents used exercise equipment at home. The household characteristics were captured by the number of cars per household, home ownership, and having a dog. The demographic variables included age, gender, ethnicity, education level, marital status, income, vehicle miles traveled per month, total weekly hours of sedentary activities at home, and weekly frequency of eating out.

3. Data Analysis

Data analysis followed these steps: ① variable selection, ② preliminary model and assumption check, ③ model comparison, and ④ final model<Figure 4>. The purposes and methods for each step of analysis are as follows.

The purpose of the variable selection step was to verify the most important predictors and to eliminate or reduce collinearity problems. This step was used to identify variables which have significant bivariate associations with the dependent variables. Patterns of correlations among the independent and confounding variables were also examined in this step to reduce the problems of multicollinearity and to enhance efficiency during the modeling process. Various bivariate analyses were used, including Pearson correlation, T-test, and ANOVA(cut off: p-value < 0.05). The second step of the analysis was to test a multiple regression analysis with the selected independent variables from the first step, adding variables from <Tables 1 and 2>. This phase was used to check collinearity among the variables with other normality and constant variance assumptions, returning to the previous step until all assumptions were satisfied. The next step was to compare the

Figure 4 _ Analysis Process



OLS and spatial regression models to evaluate the best model. In addition to the OLS regression models, a spatial regression model was used for the multivariate analysis. Moran's I statistics were used to further test the existence of spatial dependence. When the tests confirmed the presence of autocorrelations, two alternative models, including the maximum likelihood(ML) spatial lag model and the maximum likelihood(ML) spatial error model, were run in this study using GeoDa software. The ML error model is effective when the assumption of uncorrelated error terms in OLS regression is violated; the ML spatial lag model is commonly used when the assumptions of uncorrelated error terms and independent observations are violated together(Anselin. 1988). Based on the results from all the previous steps, a final model was developed for examining the relationship between the built environment and the levels of health status and health disparity.

Ⅳ. Results

1. Preliminary Model and Model Comparison

1) Health Status Model

The distribution of the 5-point Likert scale perceived health measure was non-normal. The numbers of respondents who rated their perceived health as poor, fair, good, very good, and excellent were zero(0.0%), 28(6.4%), 115(26.4%), 178(40.8%), and 115(26.4%), respectively, out of a total of 436(100.0%). The 5-point Likert scales in health status were condensed into two groups. Note that 'poor' and 'fair' were lumped together with 'good', and 'very good' was combined with 'excellent'. Thus, the numbers of respondents of 'good' and 'excellent' statuses in health became 143(32.8%) and 293(67.2%), respectively. Because of this dichotomous independent variable and the lack of significant spatial autocorrelations, a binary logistic regression model was employed in estimating health status. The model chi-square was 57.6, which is statistically significant at the 0.01 significance level<Table 3>. Meanwhile, none of the independent variables in the binary logistic regression model had a standard error of the coefficient(B) greater than 2.0, indicating that there were no strong muliticollinearities. Operationally, the classification accuracy rate should be 25% or higher than the proportional by-chance accuracy. For this model, the classification accuracy was 71.3% which was greater than the criteria(69.9%). The classification accuracy rate is more informative for the reliability of a model than R-square.

2) Health Disparity Model

For the health disparity model, several tests were performed to test if the assumptions of the OLS were met. The multicollinearity condition number of 100.1 was greater than the criteria of value(20.0), supporting the presence of multicollinearity. The Jarque-Bera test further confirmed the non-normal distribution of the error term. However, individual variables did not have strong collinearity based on the tolerance rate and VIF(tolerance > 0.2 and VIF < 4). Thus, while evidence suggested the presence of multicollinearity and non-normality problems, the magnitude was considered weak. According to the Breusch-Pagan and several other spatial dependence tests, strong evidence was found for heteroskedasticity and spatial dependency. The Moran's I score was 0.27, which indicated the existence of strong spatial autocorrelations at the 0.01 significance level. Based on the results from these tests, a spatial regression model was selected.

The spatial regression models improved the general model fit as indicated by higher R^2 and

Table 3 _ Built Environmental and Personal Correlates of Health Status and Health Disparity

Class	Measurements	Variable coding and descriptive statistics	Health status		Health disparity	
			B	Exp(B)	B	Beta
Objectively measured land use	Distance to Seattle downtown	(ft)Mean=21806.653, SD=10386.685	–	–	6.215E–08***	.060***
	Number of bank	10=0, 11=1, 12=2, 13=3, 14=4, 15=5+(Mean=11.087, SD=1.326)	–	–	–.001***	–.163***
	Number of churches	10=0, 11=1–4, 12=5–8, 13=9–12, 14=13–16, 15=17–20, 16=21–24, 17=24+(Mean=12.264, SD=1.575)	–	–	–.000	–.053
	Number of convenience stores	10=0, 11=1, 12=2, 13=3, 14=4+ (Mean=11.521, SD=1.301)	–	–	.001***	.103***
	Number of grocery stores	10=0, 11=1, 12=2, 13=3, 14=4, 15=5, 16=6+(Mean=12.491, SD=1.889)	–.162***	.851***	–	–
	Number of park	(Mean=1.53, SD=1.402)	.259***	1.295***	–.001***	–.085***
	Distance to the closest library	10=up to 0.3mile, 11=0.3–0.6mile, 12=0.6–0.9mile, 3=0.9–1.2mile, 14=1.2–1.5mile, 15=1.5–1.8mile, 16=1.8+mile(Mean=12.622, SD=1.524)	–	–	–.001***	–.137***
	Distance to the closest museum	10= up to 0.6mile, 11=0.6–0.9mile, 12=0.9–1.2mile, 13=1.2–1.8mile, 14=1.8+mile(Mean=11.860, SD=1.383)	–	–	.000	.038
	Distance to the closest theater	10= up to 0.6mile, 11=0.6–1.2 mile, 12=1.2–1.8mile, 13=1.8+mile(Mean=11.211, SD=1.073)	–	–	–1.260E–06	–.000
Objectively measured infrastructure	Average traffic volume	(vehicles per way/day) Mean=10957.832, SD=6933.391	–	–	–1.977E–07***	–.128***
	Number of bus stops	(count)Mean=47.340, SD=27.335	–	–	8.576E–05***	.219***
Subjectively measured land use	Social support for walking and biking in the neighborhood	(latent factor)Mean=0, SD=1	.225**	1.252**	–	–
Attitude	Total weekly minutes of vigorous activity	11=0hr, 12=1–149hrs, 13=150+hrs (Mean=11.888, SD=0.838)	.343**	1.409**	–	–
Demographics	BMI	(Mean=25.181, SD=4.395)	–.095***	.910***	–	–
	Race	0=nonwhite: 44, 1=white: 392	–	–	.002*	.051*
	Education	1=never attended school or only kindergarten, 2=grades 1 through 8(elementary), 3=grades 9 through 11(some high school), 4=grade 12 or GED(high school graduate), 5=college 1 to 3 yrs(some college or technical school), 6=college 4yrs or more(college graduate), 7=graduate school or more(Mean=5.775, SD=0.942)	.328***	1.388***	–	–
	Average yearly household income	1=~$9,999, 2=$10,000~$ 14,999, 3= $15,000~$19,999, 4=$20,000~$24,999, 5=$25,000~$34,999, 6=$35,000~$49,999, 7=$50,000~$74,999, 8=$75,000+ (Mean=6.415, SD=1.435)	–	–	–.000	–.045
		Constant coeff.	–1.167	.311	.023**	–
		Lag Coeff.(Rho)	–	–	.947***	–
		Prob.> X^2	–	.000	–	–
		Negelkerke R^2	–	.172	–	–
		Accuracy rate(>69.9 %, criteria)	–	71.3%	–	–
		R^2	–	–	–	.627
		Likelihood(L)	–	–	–	1564.92

note: * < 0.1 level, **<0.05, and *** < 0.01 level
The count and distance variables were the total count within a 1km and the closest distance within a 3km from home, respectively. Since Geoda software does not provide standardized coefficients, Beta values of health disparity model were calculated based on a formula $bj^*=(sj/sy)bj$(Schuerman. 1983).
bj*: standardized coefficient bj: unstandardized coefficient
sj: standard deviation of the jth independent variable sy: standard deviation of the dependent variable

Log likelihood(L) values. For the maximum likelihood(ML) spatial model, the 3km distance spatial weight was used to compute the spatial dependence and correlation. The R^2 of OLS, ML spatial lag, and ML spatial error models were 0.30, 0.63, and 0.62, respectively. The L values were 1438.92 for the OLS model, 1557.83 for the LM spatial error model, and 1564.92 for the ML spatial lag model. However, the Likelihood Ratio test and the parameters of rho(ρ) and lambda(λ) were significant at the 0.01 level, pointing to the continued existence of spatial dependencies. Because other test results were similar between the two ML models, the ML spatial lag model was selected as the final model based on the model performance parameters(e.g. R^2 and Log likelihood values).

2. Final Model

1) Health Status Model

From the health status logistic regression model<Table 3>, more parks, social support for walking or biking, total weekly minutes of vigorous activity, and level of education increased the probability of the 'excellent' health status. Because parks promote walking, biking, and physical activity, the number of parks played a role in increasing health status. Clearly, the presence of social support for walking or biking in the neighborhood promotes those activities and the total weekly minutes of vigorous activity may be a barometer thereof. Only the level of education from demographic factors had a positive correlation with health status. Variables that were negatively related to the probability of 'excellent' health status include lower obesity and more grocery stores. Clearly, higher obesity was associated with lower perceived health status. More grocery stores decreased health status because such destinations tended to supply unhealthy foods. The general results supported the hypothesis that areas with more supportive built environments have higher health status than areas with less supportive built enviro nments. Built environmental variables related with physical activity included the number of parks and social support for walking or biking. The only environmental condition associated with unhealthy diets was the number of grocery stores.

2) Health Disparity Model

Health disparity was positively related to the distance from the downtown area. Spaces near downtown Seattle could be considered as generally favorable for physical activity, with smaller street blocks, higher density, more destinations, and other un-captured conditions such as stronger social support and visual interests. Therefore, this finding supported the hypothesis that areas with supportive built environments promoting physical activity have lower health disparity. That is, supportive built environmental destinations which promote physical activity had a lower disparity. Those destinations included easy access to banks and parks, whereas less supportive destinations included libraries. Parks tended to produce recreational trips and therefore promote physical activity. The numbers of banks and libraries were associated with lower and higher disparities, respectively. Banks are usually considered pedestrian friendly destinations to promote walking and biking, while libraries are designed for automobile accessibility and are therefore considered negative land use for physical activity perspectives. Thus, this finding appeared to support the research hypothesis. Convenience stores were associated with higher disparity. The food environment is another significant factor relating to health disparity. Convenience stores are usually considered to be less supportive food destinations because, generally, they supply high-fat and high-sugar foods. This finding supported the hypotheses that areas with supportive built environments which increase healthy dietary habits have a lower health disparity than areas with less supportive built environments. From the transportation infrastructure variables, health disparity had positive relationships with the number of bus stops it was also negatively correlated with traffic volume. This finding did not support the research hypothesis, because bus stops are shown to promote walking and biking, and higher traffic volume is generally considered a deterrent to physical activity. From the demographic factors, the white population was significantly associated with increases in health disparity. This finding indicates that white populations tended to feel more relative disparities in perceived health status.

V. Discussion

As confirmed by this study, the built environment is significantly associated with perceived health status and health disparity. Multivariate and disaggregated analyses showed that the built environmental conditions which promote physical activity may also improve health status. Moreover, food destinations(e.g. access to convenience stores or grocery stores) showed significant roles in health status and health disparity. While land use and the regional location generally supported the research hypothesis, infrastructure variables showed no significance or an opposite direction of association with health disparity.

This paper is theoretically and practically significant for the following reasons. It contributes to a better understanding of the specific built environmental variables that are associated with health status and health disparity by proposing a conceptual framework based on theoretical foundations which incorporate several relevant theories and models(ecological theory, general systems theory, and the behavioral model of environment), as well as previous literature dealt with in a preceding study(Kim. 2007). Moreover, this fills a gap in the health disparity–environment relationship literature by considering detailed and objectively measured built environmental variables and by employing advanced analytical techniques. Modeling health status and health disparity using the disaggregated individual unit of analysis refines previous work which relied upon larger aggregates(e.g. census blocks). This study also addresses the spatial autocorrelation of interdependence and interaction among spatial attributes, something which traditional linear regression models cannot do. Further, this study used rigorous and systematic modeling processes to identify the most effective set of explanatory variables and an optimal statistical model, and then it developed and compared spatial error and spatial lag models(with OLS regression) to select the best one. Above all, this study provides insights into the relationship between the built environment and health status, and between the built environment and health disparity.

As one of the first studies examining health disparity with detailed objective and subjective environmental conditions, it raises new questions and reveales inconsistent findings. Several limitations of this study should be noted, which can lead to new directions for future study. First, this research can be extended to multilevel analysis. To simultaneously examine associations between variables measured from two different spatial units, a Hierarchical Linear Model(HLM) can be employed to identify the group–level built environmental correlates of health disparity and health status while controlling for demographic and social environmental(individual–level) variables. Second, there could be potential causal relations among the explanatory variables. There may be sequential or complex relations among the environmental, behavioral, and demographic variables including health conditions. Common quantitative methods used in this study such as correlation and multiple regression models cannot detect the causality with cross–sectional data. In order to build causal modeling, Structural Equation Modeling(SEM) with longitudinal data may be a necessary direction for future research. Finally, the setting of this study is Seattle which presents a heavily urbanized development structure and a high percentage of white individuals. The results should be interpreted within the local context of this study area. For future study, it could include spatial settings with different environmental and socioeconomic condition. If an empirical study deals with urban areas in Korea, it will provide diverse and valuable policy recommendations for increasing health status and reducing health disparity from multidisciplinary perspectives.

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ABSTRACT

Effects of Built Environmental Factors on Perceived Health Status and Health Disparity

Keywords: Perceived Health Status, Health Disparity, Built Environment, Spatial Autocorrelation, Spatial Regression Model

This study analyzed built environments to see how strongly conditions which promote physical activity and healthy diets are associated with higher levels of perceived health and lower health disparity. This study examined built environmental and personal factors using a 436-respondent telephone survey and GIS-derived environmental data from Seattle, Washington. Logistic regression was used to estimate perceived health status while spatial regression was used for health disparity to account for autocorrelations. Positive built environmental correlates of perceived health status included access to parks and social support for walking or biking negative correlates included access to grocery stores. For health disparity, supportive environmental conditions, including easy access to downtown, banks, and parks, and difficult access to convenience stores and libraries were associated with lower disparity levels. The roles of the built environment were determined to be significant for perceived health and health disparity once personal factors were controlled for.

도시환경이 건강도 및 건강격차에 미치는 영향 연구

주제어: 자가건강도, 건강격차, 도시환경, 공간자기상관, 공간회귀모형

최근의 수많은 연구들은 도시환경이 급증하는 비만, 당뇨, 암, 심혈관계질병 등과 밀접하게 연관되어 있다고 증명하고 있다. 특히, 병원 접근성, 운동시설 및 식생활 관련 도시환경 시설의 불균형 등은 개인의 건강격차를 증가시켜왔다. 본 연구는 도시환경의 영향이 건강도와 건강격차에 미치는 역할을 분석하는 데 목적이 있다. 본 연구에서는 미국 시애틀을 공간적 범위로 하여 건강도 모형에는 로지스틱 회귀모형이, 건강격차모형에는 공간회귀모형이 이용되었다. 공원 접근성, 걷기와 자전거타기를 유도하는 사회여건이 건강도와 양의 관계를 보였고, 그로서리스토어 접근성은 음의 관계를 나타냈다. 헬스격차와는 다운타운, 은행, 공원과의 접근성이 양의 관계를, 편의점과 도서관 접근성은 음의 관계를 보였다. 이 연구는 도시환경적 요소가 개인 건강도와 건강격차에 유의미한 연관성이 있음을 시사하고 있으며, 기존 건강관련 연구의 의학 및 보건학적인 접근의 한계를 뛰어넘어 도시계획적 접근으로 다루었다는 점에서 연구의 의의를 찾을 수 있다.