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Contributions Of Individual, Physical, And Social Environmental Factors To Bicycling: A Structural Equations Modeling Study Of Six Small U.S. Cities

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Contributions Of Individual, Physical, And Social Environmental Factors To Bicycling:
A Structural Equations Modeling Study Of Six Small U.S. Cities

By

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DISSERTATION

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ABSTRACT

Bicycling is widely promoted in many countries as a sustainable means of transportation and a form of physical activity as well. However, the level of bicycling in the US is low compared to some European countries with similar economies and levels of auto ownership. Differences in the physical and social environments in these countries may explain this phenomenon. Previous research has established an association between environmental factors and bicycling. However, empirical knowledge about the influences on bicycling, and relative importance to bicycling, of the physical and social environments as well as individual factors is limited. Additionally, the majority of bicycling in the US is for recreation rather than transportation purposes but few studies have examined the question of bicycling purpose. We use data from an online survey conducted in 2006 in Davis, CA, which has a high bicycling level, and 5 comparison small cities in the western US to examine the contributions of physical and social environments to bicycling. Several aspects of bicycling are examined: bicycle ownership and regular bicycling, as well as bicycling for transportation compared to bicycling for recreation, bicycling distance and daily probability of transportation bicycling. The study employs Structural Equations Modeling to assess the complex relationships between bicycling and environment while controlling for socio-demographics, travel constraints, and attitudinal factors.

Individual factors, especially attitudes, play a more important role than environmental factors in explaining bicycling. The attitude of liking bicycling is the most important factor in explaining bicycle ownership and regular bicycling. It also leads to a greater

likelihood of transportation-oriented bicycling. The attitude of environmental concern combined with preference for non-motorized travel modes strongly impacts bicycling, especially transportation bicycling. Bicycling self-efficacy contributes to bicycle ownership and regular bicycling, as well as transportation bicycling. It also works as an important mediator through which supportive bicycle infrastructure exerts an influence on bicycling.

Both the physical and social environments show significant influences on bicycling, after accounting for socio-demographics, travel constraints, attitudes, and residential preference for bicycling. Supportive bicycling infrastructure encourages, though indirectly through bicycling comfort, the following: owning a bicycle, regular bicycling, higher shares of bicycle rides for transportation, and bicycling longer and more frequently for transportation. A greater mix of land uses may lead an individual to bicycle mostly for transportation, but result in relatively fewer bicycling miles for transportation. Hilly topography discourages owning a bicycle, regular bicycling, and bicycling mostly for transportation, but may encourage bicyclists to be more recreationally oriented. A bicycling culture, especially if a transportation bicycling culture, shows stronger influences on transportation-oriented bicycling than the physical environment does, while controlling for individual factors and residential preference for bicycling. Additionally, the analysis shows a residential self-selection effect, in which people who have a higher level of residential preference for bicycling are more likely to own a bicycle and bicycle regularly, especially to bicycle mostly, more miles, and more frequently for transportation.

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1. INTRODUCTION

Bicycling as a mode of transportation is now getting more attention in the US, for good reasons. Bicycling makes efficient use of limited roadway capacity and thus can help to reduce peak-period congestion. The bicycle is a low-polluting alternative to driving, producing essentially no air pollutants during operation. It is also a low-cost alternative to driving, requiring no more than the purchase of a bicycle and related gear. For individuals who do not have the option of driving, whether for financial or other reasons, the bicycle can be an important means for getting to destinations, particularly for trips that are too long for walking or are not served by transit (Murphy and Knoblauch 2004). Bicycling is also a source of physical activity at a time when physical activity is declining and levels of obesity are reaching epidemic proportions (Killingsworth, 2003).

Because bicycling has these benefits, communities throughout the US are giving increased priority to bicycling, which has now more and more often been the target of policy efforts. For inspiration, they often look to other countries with similar economies, where bicycling is far more prevalent. The share of urban trips by bicycle in Canada, for example, is twice that of the US and the share in European countries is anywhere from four times (in the U.K., France, Italy) to 28 times (in the Netherlands) higher than in the US (Pucher and Dijkstra, 2003). Furthermore, even though there is a significant amount of bicycling in at least some parts of the US, the majority of this bicycling is for recreation rather than transportation. Pucher and Dijkstra (2000) report that more than two-thirds of bike trips are for recreation in the US, and that the percentages of bicycling trips for work, school, and shopping in the Netherlands (60.0%) and in Germany (60.1%) are twice that in the US. Since these countries are among the wealthiest in the world and also have high car ownership rates, what causes the differences?

From one perspective, these numbers suggest significant potential for increasing bicycling in the US. On the other hand, they may reflect important differences between the US and these other countries that could limit the potential of bicycling in the US. Studies show that the physical and social environments in European countries are different in important ways from the environment in the US. (Pucher and Dijkstra, 2000; Pucher and Buehler, 2006; Pucher and Buehler, 2008). European countries have more compact land-use patterns with higher average urban densities and consequently shorter average trip lengths than those of the US. Many cities in the US lack appropriate facilities for cycling compared with those in European countries. The extent of the car-dependent culture and lifestyle also make the US different from other countries. More pro-bicycling policies and programs as well as restrictions on driving in European countries have reinforced wider social support for bicycling. Although most are not easily replicated in the US and only over considerable time, these factors apparently help to explain much higher levels of bicycling in Europe than the US (Pucher and Buehler, 2008). They also could be important reasons for the higher share of transportation bicycling in European countries.

However, empirical evidence of the impacts of the physical and social environments on individual bicycling behavior is still limited and sometimes contradictory. Some studies have revealed associations between the physical environment and bicycling: people living in communities with greater land-use mix are more likely to bicycle (e.g. Moudon et al., 2005; Cervero and Duncan, 2003). Bicycle infrastructure, including bike lanes, bike path, bike racks, bike lockers, etc., is positively associated with bicycling (e.g. Dill and Carr, 2003; Nelson and Allen, 1997; Stinson and Bhat, 2004; Geus et al., 2007). However, in contrast, some studies show that land use-mix and bike lanes, as well as accessibility to some destinations, are not associated with bicycling (e.g. Guo et al., 2007; Geus et al., 2007; EPA, 2003). Similarly, although some studies (e.g. Geus et al., 2007) report that the social environment affects bicycling significantly, Moudon et al. (2005) found an unclear relationship between social support for bicycling and bicycling. Studies that have examined the question of bicycling purpose are even fewer; existing research provides little evidence on factors that differentiate transportation bicyclists from recreation bicyclists and their relative importance in influencing bicycling for each purpose. One recent study (Xing et al., 2010) shows that physical and social environment factors have important influences on the balance between transportation and recreational bicycling: a culture of utilitarian bicycling and short average distances to some destinations are key factors for transportation bicycling. Bicycle infrastructure appears to play an indirect role through its effect on perceived bicycling safety and through the self-selection effect, by attracting bicycling-inclined people to bicycling-supportive communities.

In addition, even when studies have shown associations between the environment and bicycling, it is not certain whether the environment has a true impact on bicycling. It is possible that the environment has no impact on bicycling at all but is merely associated with bicycling because of its association with an unmeasured variable that causes both. Under this situation, the association between the environment and bicycling is known as a spurious effect (Cohen et al., 2003, pp. 78-79). For example, the possibility that an individual's preference for bicycling leads him to choose to live in a community like Davis, called "self-selection" (Handy et al., 2006), raises questions about a causal link from the environment to bicycling. In this case, the preference for bicycling causes both the environment (through residential location choice) and bicycling, making it appear that the environment and bicycling are related.

Further, previous studies focus on the statistical significance of the association; however, the magnitude and relative importance of the impact of the environment on bicycling is still unclear. Using single equation models, most bicycling studies only explore the direct effect of the environment on bicycling but ignore indirect effects resulting from relationships between explanatory factors; these relationships are called "endogeneities" in a model. For example, in Geus et al. (2007), self-efficacy is correlated with bicycling, as is a bike lane in good condition in the neighborhood. However, a bike lane in good condition also has an indirect impact on bicycling by helping to increase individual self-efficacy for bicycling. Ignoring indirect effects means that the total true impact of the environment cannot be estimated. This may lead to erroneous conclusions that direct policy makers to invest in strategies that target less important factors and thus spend their limited budgets ineffectively. Assessing the true influence of the environment on bicycling behavior helps assure the effectiveness of public policies that aim to increase bicycling through changes to the environment. The true impacts of the physical and social environments on bicycling are thus an important question. To answer this question, more robust models than single equation models must be employed.

This study aims to map out the direct and indirect effects of the physical and social environments as well as individual attitudes on bicycling by using structural equations modeling. The purpose of this study is to provide a stronger empirical basis for policy decisions promoting bicycling, by contributing to an improved understanding of the influences of physical and social environments on bicycling. In particular, this study is designed to address the following research questions:

1) Do the physical and social environments have true influences on bicycling, and if so, in what ways?

   a) What are the relative effects of the social environment and physical environment on bicycling behavior, if these effects can be separated?

   b) What are the relative effects on bicycling behavior of different aspects of the physical environment, particularly bicycle infrastructure and land use patterns?

2) Do individual attitudes have true influences on bicycling, and if so, in what ways?

   a) What is the relative importance of affection for bicycling on bicycling behavior? Do bicycling behaviors, in turn, influence individuals' affect for bicycling, and if so, how important is this effect?

   b) How significant is the "self-selection effect", in which an individual who chooses his or her residential location because it is good for bicycling is more likely to bicycle?

3) In what ways do these relationships differ for transportation bicycling specifically, rather than bicycling in general?

The major contribution of this dissertation is to explore the complex relationships between various factors that explain bicycling behavior. Most previous studies have examined associations of relevant factors and bicycling behavior, but have not explored interactions among the factors themselves. Mapping out these interactions helps to identify the mechanisms by which these factors influence bicycling. It also enables the separation of indirect from direct effects and the estimation of the total effects of these factors on bicycling. This research employs structural equations modeling to measure the interactions among factors and identify potential causal relationships between the relevant factors and bicycling. The findings may provide a better understanding of the relative importance of the factors in influencing bicycling than current bicycling studies do.

This dissertation is organized as follows. First Chapter 2 documents relevant theories in the travel behavior and physical activity fields to develop a conceptual framework that maps out interactions between explanatory factors and bicycling behavior. Empirical research on factors associated with bicycling from both the travel behavior and physical activity fields is reviewed within this conceptual framework. Chapter 3 describes the survey design, sampling methodology and administration, survey data and variables, and hypothesized conceptual model, as well as methods employed in data analysis. The issues of dealing with missing data and discussion of sample size are also documented in this chapter. Chapter 4 develops a tentative model to explore factors associated with the attitude of liking bicycling using an ordered logit procedure. The influence of individual factors and physical and social environments on regular bicycling is tested in Chapter 5 through structural equation modeling. Chapter 6 explores factors influencing transportation bicycling, again by employing structural equation modeling. The final chapter summarizes the key findings and discusses the policy implications based of the results.

2. LITERATURE REVIEW

As a starting point for understanding bicycling behavior, researchers turn to theories of behavior that can explain bicycling behavior and provide guidance on key factors that influence it. Bicycling researchers have not settled on one best theory. Instead, it makes sense to examine both travel behavior theories and behavioral theories from other fields. In this chapter, a broader set of behavioral theories are thus examined as a basis for a comprehensive conceptual framework for understanding bicycling behavior. Established travel behavior theory is the starting point, given the traditional role bicycle plays as a travel mode. Then a series of theories widely used in the physical activity field are examined, given the physical exertion involved in bicycling. The conceptual framework is then derived from these behavioral theories. Based on the conceptual framework, previous bicycling studies, from both the transportation and physical activity fields, are reviewed to develop hypotheses as to the factors that influence bicycling. Special attention is given to previous studies that examine the complex relationships between various factors and travel behaviors.

2.1 Theoretical Foundation

Theories play an essential role in all kinds of scientific research. Theories help researchers to develop hypotheses, design experiments, develop models, and interpret results. Implicitly or explicitly, each step of research is guided by theory. This section thus starts by reviewing relevant theories that are important in the formulation of a conceptual model for understand bicycling behavior.

Bicycling, a means of transportation as well as a form a physical activity, is an individual behavior driven by individual decisions. This section thus looks at some well-embraced travel behavior theories, from traditional utility maximizing theory to some of its extensions—the activity-based approach and the concept of positive utility of travel. Additionally, a broader range of human behavior theories widely applied in the physical activity field, including reasoned action and planned behavior, social learning or social cognitive theory, social support, and ecological approaches, are also presented in this section. Finally, a conceptual framework describing the relationship between bicycling and its potential explanatory factors, derived from the theories described and on which the dissertation relies, is formed and presented.

2.1.1 Travel behavior theories

Travel behavior theories have been long concerned with predicting travel demand as to who travels, by what mode, where to they go, and how often, as aggregated over the population. The forecasting of the trips of a large number of individuals, i.e. aggregate travel behaviors, was the dominant interest in the field for many decades after World War II. Consequently, applications of transportation theories often focused on forecasting travel demand only as influenced by population-level demographic and economic characteristics. However, the limitations of predicting trips using aggregated data, which, for example, may lead to loss of variability in situations with heterogeneous individuals (Fleet and Robertson, 1968), became apparent. Meanwhile urban planners found that conventional travel behavior theories were not helpful in forecasting modal split and evaluating the effects of changes in infrastructure (Domencich and McFadden, 1975, pp.

2-3). In response, theories supporting discrete choice analysis methods with disaggregate data (that deal with micro-level, e.g. with the household or individual as the analysis unit, rather than macro-level, e.g. zone or city.) emerged during the late 1960s and the 1970s to provide more extensive, reliable, and accurate estimations of travel demand. Although travel behavior theories and their empirical applications are being improved all the time, the fundamental core of travel behavior theory remains the utility maximizing theory derived from conventional economic consumer theories. Therefore this section starts with a presentation of a general utility maximizing theory. With this theoretical background, the development of theoretical variations from constant utility to random utility is then documented.

Utility maximization theory

Utility maximization theory is widely used in economics and was originally brought to the travel behavior field by Daniel McFadden. This economic theory states that consumers make decisions that trade-off purchases of different goods so as to maximize their utility subject to their budget constraints. Similarly, a traveler also maximizes utility by making optimal choices (mode choices, destination choices, etc.) from the available set of alternatives, which is determined by income, time budgets or /and other external constraints. The utility of each choice is a function of the attributes of the alternatives (e.g. cost, travel time, convenience, safety, etc.) and their relative importance to the individual. Travel choices differ from consumer choices in that they are usually discrete (e.g. this mode versus that mode) rather than continuous (e.g. how much to spend for a particular good).

In applying utility maximizing theory, travel behavior researchers generally assume that utility is not constant, taking what is called the random utility approach. The random utility approach takes into consideration unobserved characteristics of individuals and alternatives, such as variations in tastes or unmeasured attributes of choices; in other words, the observer lacks information related to the decision-makers and/or the alternatives. The utility function consists of two parts: a non-stochastic (or non-random) component and stochastic (or random) component. The non-stochastic component is determined by the observed attributes of alternatives and representative tastes of the population; the stochastic component represents variations in individual tastes and/or unobserved attributes of alternatives. McFadden embraced the probabilistic random utility approach as an extension of utility maximization theory and initiated its wide application in travel behavior studies (Domencich and McFadden, 1975). Based on utility maximization theory, the probability that an individual drawn randomly from the population chooses a particular alternative rather than the others from the choice set thus can be mathematically expressed. This approach can be put into practice for analyzing discrete choice behaviors by specifying the probability distributions of the stochastic components and the functional form of the non-stochastic components of utility (McFadden, 1974).

Although in the transportation field the original application of the theory was for forecasting travel demand rather than understanding travel behavior (Handy, 2006), utility maximization theory and its extension not only greatly improve the accuracy of travel demand forecasts but also provide a useful framework for understanding individual choice behaviors. It suggests the mechanism by which a certain factor influences the travel behavior of interest and thus guides the selection of explanatory variables in empirical studies. In this approach, utility is assumed to be a function of individual tastes (which are associated with socioeconomic characteristics such as income, family size, auto ownership, etc.) and attributes of the alternatives (e.g. time, cost, etc.); the estimates of the coefficients in the function indicate the relative importance of the tastes and attributes.

Travel behavior theory and its applications, especially its traditional use in mode choice models, play an important role in transportation planning. It helps to explain the mechanism by which mode choice decisions are made, in which the mode with the highest utility has the highest probability being selected. Individual socio-economic characteristics and attributes of the travel modes, especially travel time and cost, are assumed to contribute to utilities of travel modes and are usually incorporated into models guided by this theory. As an example, the wide-spread preference for driving over bicycling is explained according to this theory by shorter travel times for driving that lead to a greater utility of driving for the traveler than bicycling.

However, focusing on travel cost or time ignores other factors that may contribute to bicycling utility and cannot help to explain why some people bicycle more frequently and for longer distances despite the inferiority of bicycling with respect to travel time. Domencich and McFadden (1975) discussed the potential impacts of attitudes, subjective perceptions, and intentions of individuals on travel behavior, and they stressed the importance of positioning the travel behaviors of interest in the context of auto ownership or availability and residential and job locations in the long-term study of individual travel decisions. They also argued that the relationships between travel decisions and these variables are reciprocal, thus suggesting the importance of using simultaneous models for explaining travel, residential and job location, and auto ownership decisions together, particularly if long-run panel data are available.

The activity-based approach and the concept of the positive utility of travel also help to expand the list of factors that may influence the utility of travel. Historically, the focus on travel time or distance as an explanation for mode choice stems from an overly limited view of travel behavior. For example, travel behaviors are often treated separately from the series of activities in which an individual participates, and the role of travel as the link between two sequential activities is neglected. However, loosely speaking, even the travel itself can also be viewed as an activity. The two concepts expand the usefulness of traditional travel behavior theory by suggesting a wider range of factors that affect the utility of travel modes, including attitudes, environment, safety, and others.

Activity-based approach

Originating during the 1970s with work by Hagerstrand (1970), Chapin (1974), and Fried (1977), the activity-based approach emphasizes the link between travel and activities and brings a comprehensive framework to travel behavior theory. It is based on the fundamental concept that travel behavior is derived from the demand for participating in activities at different locations. The activity-based approach sets a more extensive context for travel behavior by situating it within the series of activities undertaken by an individual in the time-space dimension; it addresses the full behavior pattern formed by all travel and activities or tours (trip chains) within a certain time period (e.g. a day). Say, for instance, that a family is going to participate several out-home activities on a certain day. The family members would be confronted with several choices for destinations, transportation modes, and routes to destinations, among other choices. The decisions process would heavily depend on interpersonal interactions, environment, and household, time, cost, or transportation system constraints (these activity needs and constraints are tied to household lifecycle). After the family decides on a schedule of a combination of trips and activities within the constraints of time and space, the individual daily activity pattern comes into form (McNally, 2000). This method establishes an association between activity-travel patterns and household lifecycle which is believed to be a predictor of travel behavior. Thus, travel behavior can be better understood through empirical models that account for activity patterns.

The activity-based approach pays more attention to the underlying motivations for travel behavior than conventional travel behavior theory does. Commonly accepted contributions of this approach include “(a) reconsider[ing] the definition of the phenomenon being modeled, (b) giv[ing] more explicit recognition to the derived demand nature of travel and (c) pay[ing] more attention to the sociodemographic characteristics, of individuals, and households that affect the demand for activity participation (and hence travel) and that often constrain activity and travel choices” (Pas, 1985). Practically, it extends the range of methods and scope of applications of research on travel behavior. For example, it incorporates household, environmental, and auto ownership constraints into analyses of travel behavior. It also supports the development of more complex models that simultaneously integrate auto ownership, mode choice, residential choice, etc. Additionally, this approach necessitates the collection of data about interpersonal, time, spatial, household, and environmental constraints and has induced a shift toward the use of activity-based surveys in place of travel-diary surveys.

Positive utility of travel

While the activity-based approach is based on the idea that the demand for travel is derived from the demand for activities, the concept of the positive utility of travel posits that travel behavior also has value for its own sake (Salomon and Mokhtarian, 1998; Mokhtarian et al., 2001). In this approach, both the disutility (negative costs) and the positive benefits of travel, such as the enjoyment of beautiful scenery, adventure seeking, enjoyment of independence, and value of mobility, are acknowledged as important influences on behavior.

This approach suggests that given that people's tastes regarding travel behavior vary and travel can offer positive utility in its own right, there is a need for further research to segment the population based on their views of the positive aspects of travel. The value of this approach is to extend the scope of explanatory factors for travel behavior. Instead of considering just the opportunity cost associated with traveling, researchers might examine activities conducted while traveling (e.g. listening to the radio, watching the scenery, and thinking) and their contribution to the relative utility of different choices. This approach emphasizes the need to understand individuals' cognitive factors, such as the attitude of liking traveling, to forecast travel demand more accurately.

2.1.2 Physical activity behavior theories

Since bicycling involves physical activity, the main theories used in the physical activity and health behavior fields, including the theory of planned behavior, social cognitive theory, the concept of social support, and the ecological approach, are described here. These theories also contribute to the development of the conceptual framework on which the dissertation is based.

Theory of Reasoned Action and Theory of Planned Behavior

The Theory of Reasoned Action, a precursor to the Theory of Planned Behavior, states that individual performance of a given behavior is primarily determined by a person's intention to perform that behavior (Ajzen and Fishbein, 1980). Behavioral intention is driven directly by two motivation factors, attitude toward the behavior and subjective norm. Attitudes are influenced by behavioral beliefs (i.e., beliefs about the outcomes of the behavior and the value of these outcomes), while subjective norms depend on normative beliefs (i.e., beliefs about what other people think the person should do, as well as the person's motivation to comply with the opinions of others). The Theory of Planned Behavior strengthened this theory by adding another important factor – perceived ability to perform the behavior of interest, that is, perceived control over the behavior as impacted by control beliefs (Ajzen, 1991). This factor later was recognized as self-efficacy.

The Theory of Planned Behavior helps in taking a broader view of bicycling as a human behavior besides its specific roles as a means of transportation and a form of physical activity. This theory provides a more sufficient conceptual framework for studying bicycling: in addition to attributing bicycling to socio-demographics and constraints as in travel behavior theory, the importance of other explanatory factors, such as attitudes toward bicycling, subjective norms (perceived social norms), and self-efficacy, should be examined in efforts to understand bicycling.

Social Cognitive Theory and Social Support

Social Cognitive theory, developed from social learning theory and commonly attributed to Bandura (1986), proposes that rather than being driven by internal or external motivations or automatic mechanisms, human behavior should be understood in a complex reciprocal causation model in which individual behavior, personal factors including cognition, and environment, both socio-cultural and physical, work together and influence each other. Individual behavior is formed and shaped by self-beliefs and environment; on the other hand, individuals can change their environment and cognitions through their behaviors. Bandura stated that the influences from these different sources do not have equal strength; the influences may take time to occur and do not necessarily occur simultaneously. The fundamental part of this theory is the concept of self-efficacy—the confidence of an individual when performing the behavior, which is believed to be the most important intrapersonal factor determining the behavior: only individuals with self-efficacy have the intention to be involved in the behavior. To strengthen the behavior, Bandura (1989) emphasized the importance of social support, which provides incentive and courage to perform the behavior especially when confronted with obstacles and stresses. Social support is often accounted for in physical activity research, but in various forms. For example, social support for bicycling can take the form of bicycling accompanied by family members or friends, bicycling education, or even providing a friendly bicycling trip information system. Social Cognitive theory suggests, as an underlying mechanism of behavior, that an individual without self-efficacy would not perform the behavior even with expected benefits from the output of the behavior.

The importance of social support, emphasized by the theory of Social Support, has also gained the attention of behavioral researchers. Most importantly, the theory of Social Support focuses on the interactional relationships between the individual, the environment where the behavior occurs, and individual cognition and beliefs and thus improves the explanatory power of the conceptual framework. It also points to the need for more complicated models, such as simultaneous models, that can account for the interactions among these factors. One weakness of this theory is that although it recognizes the influence of physical environment on behavior, both the theory and its applications stress the importance of social factors for their function in cognitive development. Ecological approaches remedied this limitation and put more weight on the impacts of physical environment.

Ecological approaches

Ecological approaches, a further development in social cognitive theory, have been embraced by researchers in the physical activity field. Based on this theory, researchers attempt to understand the behavior of interest through observing a larger, interacting, holistic system. This theory states that effective interventions exert impacts on individual behaviors through multiple levels: intrapersonal, interpersonal, institutional, and community factors as well as public policy; some researchers categorize factors into three levels as individual, organizational, and governmental factors (Sallies and Owen, 2002). The intrapersonal level focuses on individual factors including attitudes, cognitions, and self-efficacy. The interpersonal and institutional level refers to relationships with family members, friends, neighbors, and institutions like schools, workplace, and church that reflect the social culture around the behavior of interest. The community level indicates the physical environment, or the characteristics of geographic areas. The public policy level is about the policies, procedures, and laws relevant to the behavior of interest. The behavior can be expected to be maintained in the long-run as a habit if exerted on by interventions that have simultaneous impacts on all these levels. This theory positions the importance of the environment, including both physical and social environments, on a par with individual factors in encouraging or changing the behavior and suggests a "reciprocal causation" between the individual and the environment.

Ecological models are widely used in physical activity research within the field of public health. The ecological approach provides a useful conceptual framework for understanding bicycling behavior from a broader standpoint. The conceptual framework for this dissertation follows this approach and guides the development of empirical models for exploring the determinants of bicycling behavior.

2.1.3 Summary of theoretical foundations

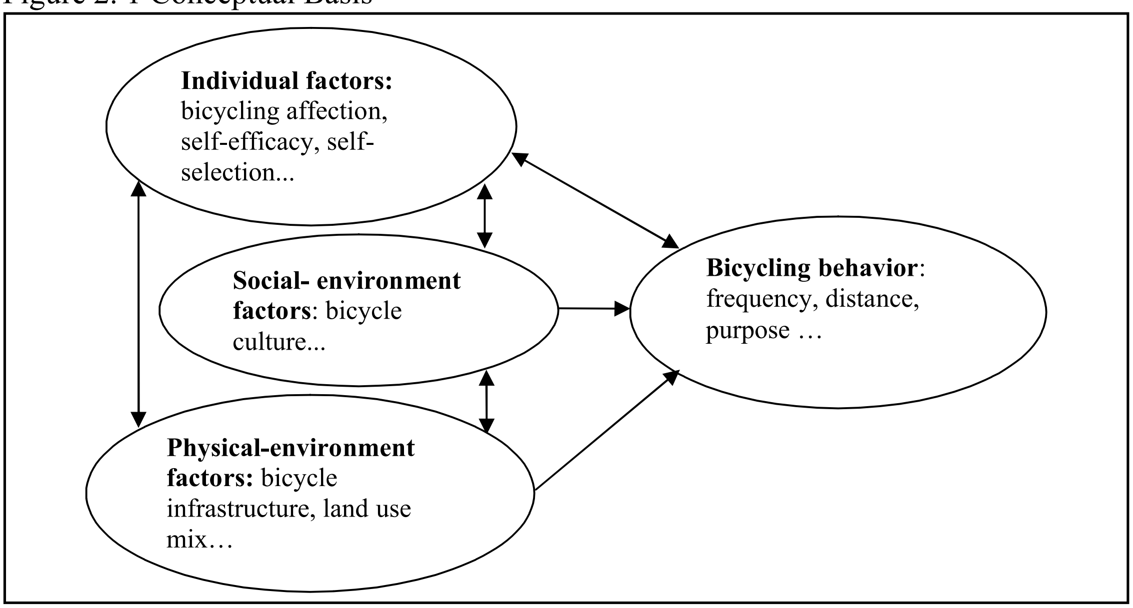
This section described the mainstream theories relevant to bicycling, from conventional travel behavior theory to ecological approaches heavily used in the physical activity field. Driven by the change of purpose from forecasting to explaining (in order to enhance or limit) the behavior, a richer spectrum of determinants of behavior and more complex relationships between these factors and behavior have been articulated in these theories. For example, the concept of positive utility of travel helps researchers to better understand the diversity of individual travel demand by emphasizing positive aspects of travel, in comparison to traditional analyses that focus on negative aspects of travel. Theories applied in physical activity research provide guidance on more potential explanatory factors, including cognitions and beliefs, self-efficacy, and social environment. Further, the reciprocal relationships between individual behavior and its associated factors identified in these theories suggest a need for more complicated empirical models to better understand bicycling behavior.

2.2 Theoretical Basis for Bicycling Derived from Travel and Physical Activity Behavior Theories

Bicycling, as a travel behavior, is not only a means of reaching a destination but also a form of physical activity. Therefore, theories focusing on both travel behavior and physical activity help in constructing the conceptual framework for understanding bicycling behavior. We borrow heavily from ecological models, widely used in physical activity research, to develop the conceptual framework for bicycling for this study. Specifically, we explore a comprehensive set of factors at multiple levels as potential influences on various aspects of bicycling behavior. The framework (Figure 2.1) based on this ecological model distinguishes between individual factors, social environment factors, and physical environment factors in explaining bicycling behavior. Individual factors include affection, beliefs, and self-efficacy, as well as residential self-selection ("The tendency of people to choose locations based on their travel abilities, needs and preferences" (Litman 2011, p. 8). Social-environment factors reflect the social culture, also known as the external or group culture (Jenkins 2004), which is created through social interactions and reflected in the collective behaviors of its residents. Physical-environment factors depend on the nature of land use patterns, transportation infrastructure, and the natural environment.

The three sets of factors are hypothesized to directly affect bicycling behavior (Figure 2.1). Individual factors contribute to the motivation to bicycle, while social and physical environment factors determine the quality of bicycling conditions and may enable and encourage bicycling, or hinder and discourage it (Handy 1996; Handy 2009). From the perspective of travel behavior theory, bicycle infrastructure influences the utility of bicycling for an individual, affecting travel time, safety, comfort, enjoyment, and other qualities of the bicycling experience that may be important to an individual when deciding whether or not to bicycle. Communities invest in bicycle infrastructure in order to increase the utility of bicycling and thus increase the likelihood that individuals choose bicycling over other options. Note that these factors may affect each other over time; a supportive social environment for bicycling, for example, may lead to community investments in bicycle infrastructure, while good infrastructure, in turn, may help to generate a supportive environment. The two-headed-arrows in Figure 2.1 illustrate the possible interactions of the categories of variables and one-headed-arrows represent causal links between any two categories.

Figure 2. 1 Conceptual Basis



Note that in this model we do not assume that the relationships between the physical and social environments and bicycling behavior are reciprocal, even though both social cognitive and ecological models suggest they are. Unlike more immediate relationships between individual factors and bicycling behavior or individual factors and the environment, which could influence each other in a relatively short time, bicycling behavior is likely to affect the environment only in the long run. For instance, it may take a long advocacy effort on the part of bicyclists to get the city to approve and construct a bicycle lane. Behavior may influence the social environment in an even slower way than it does the physical environment; change in the social environment usually lags behind change in the physical environment. Bandura (1989, pp. 62-63) cited other researchers' work in arguing that behaviors create opportunities to provide an enriched physical environment that could then accelerate the development of a relevant social culture. Due to the lack of long-term longitudinal data, we simplify these relationships and focus on a short-term model.

This conceptual framework offers a way of understanding the findings of empirical studies reviewed in the following section. Further, it provides guidance for the research design, proposed hypotheses, data collection, variables selection, establishment of the models, as well as interpretations of the outputs. It is the foundation for this research that aims to explore the complex relationships between individual, environment, and bicycling.

2.3 Empirical Literature Review

This section provides a detailed literature review of previous bicycling studies. Bicycling research attempts to understand factors contributing to variations in bicycling behavior. Bicycling behaviors of interest, empirical methods employed, and explanatory factors examined in previous bicycling studies, both from travel behavior and physical activity area, are presented. Explanatory factors fall into categories illustrated in the conceptual framework (Figure 2.1). Special attention is given to previous studies that examine the complex relationships between various factors and travel behaviors as a basis for constructing the hypotheses for this dissertation.

2.3.1 Literature review of factors associated with bicycling: from travel behavior and physical activity field

Previous research provides evidence of the importance of individual, social-environment, and physical-environment factors on bicycling behaviors (e.g. cycling share, time, distance, bicycling choice, bicycling frequency, bicycle commuting) as well. In this section, bicycling behaviors of interest, methods used, and factors examined in previous studies are documented.

Bicycling of Interest: Bicycling Percentage, Time or Distance, Choice, Frequency, and Purposes

To provide answers to specific policy questions facing planners, researchers focus on various aspects of bicycling. Some studies explore the reasons that the shares of bicycling in some cities or areas are greater than those in others (e.g. Dill and Carr, 2003; Rietveld and Daniel, 2004). Some aim to explain variations in bicycling frequencies (e.g. Stinson and Bhat, 2004). Some studies, especially physical activity studies, are more interested in the time spent bicycling or the distance covered, as this aspect is important for health (e.g. Troped et al., 2003). In some studies, bicycling is analyzed regardless of its purpose (e.g. Moudon et al., 2005); others focus on bicycling for a specific purpose, such as bicycling for transportation including bicycle commuting (e.g. Geus et al., 2007; Cervero et al., 2009) or bicycling for recreation (e.g. Kamphuis et al., 2008).

However, research on the question of bicycling purpose is limited. Most previous bicycling research focuses on utilitarian bicycling rather than recreation bicycling. These studies point to several factors that affect the choice to bicycle or the frequency of bicycling for transportation. Motivated by an interest in making efficient use of limited roadway capacity and reducing peak-period congestion, most studies of transportation-oriented bicycling focus on bicycle commuting.

Little is known about the factors that affect bicycling for recreation, as only a few studies focus on bicycling for this purpose (Kamphuis et al., 2008). Even fewer studies look directly at the differences between transportation and recreation bicycling. Those that do tend to come from the physical activity literature rather than the transportation literature. Hoehner et al. (2005) explored factors associated with engagement in any transportation-oriented bicycling versus non-transportation bicycling. Troped et al. (2003) concluded that certain physical-environment factors significantly affect weekly minutes for transportation-motivated physical activities (walking and bicycling to or from work, school, or store), but have no impact on weekly minutes for recreational activities. Studying bicycling in general rather than by purpose may mask important differences in the effects of specific factors. For instance, longer trip distances are generally believed to decrease bicycling for transportation, but may be positively associated with recreational bicycling.

Methods of analysis

Besides differences in the aspect of bicycling of interest, previous studies differ in their methods, reflecting differences in research design and data availability. In this section, various analysis techniques are introduced: some studies on bicycling employ descriptive analyses to report bicycling characteristics; most studies reviewed here examine factors influencing bicycling with explanatory methods. The following review of bicycling studies is organized by the two types of analysis methods.

● Descriptive analysis

Descriptive analysis focuses on univariate distributions, i.e. characterizing the variables themselves. Some studies (e.g. Bureau of Transportation Statistics, 2002; Federal Highway Administration, 1992; National Highway Traffic Safety Administration and Bureau of Transportation Statistics, 2003; Pucher and Dijkstra, 2003) use descriptive analysis to report general information about bicycling behavior, e.g. share of male/female bicyclists, share of bicyclists at a certain age-level, etc., in a specific area. Using this method, the studies illustrate different observed patterns of bicycling in different areas. However, the specific characteristics of each pattern and the differences between the patterns cannot be explained by this descriptive method.

● Explanatory analysis: single equation modeling

Explanatory analyses are used to explore or confirm relationships between variables and thus bivariate or multiple variable methods are applied. Three types of explanatory analyses, single equation modeling, simultaneous equation modeling, and structural equation modeling, are briefly introduced in this section.

Most bicycling studies use single equation models, including multiple variable linear regressions and various discrete choice models, to examine factors associated with bicycling. The limit of a single equation model is that it only reveals associations rather than accounting for multiple directions of relationships between factors and bicycling.

Two types of explanatory analyses with single equation modeling, studies with aggregate data and disaggregate data, are reviewed separately. Based on different sources of data, studies using disaggregate data are categorized into three types: secondary survey data, original survey data, and joint data. The advantages and limitations of two types of disaggregate analysis are also discussed briefly in this section.

Analysis with aggregate data Studies with aggregate data test macro-scale variables related to bicycling using as a analysis unit a large geographic area such as census tract, Traffic Analysis Zone (TAZ), or city. Previous studies apply multiple linear regression analyses to aggregate data to test the influence of macro-scale demographic and geographic factors on bicycle use. Bicycle use is usually examined as a continuous measurement, such as bicycling share, in in these studies. For example, Baltes (1997) uses 1990 U. S. Census Metropolitan Statistical Area Data from 284 metropolitan statistical areas to reveal factors influencing the share of bicycle commuting; Nelson and Allen (1997) explain the relationship between the share of bicycle commuting and miles of bikeway per 100,000 people, based on the city as the unit of analysis; Dill and Carr (2003) use census data from 35 large cities across the U S to analyze factors associated with cycling rates in the cities. Pucher and Buehler (2006) analyze factors related to the natural log of the odds of cycling—the ratio of the share of bicycling to its complement—with state/province as the analysis unit in the U. S. and Canada.

Aggregate analysis sheds light on the factors influencing bicycle use by supplying statistical evidence on factors predicting bicycling. However, relying on aggregate data, which is easier to obtain, limits the analysis of micro-level detail factors; e.g. the impacts of an individual's socio-demographic characteristics are not revealed in such analysis. In addition, the expectation that the relationship between factors and bicycling for an individual in the group from which the aggregate data were collected can be inferred from the relationship for the group as a whole could lead to a widely recognized error, the "ecological fallacy."

Analysis with disaggregate data Analysis with disaggregate data reveals particular micro-level factors associated with bicycling with the individual or household as the analysis unit. In disaggregate studies, bicycling is usually examined as a discrete measurement: dichotomous choice—bicycling or not (Cervero and Duncan, 2003; Moudon et al., 2005; Krizek and Johnson, 2006; Geus et al., 2007); polytomous choice—bicycling versus driving or other modes (EPA, 2003; Wardman et al., 1997; Plaut, 2005; Wardman et al., 2006); or ordinal choice—various bicycling frequency choices (Stinson and Bhat, 2004). Accordingly, discrete choice models are commonly employed in analyses using disaggregate data. Studies using disaggregate data are divided into three categories according to the source of survey data used: analyses with secondary survey data, analyses with original survey data, and analyses with joint data.

Some disaggregate bicycling studies use secondary survey data, i.e., data from surveys designed for other purposes. Plaut (2005) analyzes the choice of cycling to work using the national data set from the annual American Housing Survey (AHS), which includes detailed commuting information for individuals. The US Environmental Protection Agency (2003) has led a study on choice of mode to school with a multinomial logistic model based on two consistent travel surveys in Alachua County, Florida. For researchers, secondary survey data are easily obtained and analyzed compared with first hand data collection. However, because a limited number of potential factors associated with bicycling can be created from existing surveys designed for other purposes, the model specification may be dictated more by the data than conceptual considerations.

Some studies collect and analyze disaggregate data from original surveys on bicycling, which provide the opportunity for researchers to test more specific factors hypothesized to influence bicycling. Two types of original surveys are categorized according to different methods: one is designed as a revealed preference survey, in which individuals' actual choices are reported (e.g. Geus et al., 2007; Shafizadeh and Niemeier, 1997; Stinson and Bhat, 2004); the other is a stated preference survey, in which individuals' choices under hypothetical conditions are reported (Wardman et al., 1997; Wardman et al., 2007). Stated preference surveys on cycling compensate for a small share of cycling or for nonexistent bicycle facilities in the surveyed area. Both types of original surveys with the individual as the unit of analysis supply perceived neighborhood-level measures of the bicycling environment. Bicycle use is examined in these studies by applying multiple variable analysis including discrete choice models.

Some disaggregate studies with an emphasis on bicycle use join different types of data to measure specific explanatory variables. Geographic information system (GIS) data is joined with survey data in some studies (e.g. Krizek and Johnson, 2006; Moudon, 2005) to examine objective measures of the physical environment, as opposed to the perceived measures in the studies mentioned above. Multiple variable discrete choice models, such as discrete logit models, are usually used in these studies. The objective neighborhood environmental characteristics associated with bicycling are revealed through these analyses.

- Explanatory analysis: multi-directional causal modeling

In single equation models, a single dependent variable is a function of explanatory variables. Associations are assumed to exist between the dependent variable and the explanatory variables. Some researchers seek a better understanding of complicated behaviors by hypothesizing multi-directional causal relationships between relevant variables. In these studies, multi-directional causal modeling is employed to examine the effect of one variable on another. A dependent variable (endogenous variable) in one equation could be an explanatory variable in other equations and all dependent variables are jointly determined by all the equations simultaneously. Based on the type of endogenous variables, the multi-directional causal modeling employed by previous travel studies fall in two major categories, causal modeling with continuous and discrete endogenous variables.

Continuous endogenous variables Multidirectional causal modeling with continuous endogenous variables is subdivided further into the pure structural model (also known as simultaneous equations model) that contains only observed endogenous variables, and the general structural model that also includes latent endogenous variables. A special case of the latter specifying only the relationships between latent variables (unmeasured variables, generated by several observed indicators according to a hypothetical construct) and their observed indicators is known as a measurement model. To the best of our knowledge, no prior study on bicycling has employed either of the approaches to confirm relationships between hypothesized explanatory factors and bicycling

Discrete endogenous variables Special cases of a more general multi-directional causal modeling emerged later with discrete endogenous variables. One team of researchers (Pinjari et al., 2008) employed this approach with dichotomous (residential location type) or ordered (number of bicycles) endogenous variables to test whether a causal relationship exists between neighborhood attributes and bicycle ownership based on disaggregate data. The results indicate that a residential self-selection effect is caused by socio-demographic characteristics such as number of children and home ownership. An important finding is that self-selection effects may lead to severe overestimation of the impact of bicycle-friendly neighborhood type on bicycle ownership, because the effect of bicycle-friendly neighborhood type is as a mediator between preferences and bicycle ownership rather than an independent factor.

Factors examined in previous bicycling studies

All explanatory factors examined in previous studies fall into one of three categories: individual factors (including socio-demographics and attitude factors), physical-environment factors, and social-environment factors, as described in the conceptual framework (Table 2.1).

- Individual factors

Previous research on bicycling provides evidence of socio-demographic factors associated with cycling behavior. Bicycle ownership or number of bicycles in household is an important determinant of cycling behavior (Moudon et al., 2005; Cervero and Duncan, 2003; Krizek and Johnson, 2006). Some studies show that men make more bicycle trips than do women (Williams, 1996; Stinson and Bhat, 2004; Wardman, 2007). Age is shown to be negatively associated with bicycle-work trips (Plaut, 2005; Wardman et al., 2007); however, in some studies, age is not significant (Stinson and Bhat, 2004) or even positively related to cycling (Krizek and Johnson, 2006). The effect of income is not clear in some studies (Goldmith, 1992; Stinson and Bhat, 2004). Niemeier and Rutherford (1995) indicate that people with higher incomes are less likely to bicycle, which is also indicated in recent studies on the propensity to cycle (Plaut, 2005; Wardman et al., 2007). In contrast, Shafizadeh and Niemeier (1997) indicated that higher income respondents tended to report longer bicycle commuting travel times. Owning no cars is positively associated with the propensity to bicycle (Stinson and Bhat, 2004; Plaut, 2005). The Non-Caucasian race is associated with reduced likelihood to bicycle in some studies (Plaut, 2005; Moudon et al., 2005) while it has a positive influence on cycling in Cervero and Duncan's (2003) study. Plaut (2005) reveals that education is positively related to bicycling. Moudon et al. (2005) find healthier people are more likely to bicycle.

Attitude, in general, is an individual's specific cognitive, affective, conative, and normative beliefs toward an object. Cognitive beliefs denote what people perceive; affective beliefs indicate what people like; conative beliefs are what people intend; and normative beliefs are about what people think should be done. Given the importance of attitudes in explaining driving behavior (e.g. Ory, 2007), it seems likely that attitudes of various sorts influence bicycling. However, few studies have examined this possibility. One recent study of bicycling among a working population found that people who have external self-efficacy (as indicated by the willingness to cycle even if the weather is bad) are more likely to bicycle for transport (Geus et al., 2007). Ecological-economic awareness (agreement that cycling is cheaper, better for the environment, etc.) also correlated closely with bicycle commuting in this study. Gatersleben and Appleton (2007), using stated preference methods, found that people who like bicycling would bicycle commute under most circumstances. Using factor analysis and binary logit models, direct trip-based benefit (constructed mainly of the characteristics time-saving and comfort, and to a lesser extent, flexible and pleasant.), awareness (higher scores on environmental benefit, health benefit and mentally relaxing), safety (higher scores on social safety and traffic safety), cycling habit (respondents were asked which transport mode would be most likely be used for 10 different), subjective norm (determined by the question ‘‘To what extent do important people in your surroundings think you should travel by bicycle to work?” were all found to be positively associated with both longer and shorter bicycle commuting trips and choice of daily bicycle commuting (Heinen et al., 2011).

Another set of potentially important individual factors are constraints. Factors that may constrain the ability of an individual to bicycle include physical ability and health condition that may constrain bicycling, though previous bicycling studies have not examined these factors.

Previous studies of bicycling have not explored the possibility of “self-selection” (Cao et al., 2009), defined in this case as the possibility that residents of a city choose to live there in part because of the supportive bicycling environment. Although it is reasonable to assume based on prior studies that a pro-bicycle environment leads to more bicycling, it is also possible that an individual’s preference for bicycling leads him to choose to live in a community like Davis. In this case, the path of causality runs directly from preferences to bicycling behavior but also indirectly from preferences through pro-bicycle environment to bicycling behavior.

- Physical-environment factors

In this study, the physical environment is classified into the “built environment,” consisting of “urban design, land use, and the transportation system, and encompasses patterns of human activity within the physical environment" (Handy et al., 2002), and the "natural environment," such as weather, climate, topography, and scenery, etc. Most previous studies focus on testing the links between built-environment factors and bicycling behavior. Since bicycling is not only a travel behavior but also a form of physical activity, we follow the general categories summarized by Handy (2005) from various measures of the built environment in physical activity studies, in which the physical environment is measured more broadly than it is in travel behavior studies. The general groups of physical-environment factors examined in previous cycling studies include measures of land use, transportation system, accessibility, safety, and neighborhood type, all of which are measures of the built environment. Some studies measure topography and darkness, which fall into the category of "natural environment." The definitions of the measures and their influences revealed in previous bicycling studies are illustrated in Table 2.1.

"Land use factors" reflect "the spatial distribution of human activities" (Handy, 2005). The "land use factors" examined in bicycling research include: measures of population and/or employment density (Guo et al., 2007; Cervero and Duncan, 2003); land use mix, referring to mixed-use of residential, commercial and other land use types (Guo et al., 2007; Moudon et al., 2005); and land-use mix in the origin/destination of the trip (Cervero and Duncan, 2003). Some studies show significant impacts of employment density and land-use mix on bicycling (Parkin et al., 2008; Moudon et al., 2005).

“Transportation system” refers to bicycle infrastructure (bike lanes, paved shoulders, separated bicycle paths, bicycle network connectivity, etc.) and “the services mak[ing] up the transportation system” (Handy, 2005), e.g. cycling facilities in the form of bike racks and bicycle lockers, etc. Although many studies show that bicycle infrastructure and services promote cycling, some studies have failed to confirm this point (e.g. Geus et al., 2007; United States Environmental Protection Agency, 2003).

“Accessibility” reflects “both the locations of land uses and characteristics of the transportation system” (Handy, 2005). Two types of accessibility have been measured in travel behavior studies: one type is distance or travel time to destinations; the other type is “a cumulative opportunities measure, which counts the number of potential destinations or amount of activity of the specified type within a particular distance” (Handy, 2005). Previous cycling studies have measured the first type of accessibility as distance to destinations, such as the work place or trail (Stinson and Bhat, 2004; Moudon et al., 2005); or bicycling time to destinations, including the food store and bus stop (Geus et al., 2007; EPA, 2003). The second type of accessibility has been measured by the number of jobs, stores and schools within a particular distance or area (Cervero and Duncan, 2003; Moudon et al., 2005; Handy and Xing, 2010). The influences of the two types of accessibility factors are not clear: some studies indicate statistically significant impacts of accessibility on bicycling; some do not.

“Safety” refers to perceived or observed bicycling safety. Safety has been measured in cycling studies as perception of traffic speed, presence of streetlights, risk of accident, fearing of crime when bicycling (Geus et al., 2007), observed cycling fatality rate in an area (Pucher and Buehler, 2006), and perceived safety to destinations, as well as perceived dangerous streets around the workplace for bicycling (Handy and Xing, 2010). In both studies of Geus et al. (2007) and Handy and Xing (2010), the factors measuring bicycling safety were found to be negatively associated with bicycling.

Some bicycling studies use a composite measure, the type of neighborhood, as opposed to specific characteristics. This composite measure may reflect all aspects of the built environment. Previous cycling studies categorize neighborhood types as urban, suburban (Stinson and Bhat, 2004), and rural; or the metropolitan area in an urban area and a non-metropolitan area (Plaut, 2005). Results show that people living both in urban or suburban areas and within metropolitan areas are more likely to bicycle.

The natural environment is also a part of the physical environment. It measures other natural characteristics of the physical environment, e. g. topology, weather, etc. Previous bicycling study shows that hilly topography (Handy and Xing, 2010) and the slope of the trip (Cervero and Duncan, 2003) are not significantly associated with bicycling, whereas darkness correlates significantly with lower likelihood of bicycling (Cervero and Duncan, 2003). Weather, rainfall, and temperature are also associated with bicycling in some studies (Dill and Carr, 2003; Pucher and Buehler, 2006; Parkin et al., 2008).

- Social-environment factors

Social-environment factors examined in previous studies are shown in Table 2.l. Several social-environment factors have been found to be associated with bicycling: “psychosocial factors” (Geus et al., 2007), “supervisor disapproval” (Handy and Xing, 2010), and “kids bike” (Xing et al., 2010). Having relatives who give social support through accompaniment while bicycling encourages bicycling (Geus et al., 2007). The perception that bicycling is a normal means of transportation in a community promotes bicycling (Handy and Xing, 2010). In contrast, the perception of an anti-bicycling social environment in a community and the workplace discourage bicycling (Handy and Xing, 2010). Other aspects, such as social support through encouraging cycling, social influence on cycling, social norms related to bicycling, tested in Geus, et al. (2007), and the social support for cycling in the neighborhood measured in another study (Moudon et al., 2005) do not add explanatory power in models of bicycling behavior.

Table 2. 1 Social and Physical Environment Factors Associated with Bicycling in Previous Studies

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
Physical environment						
Land Use	Population density	Population divided by area	Aggregate analysis: binary proportions logistic model	The proportion that cycle to work in the 8800 English and Welsh electoral wards.	+	Parkin et al., 2008
	employment-accessibility	Number of jobs (in 10 000s) within 5 miles of origin	Binary logit model	The trip by bicycle or not	-	Cervero and Duncan, 2003
	Retail/service density	Number of retail/service jobs per net commercial acre within 1 mile of origin	Binary logit model	The trip by bicycle or not	+	Cervero and Duncan, 2003
	Land use mix	More parcels within the closest office, fast food, hospital/clinic	Binary logit model	Bicycled at least once per week or not	+	Moudon et al., 2005
	Land use diversity factor	Jobs spread across the retail/service, office and manufacturing/trade/other sectors at the origin or destination, using factor analysis.	Binary logit model	The trip by bicycle or not	+	Cervero and Duncan, 2003
Transportation System	Bicycle pathway	Bicycle pathway miles per 100,000 residents	Aggregate analysis: linear regression	Commuters using bicycles in their journey-to-work in city i (%)	+	Nelson and Allen, 1997
	Type 2 lanes	The mileage of Class II bike lane/square mile	Aggregate analysis: linear regression	Percentage of workers commuting by bicycle	+	Dill and Carr, 2003
	Accessibility to bike facility	Distance to nearest on-street bicycle path <400m compared the that >=1600 m as the base	Binary logit model	Biked at least once during 24-hour period	+	Krizek and Johnson,2006
	Presence of amenities for cycling	Perceived presence of bicycle lanes and trails in the neighborhood	Binary logit model	Bicycled at least once per week or not	+	Moudon et al., 2005

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
	Bike facilities	The presence of bike racks or lockers at workplace	ordered response model	Bike commuting frequency (once or twice a month; once a week; 2-3 days per week; 4-5 or more days per week	+	Stinson and Bhat, 2004
	Bike facilities	Average score of 5 items about facilities for cyclists at the workplace	Binary logistic regression	Biked at least once a week to work in the last 6 month or not	+	Geus et al., 2007
	Cycle facilities	the availability of cycle facilities at the workplace	Binary logistic regression	Biked at least once a week to work in the last 6 month or not	+	Geus et al., 2007
	Bike-friendly design	Street and city block characteristics, e.g. the block size, gridiron streets and other design attributes	Binary logit model	The trip by bicycle or not	+	Cervero and Duncan, 2003
	Bike route	Proportion of off-road route	Aggregate analysis: binary proportions logistic regression model	The proportion that cycle to work in the 8800 English and Welsh electoral wards.	+	Parkin et al., 2008
	Transport demand intensity	employees divided by road length	Aggregate analysis: binary proportions logistic model	The proportion that cycle to work in the 8800 English and Welsh electoral wards	-	Parkin et al., 2009
	Stop frequency	The number of stops cyclists have to make on their routes	Aggregate analysis: linear regression	The share of bicycle in total number of trips per person per day in a municipality	-	Rietveld and Daniel, 2004
	hindrance frequency	Frequency of the hindrances per kilometer (such as posts, or too narrow infrastructure)	Aggregate analysis: linear regression	The share of bicycle in total number of trips per person per day in a municipality	-	Rietveld and Daniel, 2004

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
	Speed	Percentage of the trips when the bicycle is faster than the car out of the total number of trips	Aggregate analysis: linear regression	The share of bicycle in total number of trips per person per day in a municipality	+	Rietveld and Daniel, 2004
	Street density	Road km/land-area km2: medium-high (>0.2 or more) vs. the base low (<0.20)	Binary logit model	Sampled adults biked for utilitarian purposes at least 30 minutes per day for at least 5 days within last week or not	+	Cervero et al., 2009
	Cycle lane	Proportions of segments with an on-road cycle lane	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Track length	Total length of walking/cycling tracks (km)	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Traffic control devices	Proportions of segments with at least one traffic control device (speed bumps, traffic calming structures that effect the speed/ flow of traffic)	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Alternative routes	Proportions of segments with one or more other route available (that provide alternative ways of cycling around the neighborhood)	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Absence of drive way crossovers	Average score for drive way crossovers (1=most buildings have driveway, 2=half of buildings have driveway, 3=quarter of buildings have driveway, 4=no driveways)	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Verge width	Average path-location-score (1=next to road, 2=,1 m from kerb, 3=1–2 m from kerb, 4=2–3 m from kerb, 5=3.m from	Binary logistic regression	Recreational biking at least once a month vs. never	-	Kamphuis et al., 2008

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
		kerb)				
	Destination present	Proportion of segments with at least one destination present	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	Lack of garden maintenance	Average score for garden maintenance (1=.75% well maintained, 2=50–75% well maintained, 3=,50% well maintained)	Binary logistic regression	Recreational biking at least once a month vs. never	-	Kamphuis et al., 2008
	Park area	Total park area (km2)	Binary logistic regression	Recreational biking at least once a month vs. never	+	Kamphuis et al., 2008
	parking costs	measured in eurocents per hour	Aggregate analysis: linear regression	The share of bicycle in total number of trips per person per day in a municipality	+	Rietveld and Daniel, 2004
	Parking cost	The monthly cost of parking at workplace, in dollars	Binary logit model	The usual mode for the longest portion of work-trip in a typical week is bike vs. car	+	Handy and Xing, 2010
Accessibility Type I	Trip distance	Measured in miles	Binary logit model	The trip by bicycle or not	-	Cervero and Duncan, 2003
	Distance to work	Measured in miles	Ordered response model	Bike commuting frequency (once or twice a month; once a week; 2-3 days per week; 4-5 or more days per week)	-	Krizek and Johnson,2006
	Miles To Work	The distance from home to work. Continuous in miles	Binary logit model	The usual mode for the longest portion of work-trip in a typical week is bike vs. car	-	Handy and Xing, 2010

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
	Proportions of distance to work	Proportion Of journeys to work in the distance bands ‘‘under 2 km’’, ‘‘2–5 km’’, ‘‘5–10 km’’, ‘‘10–20 km’’, ‘‘20–30 km’’, ‘‘30–40 km’’, ‘‘40–60 km’’, ‘‘60 km and over’’ at ward level	Aggregate analysis: binary proportions logistic regression model	The proportion that cycle to work in the 8800 English and Welsh electoral wards.	-	Parkin et al., 2008
	Bike time	Bike time (in minutes) for the trip	Multinomial logit model	Drive, school bus, walking, biking to school, auto as the base mode.	-	EPA, 2003
	Trail proximity	Shorter distance to the closest trail	Binary logit model	Bicycled at least once per week or not	+	Moudon et al., 2005
Accessibility Type II	Employment accessibility	Number of jobs (in 10,000) within 5 miles of origin	Binary logit model	The trip by bicycle or not	+	Cervero and Duncan, 2003
	Accessibility of store	Smaller total area of the convenience store parcels within 3 km buffer	Binary logit model	Bicycled at least once per week or not	+	Moudon et al., 2005
	Accessibility of destinations	Presence of destinations (grocery stores and schools) in neighborhood	Binary logit model	Bicycled at least once per week or not	+	Moudon et al., 2005
	Distance to destinations	Average perception of distances from home to “your usual grocery store”, “the nearest post office”, “a restaurant you like”, “a bike repair shop”, “your workplace”, “the local elementary school”	Binary proportions logit model	Proportions of transportation biking vs. that of recreational biking	-	Xing, et al., 2010
Safety	Street safety	Death rates in traffic accidents (fatalities per year): >10 vs. the base 0--10	Binary logit model	Sampled adults biked for utilitarian purposes at least 30 minutes per day for at least 5 days within last week or not	-	Cervero et al., 2009

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
	Bike Dangerous Work	Agreement that “The streets near my workplace are dangerous for bicycling”	Binary logit model	The usual mode for the longest portion of work-trip in a typical week is bike vs car	-	Handy and Xing, 2010
	Cycling fatality rate	Fatality rate per 100,000 people cycling	Aggregate analysis: linear regression	Bike share of work trips	-	Pucher and Buehler, 2006
	Safe destinations	Average perception of safety bicycling to “your usual grocery store”, “the nearest post office”, “the local elementary school”, “a restaurant you like”, “the nearest bike shop”	Binary proportions logit model	Proportions of transportation biking vs. that of recreational biking	+	Xing, et al., 2010
	safety level	number of victims of serious accidents per 100 million bicycle-kilometres between 1996 and 2000	Aggregate analysis: linear regression	The share of bicycle in total number of trips per person per day in a municipality	+	Rietveld and Daniel, 2008
Neighborhood Type	Home location	Urban residence or suburban residence (base is rural residence)	Ordered response model	Bike commuting frequency (once or twice a month; once a week; 2-3 days per week; 4-5 or more days per week)	+	Stinson and Bhat, 2004
	Home location	Living in urban area within MSA*	Binary logit model	Commuting by bike vs. by car	+	Plaut, 2005
	Work location	Whether the work location is in an urban area (base: rural/suburban location)	ordered response model	Bike commuting frequency (once or twice a month; once a week; 2-3 days per week; 4-5 or more days per week)	+	Stinson and Bhat,2004
Natural Environment	Slope	Proportion of 1 km squares with slope 3% or steeper	Aggregate analysis: binary proportions	The proportion that cycle to work in the 8800 English and Welsh	-	Parkin et al., 2008

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
			logistic model	electoral wards		
	Landscape control variable	Slope >=3% vs. the base slope<=3%	Binary logit model	Sampled adults biked for utilitarian purposes at least 30 minutes per day for at least 5 days within last week or not	-	Cervero et al., 2009
	Darkness	Before sunrise or after sunset at the time of trip	Binary logit model	The trip by bicycle or not	-	Cervero and Duncan, 2003
	Raining days	The number of days during the year in which rain exceeds one-tenth of an inch (or the equivalent in snow).	Aggregate analysis: linear regression	Commuters using bicycles in their journey-to-work in city i (%)	-	Nelson and Allen, 1997
	Days of rain	Average annual number of days of rainfall (.01 inches or more)	Aggregate analysis: linear regression	Percentage of workers commuting by bicycle	-	Dill and Carr, 2003
	Rainfall	Total annual rainfall in millimeters	Aggregate analysis: binary proportions logistic model	The proportion that cycle to work in the 8800 English and Welsh electoral wards.	-	Parkin et al., 2008
	Precipitation	Precipitation (cm)	linear regression	Bike share of work trips	-	Pucher and Buehler, 2006
	Temperature	Temperature (C°)	linear regression	Bike share of work trips	+	Pucher and Buehler, 2007
	Temperature	Mean temperature in degrees centigrade	Aggregate analysis: binary proportions logistic model	The proportion that cycle to work in the 8800 English and Welsh electoral wards.	+	Parkin et al., 2008
Social environment						
	Social support: accompany	Relatives give social support through cycling together	Binary logistic regression	Biked at least once a week to work in the last 6 month or not	+	Geus et al., 2007

Category	Definition	Measure	Methodology	Aspect of Bicycling	Association	References
	Supervisor disapproval	Agreement that "My supervisors disapprove of commuting by bicycle"	Binary logit model	The usual mode for the longest portion of work-trip in a typical week is bike vs. car	-	Handy and Xing, 2010
	Kids bike	Agreement that "Kids often ride their bikes around my neighborhood for fun"	Binary proportions logit model	Proportions of transportation biking vs. that of recreational biking	-	Xing et al., 2010

Note: "+/-": positive/negative relationship.
* MSA refers the metropolitan statistical area.

2.3.2 Literature review of relationships among factors associated with travel behavior

Given the limitations of modeling methods of current bicycling studies, it is helpful to review evidence from previous travel behavior research that explored relationships among factors and various travel behaviors by employing structural equation modeling. The main purpose is to find more potential factors that might be important in explaining bicycling behavior as well as the underlying interrelationships among factors and bicycling.

Vehicle Ownership

Mutual causal links between vehicle ownership and use have naturally been examined in some travel behavior studies. Golob (1989), for example, assesses the strength of the impacts on trip generation of income and car ownership by using a structural equation model applied to panel data. In this study, car ownership is a function of increasing income and exogenous to the travel behavior variables. The results show that the strongest link is from car ownership to trips. Similarly, Simmer and Axhausen (2001) employ structural equations modeling to test a hypothesis as to the path linking car ownership and use. Car ownership is hypothesized to have a direct effect on car usage and be directly influenced by socio-demographics, gender and employment status. The results confirm that car ownership leads to the use of the car. These findings may imply an important role for bicycle ownership in explaining bicycling, as car ownership does for driving. Bicycle ownership may also be affected by individual factors.

Attitude

Attitudes, perceptions, or intentions are hypothesized to have causal impacts in some travel behavior studies that use structural equation modeling. Tardiff (1976) confirms a stronger link from behavior to attitudes than vice versa by using path analysis, a special case of structural equation modeling. Another study, Dobson et al. (1978), tests the nature of the interrelationships between traveler attitudes and behavior by using structural equations on data gathered from Los Angeles central business district workers and reveals mutual causal links between attitudes and behavior. In this paper, attitude is a function of demographic characteristics, e.g. income, and behavior. Attitudinal variables have the greatest direct impacts on travel behavior among the other variables tested in the study by Bagley and Mokhtarian (2002) using data for five neighborhoods in the San Francisco Bay Area. A more recent study (Ory, 2007) hypothesizes more generally that attitudes, including support for environmentally-friendly solutions to transportation problems, are influenced directly by personality traits, lifestyle, enjoyment of travel, and the ability to travel by different modes. This study shows that specific attitudes, such as enjoyment of travel, directly influence travel behavior; and vice versa.

Some previous studies focus on exploring impacts of internal or individual culture, reflected by an individual's self-concept, understanding, and belief (Jenkins, 2004). For example, attitudinal and lifestyle factors in the study by Bagley and Mokhtarian (2002) and attitude factors in Ory's (2007) study are confirmed to affect travel demand directly. These factors identify different types of individuals according to hobbies, interests, and enthusiasms, which are also considered as attitudes.

Physical and Social Environment

Some studies have explored the causal relationship between the built environment and travel behavior. The study by Bagley and Mokhtarian (2002) is the first disaggregate structural equation modeling employed to test whether a causal link exists from built environment to travel behavior. Controlling for attitudinal, life style, and socio-demographic variables, Bagley and Mokhtarian found little influence of the residential location on travel behavior. The result shows that the correlations between the built environment and travel behavior may be caused by the interactions of built environment with other variables. However, using a quasi-longitudinal study design, Cao et al. (2007) applied structural equations modeling to data from individuals who had recently moved to explore the impact of the built environment on travel behavior. They found a causal relationship between the built environment and driving and walking behavior. Specifically, increased accessibility leads to a decline in driving, i.e. close destinations combined with good alternatives to driving discourage driving and encourage more walking.

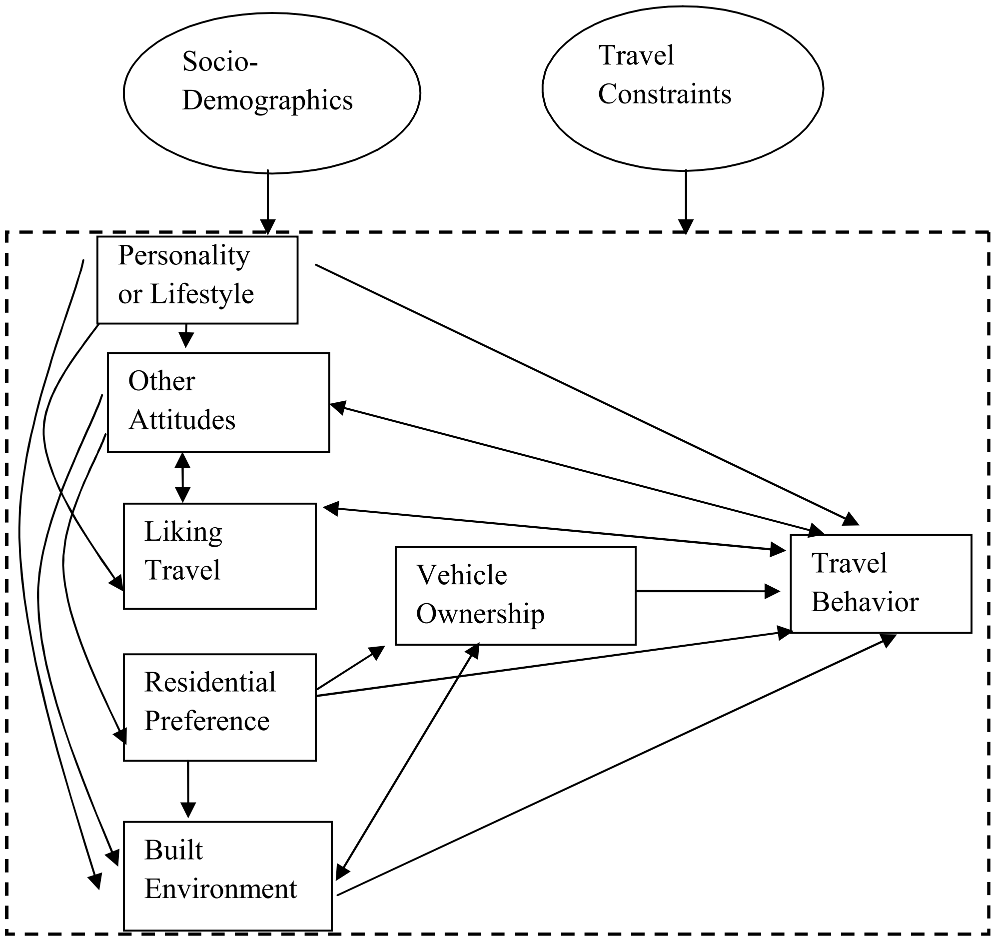
Social-environment factors, reflecting the external or group culture created by relationships between individuals in their social interactions, have rarely been examined in travel behavior studies.

Residential Self-selection

Residential self-selection is defined as "the tendency of people to choose locations based on their travel abilities, needs and preferences" (Litman, 2011). Residential self-selection was found to have an impact in the study by Cao et al. (2007). They constructed self-selection as a function of neighborhood preferences, travel-related attitudes, as well as socio-demographics and found that residential self-selection has a direct influence on travel behavior.

In summary, the confirmed causal links between the categories in these studies are illustrated in Figure 2.2. Nine categories of factors are found to have interactions in previous travel behavior studies. The categories are separated into exogenous variables (which are independent variables with no prior causes portrayed in the system of interest) and endogenous variables (which in this particular model are also all, with the exception of travel behavior, mediating variables, that is, they are both effects of some variables, whether exogenous or mediating, and causes of other variables, whether mediating or purely dependent); they are separated by the dashed rectangular box in Figure 2.2. Exogenous variables are variables that originate paths (one-way arrows), but never receive a path; i.e., no exogenous variables will appear in the left-hand side of an equation, in the system of model equations. Endogenous variables are variables that receive at least one path (one-way arrow or one direction of a two-way arrow). An endogenous variable category is shown as a solid rectangle; while an exogenous variable category is represented by an ellipse. Each category contains a set of individual variables. One-way arrows indicate the direction of a causal link from the category at the blunt end to the category at the pointed end; two-way arrows indicate causality in both directions.

Figure 2. 2 Confirmed Causal Links in Travel Behavior Studies



2.3.3 Summary of empirical literature review

Overall, although previous bicycling studies provide important insights into factors associated with bicycling, they do not effectively yield support for causal connections between environment and bicycling. In most bicycling studies, explanatory variables are treated as exogenous variables in single equation models, ignoring all possible endogeneity bias between them and accordingly yielding incomplete and potentially invalid results. Travel behavior studies employing structural equations modeling shed light on potential relationships between environment and bicycling. To capture the interactions among factors and with bicycling behavior, a structural equations model, developed from multiple single equations, will help to illuminate more plausible relationships between the variables.

2.4 Summary

In this chapter, theoretical foundations from conventional travel behavior theory to relevant theories applied in the physical activity field were first documented to provide guidance for the conceptual framework of this dissertation. Then previous bicycling studies from both travel behavior and physical activity field were reviewed. The methods and examined factors associated with bicycling in these studies shed light on potential factors to be examined in this research. To more fully understand the potential relationships between bicycling behavior and individual characteristics, social environment, and physical environment, this chapter also examined structural equations modeling in travel behavior research due to the model limitations in precious bicycling studies.

3. METHODOLOGY

A sufficient number of bicycling studies show associations between physical and social environments and bicycling. However, they leave open many questions about causal connections between the environment and bicycling. Importantly, most of them ignore possible endogenous relationships between factors, resulting in incomplete and potentially invalid results. This chapter introduces the original design conceived to address our research questions, the methodology of data collection, survey sampling and administration, hypotheses of relationships among associated factors with bicycling derived from travel behavior and physical activity behavior theories (discussed in Chapter 2), and the variables measured in the survey in detail.

3.1 Research Design

As discussed in Chapter 2, several theories point to the potential importance of attitudes in explaining bicycling behavior. For example, social cognitive theory suggests that people's feelings, beliefs, and thoughts about bicycling influence their bicycling behaviors. The concept of the positive utility of travel implies that positive benefits such as enjoyment of bicycling overcome the disutility of bicycling and contribute to getting people on a bicycle (Salomon and Mokhtarian, 1998; Mokhtarian et al., 2001).

Indeed, some recent studies have confirmed that the attitude of liking bicycling is strongly associated with miles of transportation and recreational bicycling and choice of bicycle commuting, as well as bicycle ownership and regular use (Xing et al., 2010;

Handy and Xing, 2010; Handy et al., 2010). However, the determinants of bicycling affection have not been fully explored, despite the theoretical and empirical importance of attitude toward bicycling. Therefore, in the first analysis in this dissertation we examine factors associated with affect (whether an individual likes or dislikes an object or concept) for bicycling.

The important next step in this dissertation is the determination of the structure of underlying relationships between bicycling behavior and other relevant factors. In the previous chapter, the conceptual framework of hypothesized inter-relationships between individual factors, social environment factors, physical environment factors, and bicycling behavior was discussed. Any two variables in the model may be connected through both direct and indirect effects. As an example, supportive bicycling infrastructure is expected to be a direct cause of bicycling behavior, but may also affect behavior through affection for bicycling, a mediating variable. The literature review suggests that the structural equations modeling (SEM) approach is a more robust approach for capturing causal effects and intervening effects among endogenous variables and between endogenous and exogenous variables. In addition, employing this approach has several benefits. First, a SEM is more statistically realistic than a single equation model. The variables in the conceptual model are correlated with each other, and the error terms of the equations for the endogenous variables may not be independent. These concerns threaten the validity of estimates by the single equation approach. Second, it is possible to examine which relationships dominate the association between two variables by measuring the magnitudes of standardized direct (X->Y1) and indirect (X->Y2->Y1) effects. Finally, a SEM can incorporate both observed and latent variables, where the latter represent unobserved constructs whose values are inferred through assessing their influence on manifest (observed) indicators as well as on other endogenous variables. Although the SEM approach is superior to many other modeling processes, as mentioned above, one disadvantage is that it heavily relies on researchers' hypotheses of causality between variables. In other words, rather than developing a model by exploring the data, the SEM procedure is an "a priori" technique driven by theories (Kline, 1998). Multiple models following different theories may fit the same data equally well. Nevertheless, SEM is still useful in explaining and understanding complex relationships between variables of interest to the researcher. For these reasons, this dissertation employs structural equation modeling to capture the interactions between the variables as well as between the variables and bicycling behavior.

To understand what motivates an individual to choose bicycling, we first explore factors influencing bicycling in general, without regard to purpose. Then, motivated by the growing interest in increasing transportation bicycling owing to volatile gas prices, traffic congestion, and environmental problems, we focus on transportation bicycling specifically. We examine three aspects of transportation bicycling: regular transportation-oriented bicycling, transportation-oriented bicycling distance, and frequency of bicycling for transportation. A fundamental limitation of this study is its cross-sectional design due to the unavailability of longitudinal data.

Furthermore, because the possibility of "self-selection" for a bicycling community has been neglected in most previous studies, in this research we accounted for the influence of residential preference for bicycling community on bicycling. That is, in our SEMs, we hypothesized that a pro-bicycle environment leads to more bicycling and that an individual's preference for bicycling leads him to choose to live in a community like Davis. In this case, the path of causality runs directly from liking bicycling to bicycling behavior but also indirectly from liking bicycling through residential preference for pro-bicycle environment to bicycling behavior.

3.2 Survey Sampling and Administration

Data used in this dissertation were from an on-line survey conducted in US cities in 2006. Six communities were selected for the study based on several factors. Davis, California (population 67,407 in the 2000 Census), with a high bicycling level (Buehler and Handy, 2008), was selected as a starting point. The UC Davis research team then looked for comparison cities that were similar with respect to size, weather, topography, and presence of a community college or university but that differed with respect to bicycle infrastructure and culture. First, the research team looked for stand-alone cities (i.e. cities that are not directly bordered by other cities within a metropolitan area) comparable in size to Davis, with weather and topography similar to those of Davis, and with universities within their boundaries. The research team's hope was to then find communities that differed from Davis with respect to bicycle infrastructure and culture, in order to ensure variation in these potential explanatory factors. No communities perfectly fit our criteria. Chosen as comparison communities were Woodland (population

49,132 in the 2000 Census), just 10 miles to the north of Davis, Chico (population 59,444 in the 2000 Census), about two hours north of Davis, and Turlock (population 55,488 in the 2000 Census), a few hours to the south. Woodland has about half the total miles of bike lanes and paths per capita as Davis, but considerably more than Chico, despite the fact that Chico is a college town with a reputation for a pro-bicycle culture. In addition, Eugene, OR (population 137,999 in the 2000 Census), and Boulder, CO (population 94,510 in the 2000 Census) were included as comparison cities. Both cities have extensive bicycle infrastructure and enjoy reputations nearly comparable to Davis' reputation as a bicycling community. This set of cities ensures reasonable comparability with respect to the control variables but ample variation with respect to key explanatory variables. Individual-level variations will be accounted for in the analyses.

For each of the six communities, a list of a random sample of 1500 residents was purchased from Martin Worldwide; for Davis, a list with an additional sample of 1000 residents who had moved in the previous year was ordered. We mailed a letter in June 2006 to the residents in the sample, inviting them to participate in the on-line survey and providing instructions on how to access the survey. In addition, we offered to send a hard copy of the survey on request. On July 18, we sent a postcard reminder to the residents who had not yet responded, with a second postcard reminder sent August 15. As an enticement for participation, respondents could choose to be entered into a drawing for one of three $100 prizes. Of the original 10,000 addresses, over 2000 proved to be incorrect, as evidenced by the return of the letter to UC Davis. After accounting for these bad addresses, we achieved a response rate of over 10% in every city except Turlock, where the response rate was just 7.2%, with a high of 18.8 % in Davis. The overall response rate for the survey was 12.6 %, for a sample size of 965, including 59 hard copies of the survey returned. Some important socio-demographic characteristics of the final 965 valid responses are shown in Table 3.1.

Table 3. 1 Socio-demographic Characteristics of Sample in Six Cities

Sample Characteristics	Davis, CA	Chico, CA	Woodland, CA	Turlock, CA	Eugene, OR	Boulder, CO
Number	354	135	125	92	130	129
Percent of females	46.60%	41.70%	43.20%	43.80%	43.30%	40.70%
Age:						
20--34	21.60%	15.90%	12.60%	19.40%	22.20%	25.40%
35-64	64.20%	61.90%	68.50%	67.00%	65.10%	60.70%
65-over 80	15.20%	22.20%	18.90%	13.60%	12.70%	13.90%
Education level >=High School	99.40%	99.20%	98.20%	98.90%	99.20%	99.20%
Education level >=Bachelor	88.60%	60.20%	53.60%	48.30%	56.30%	84.40%
Auto ownership	96.90%	98.50%	95.90%	100.00%	93.80%	95.30%
Average HH* size	2.5	2.3	2.3	2.7	2.3	2.4
Percent of HH* with kids(<18)	31.70%	23.00%	26.80%	36.40%	24.40%	23.00%
Percent of home owners	74.90%	74.80%	84.10%	75.30%	66.90%	79.50%
Median HH* income	$80,174.1	$59,411.8	$68,584.9	$65,116.3	$56,371.0	$80,341.9
White race	77.6%	85.1%	82.9%	75.9%	85.1%	91.1%

*: Household

Although we designed the survey to be relevant to all individuals, not just bicyclists, it is possible that individuals who do not bicycle were less inclined to complete the survey. Because our survey had the added barrier of being online, non-response bias is a serious concern in the survey although the overall response rate is typical for general population self-administered paper surveys (Babbie, 1998). In fact, the survey results show that 25.6% of Davis respondents usually commute to work by bicycle, in comparison to 14%

in the 2000 Census[1]; the survey share was higher than the census share for all cities except Turlock (Table 3.2). Another suggestive finding is that response rates were the highest in Davis, with the highest bicycling level, and the lowest in Turlock, where bicycling rates were the lowest. Within the sample, chi-square tests reveal that Davis, Boulder, and Eugene have significantly higher levels of bicycling, which are represented by significant greater shares of bicycle ownership, bicycling in the last 7 days (regular bicyclists), frequent bicyclists (bicycling more than 4 days a week), and transportation-oriented (commuting, shopping, visiting people) bicyclists than do the other cities. The differences between Boulder and Davis are not significant, while Eugene is somewhat lower than Boulder and Davis on all measures except bicycle ownership. The shares of respondents who reported frequent bicycling and bicycling for transportation are higher in Davis than in Boulder. The correlation between response rates and bicycling levels suggests that the nature of the non-response bias is similar across all cities.

To evaluate the non-response bias further, a short phone survey was conducted in May 2008 in Davis only, due to budget limitations which prohibited a direct assessment of non-response bias across all the cities. Random-digit dialing was used to achieve a representative sample of 400 residents. Although most data collected from the phone survey, which can be viewed as a simple random sample of the population, show slightly

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[1] Percent of respondents who used a bicycle as the primary mode of travel to and from work at least 3 days in a typical week with good weather, which was calculated to match the percent of population who responded “Bicycle” to the census question “How did you usually get to work last week.”

Table 3. 2 Bicycling Levels: Census (2000) vs. Main Survey (2006)

	Davis	Chico	Woodland	Turlock	Eugene	Boulder
Census						
Share usually biking to work	14.4%	5.2%	2.0%	1.1%	5.5%	6.9%
Survey						
Share usually biking to work	25.6%	11.0%	4.3%	0.0%	12.4%	18.4%
Share bicycle ownership	78.0%	67.4%	55.3%	60.9%	72.3%	80.5%
Share biking in last 7 days	53.0%	37.3%	20.2%	12.0%	37.7%	50.0%
Share frequent bicyclist in last 7 days	20.9%	11.2%	4.8%	1.1%	14.6%	14.3%
Share transportation-purpose bicyclist within last year	49.6%	20.0%	14.6%	9.5%	32.9%	28.9%
Number of respondents	354	135	125	92	130	129
Response rate	18.8%	11.7%	10.2%	7.2%	12.1%	12.2%

lower bicycling levels (measured in various ways) than that from the main survey conducted in the year 2006 (Table 3.3), the chi-square tests indicate that all the shares in Table 3.2 for the main survey are not significantly different from those in the phone survey at the 5% significance level (all the p-values are greater than 0.05), implying that the non-response bias of the data for the main survey is not as serious as Table 3.2 suggests. Further, because the focus of our study is on explaining bicycling behavior as a function of other variables rather than on describing the simple univariate distribution of bicycling per se, these differences are not expected to materially affect the results (Babbie 1998).

Table 3. 3 Davis Bicycling Level: Phone Survey (2008) vs. Main Survey (2006)

	Phone Survey	Main Survey	Chi-Square Test P-values
Share bicycle ownership	76.3%	78.0%	0.576
Share biking in last 7 days	47.0%	53.0%	0.101
Share biking within last year	72.5%	74.1%	0.630
Share usually biking to work	26.6%	25.6%	0.075
Number of respondents	400	354	
Response rate	100%	18.8%	

3.3 Variables

Corresponding to the conceptual basis and literature review, the variables (shown in the Appendix) were categorized into four categories: individual factors, physical-environment factors, social-environment factors, and bicycling behavior. The factors used in the models are original responses to survey questions or derived from original survey questions. For example, most socio-demographics employed in the models are original responses. Some were generated through simply averaging, as was the case for "Biking Comfort" and "Bike Infrastructure". Some responses are re-categorized, including "Affect toward Biking" and "Like Biking" from the original variable "Liking Biking_original".

3.3.1 Bicycling behavior

In this research, bicycle ownership is loosely viewed as an aspect of bicycling behavior. In the survey, 71.5% of the total valid respondents (N=965) own or have regular access to a bicycle. Bicycle ownership is the precursor of bicycle use. However, owning a bicycle or having easy access to a bicycle, a necessary but not sufficient condition, does not guarantee the regular use of a bicycle, leaving a need for exploration of other determinants of bicycling.

The survey took a "snapshot" of the bicycling behaviors of the respondents within the previous 7 days. Respondents who bicycled at least once within the last 7 days are labeled "Regular Bicyclist."

Transportation bicycling was measured from three aspects: transportation-oriented bicycling, weekly transportation bicycling miles, and daily transportation bicycling probability (more details of the three measures of transportation bicycling are described in Chapter 6). The variable representing the split between bicycling for transportation and recreation is derived from a survey question on the proportion of the respondent's bicycling that is for each purpose. In this sample, more people bicycle completely or mostly for recreation (48.7%) than do people for transportation (34.4%), consistent with the finding of Pucher and Dijkstra (2000) that recreational bicycling is more popular than transportation cycling in the US. In the research, the scale of this variable was reversed so that larger values represent an increasing portion of transportation bicycling accompanied by a decreasing portion of recreational bicycling. Daily Probability of Transportation Bicycling loosely measures bicycling frequency as the probability of bicycling for transportation on any particular day. Weekly Transportation Miles is the reported weekly miles for transportation purposes. The latter two variables were derived from survey questions as follows.

Weekly Transportation Miles was derived from the combination of two survey questions: weekly miles of bicycling for all purposes, and share of bicycling for transportation. Some respondents reported that their weekly miles are zero, presumably because their bicycling is irregular or they do not bicycle at all. To meet the assumption of normality of residuals, we took the natural log of the value of weekly miles of bicycling for each purpose. To all zero scores (for bicyclists who reported zero weekly bicycling miles or all of whose bike rides are for recreation) we added a very small constant of 0.001 mile before the logarithmic transformation to avoid taking the log of zero, which is negative infinity.

Daily Probability of Transportation Bicycling was generated from the combination of three survey questions: the variable measuring regular bicycling behavior—"During the last seven days, on how many days did you: ride a bicycle?" with answers from 0 to 7 days; Last Bike Ride—measured by another survey question which asked people "When did you last go for a ride on a bicycle?" with six answers offered: 1. I have never ridden a bicycle; 2. Over 10 years ago; 3. Between 1 and 10 years ago; 4. Between 1 month and 1 year ago; 5. Between 1 week and 1 month ago; 6. Within the last week; and "Imputed Transportation Proportion" measuring what portions of bicycle rides are for transportation (see Table 6.1). We first combined the variable measuring regular bicycling and Last Bike Ride: the bicycling frequency of individuals who have never ridden a bicycle or last did so more than 10 years ago was coded as "0" per day; that of individuals whose last bike rides were between 1 and 10 years ago was "1/(365*5)" per day, assuming 365 days a year and bicycling once per 5 years; if the last bike rides occurred between 1 month and 1 year ago, "1/(365/2)" per day, assuming bicycling once per half a year; if the last bike rides were between 1 week and 1 month ago, "1/15" per day, assuming bicycling once per half month; if the last bike rides were within the last week (assuming these respondents bicycled once during a day, on average), then combined with the variable measuring days bicycling during the last seven days and divided by 7, i.e. 7 days a week, to get the bicycling frequency per day. For instance, if an individual bicycled 4 days during the last seven days, then the corresponding bicycling frequency would be 4/7 per day. Thus this variable represents the probability of bicycling for transportation on any particular day and takes essentially continuous values from 0 to 1.

The dichotomous variable “Regular Biking When Young” reflects whether a respondent bicycled regularly when 12 years old to any of these destinations: school, convenience store, friends’ houses, roaming or exploring, or library. This variable, measuring an individual’s early bicycling experiences, is used as an explanatory variable rather than a dependent variable in the analyses. In the sample, 75% of respondents bicycled regularly when young.

3.3.2 Individual factors

Individual factors comprise socio-demographic variables, travel constraints, and attitude variables. Socio-demographic variables include age, gender, educational background, household size, annual household income in thousands of dollars, mode ownership (indicating whether an individual has easy access to a car or bicycle), residential tenure, and race. Travel constraints include biking, health, and family travel constraints, measured, respectively, as whether the respondent has any physical or mental conditions that limit or prevent him or her from riding a bicycle, the respondent’s health condition, and the need to assist child/children or elder/elders in the household to travel outside of the home.

Attitudes were measured in various ways. First, aspects of "self-efficacy"—the confidence in one's ability to engage in the behavior—are measured in this study through averaging responses to six items reflecting level of comfort ("comfortable," "uncomfortable but I would ride on it," and "uncomfortable and I wouldn't ride on it") on different bicycle facilities (off-street, quiet street, two-lane local street with or without bike lane, or four-lane street with or without bike lane). The respondent's health condition is measured as the level of agreement that "I am in good health" on a 5-point Likert-type scale. Attitude toward bicycling (affect for bicycling) was measured on a 5-point Likert-type scale from "strongly disagree" to "strongly agree" with the statement that "I like riding a bike." Attitudes toward driving are measured by the levels of agreement on preference for driving, the need to use a car to do many things, and trying to limit driving as much as possible. Respondents also expressed their attitudes toward walking and taking transit on 5-point scales. The importance of environmental benefits when choosing modes was measured from "not at all important" to "extremely important" on a 4-point scale. The attitude toward physical exercise is measured as level of agreement, on a 5-point scale, with the statements that "It's important to get regular physical exercise" and "I enjoy physical exercise."

The influence of residential preference for bicycling on bicycling is accounted for in our study. Respondents were asked about the importance of "A good community for bicycling" for choosing their residential locations, with a four-point response scale ranging from "not at all important" to "extremely important." The variable "Residential Preference for Bicycling" reflects the degree to which a respondent chose to live in a community because of its supportive bicycling environment. It does not reflect the importance of this reason relative to other possible reasons, but on the upside it does reflect an individual's prior affinity to bicycling before moving to the respondent's current community.

3.3.3 Physical-environment factors

The variable "Bike infrastructure" reflects the respondent's perception of the bicycle system in that community, including the presence of bike lanes, a network for off-street biking, gaps in the bike route network, bike lanes free of obstacles, bike racks, path lighting, and push-buttons at intersections. These items were measured on a 4-point scale from "not at all true" to "entirely true." Together the items reflect a relatively comprehensive bicycle system. The perceived distances from home to a selection of commonly visited destinations, a reflection of the land use pattern around a respondent's home, were measured on 4-point scales from "Less than a mile" to "More than 4 miles." Hilly topography, reflecting the natural environment, is measured as the perception of whether the community is too hilly for easy bicycling, measured from "not at all true" to "entirely true" on a 4-point scale.

3.3.4 Social-environment factors

Perceptions of the attitudes and behaviors of drivers toward bicyclists were measured through agreement with several statements, such as "Most drivers seem oblivious to bicyclists" and "Most drivers yield to bicyclists." The bicycling culture is measured by respondents' perceptions of the people who bicycle in a community, through agreement on a 5-point scale with statements such as “Bicycling is a normal mode of transportation for adults in this community,” “It is rare for people to shop for groceries on a bike,” “Kids often ride their bikes around my neighborhood for fun,” “Most bicyclists look like they are too poor to own a car,” “Most bicyclists look like they spend a lot of money on their bikes,” and “Many bicyclists appear to have little regard for their personal safety.”

3.4 General Hypotheses of Relationships

For the survey data, we hypothesize important relationships among individual factors, attitudinal factors, and bicycling behavior based on the conceptual framework for bicycling derived from travel and physical activity behavior theories, as described in Chapter 2. The basic hypothesized model (Figure 3.1) includes six categories of endogenous and two of exogenous variables, as well as interactions between them.

3.4.1 Endogenous variable categories

Six main endogenous variable categories were hypothesized in the conceptual model: attitudes, liking bicycling, residential preference for bicycling, community environment, bicycle ownership, and bicycling behavior. The hypothesized relationships between each other are as follows.

Relationship between Attitude and Affection for Bicycling

In this study, attitudes include biking comfort; liking of driving, transit, walking, and biking; concern for the environment; and enjoyment of physical exercise. Attitude is assumed to be a function of socio-demographics, travel constraints, and community environment. In this study, we separate from other attitudes the affect for bicycling, measured as agreement that “I like riding a bike” on a Likert-type scale. Bicycling affect is expected to be influenced directly by socio-demographics, attitudes, community environment, and bicycling behavior.

According to previous findings summarized in the literature review, attitudes may have direct influences on bicycling. However, it is also possible that the impacts of attitudes toward other modes, the environment, and physical exercise on bicycling are mediated through preference for bicycling.

The basic conceptual model hypothesizes a bi-directional link between attitudes and liking bicycling. Individuals’ attitudes influence their affection for bicycling, e.g. people who are concerned about environmental problems and favor positive solutions are more likely to favor alternatives to driving, including bicycling; people who like physical exercise could also like bicycling as a form of physical activity. On the other hand, the attitudes of pro-environment and physical exercise may be reinforced by the attitude of liking bicycling through the perceived benefits received from bicycling.

Relationship between Attitudes and Community Environment

Community environment includes both the physical and social environments of a community. In this research, variation in community environments is identified by different subjective (perceived) characteristics of transportation infrastructure, land use patterns, natural environment, and social culture.

Relationship between Affect for Bicycling and Community Environment

The physical and social environment of a community may affect bicycling affection indirectly through bicycling behavior. For example, good bicycling infrastructure attracts people to bicycling and reinforces their affection for bicycling through the enjoyment of bicycling on good facilities.

As mentioned above, the individual's affect for bicycling is not likely to impact the community environment in the short term. However, an individual can change his community environment through residential self-selection in a relatively shorter period. Therefore, self-selection for supportive bicycling residential locations, resulting mainly from affection for bicycling, directly influences the community environment.

Relationship between Community Environment and Bicycling Behavior

The community environment, including physical and social environments, may have a direct influence on bicycling behavior based on the logical assumption that an individual in a community with a better bicycle infrastructure system is likely to bicycle more than another individual in a community with less bicycle infrastructure, all else equal. Some previous travel behavior studies also provide evidence of a causal link from the physical environment to travel behavior.

Liking Bicycling and Bicycling Behavior

Affect for bicycling, an attitude toward bicycling, undoubtedly influences bicycling behaviors. However, it is still unknown whether bicycling behaviors also affect bicycling affect through the response to the bicycling experience, i.e. enjoyment, comfort, etc. Although few studies have examined the relationships between affect for bicycling and bicycling behavior, causal relationships between travel liking and travel amounts (by vehicle, airplane, or other) hold in both directions as found by Ory (2007).

Residential Preference for Bicycling and Biking Behavior

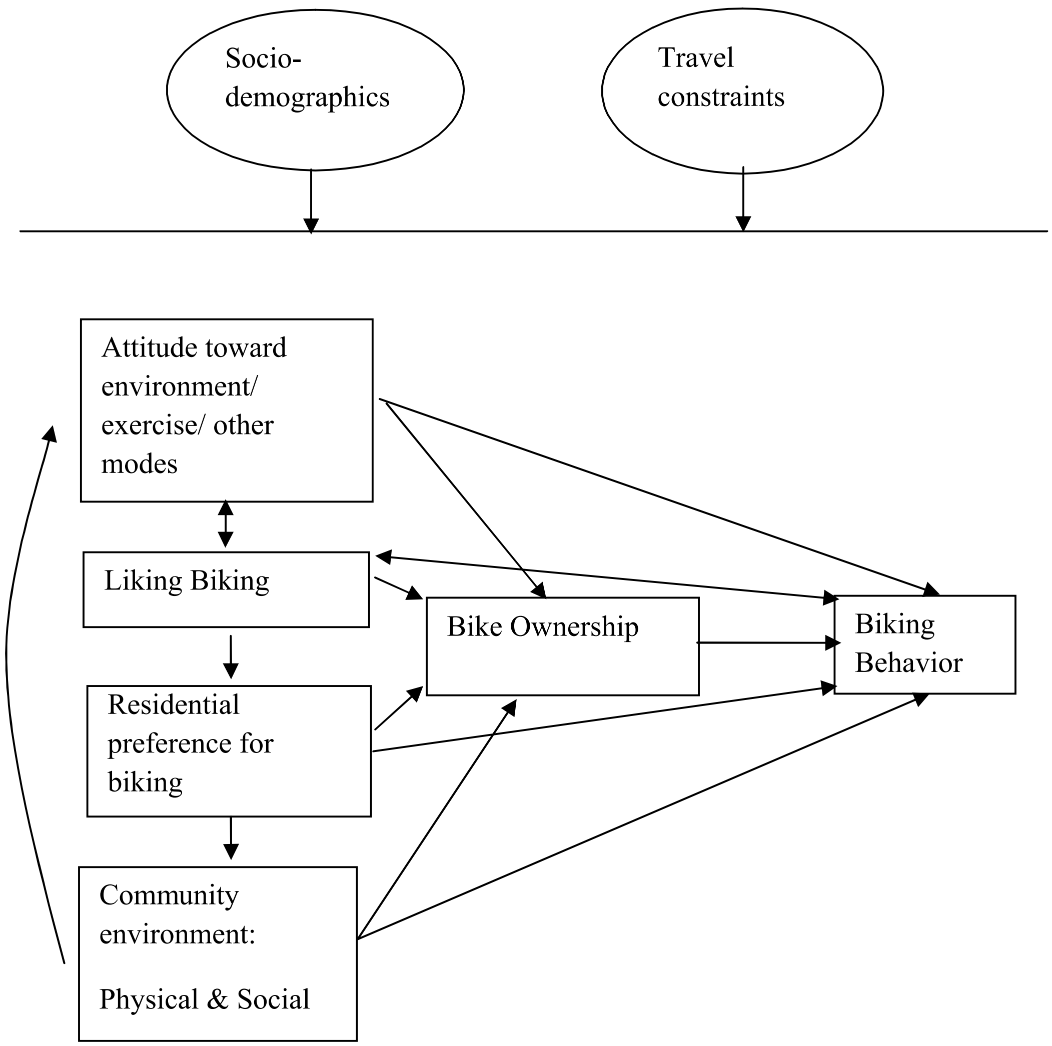
According to the concept of self-selection, the residential preference for bicycling community is a function of travel constraints, socio-demographics, and bicycling affect. It has been found that individuals with a preference for walking tend to selectively live in a neighborhood conducive to walking (e.g. Handy and Clifton, 2001). Analogously, the attitude of liking bicycling could play an important role in individuals' self-selection of a supportive bicycling environment.

The conceptual model suggests that residential preference for a bicycling-friendly neighborhood influences bicycling behavior, while bicycling behavior may also feed back to residential preference but possibly indirectly through attitudes such as liking bicycling. For example, through pleasant bicycling experiences an individual may achieve a higher affection level for bicycling, which may later lead to a preference for living in a place supportive for bicycling. Thus, we hypothesize a direct influence of bicycling behavior on the attitude of liking bicycling, which we hypothesize to directly affect residential preference for bicycling. On the other hand, the residential self-selectors, who prefer bicycling, are more likely to already be bicyclists. There would be no reason for them to stop bicycling after moving to a pro-bicycling community. Therefore, there is a strong causal link from self-selection to bicycling behavior.

Mode Ownership

In studies of travel mode choice, mode ownership or availability is always a key factor explaining mode use. For example, auto ownership is one of the principal explanatory factors of auto trip generation and frequency (e.g. Ortuzar and Willumsen, 2001; Garling et al., 1998). Bicycle ownership or availability is a natural precursor of bicycle use. A substantial share of trips made by households that do not own automobiles are nevertheless made by automobile, through getting rides with, or renting cars (Lovejoy and Handy, 2007). For bicycling, ownership is likely to be more important, as “getting a ride” without owning a bicycle is not practical (with the exception that children ride on the handlebars sometimes, or, perhaps, of tandem bicycles), although borrowing someone’s bicycle is certainly a possibility. There are several possible explanations for owning a bicycle: a person might like bicycling and intend to bicycle and thus gets a bicycle as a starting point; another might not like bicycling but have to get a bicycle owing to a lack of transportation alternatives; or a person may just happen to have a bicycle, e.g. if it were given by someone, or left at that residence by a previous occupant. Taking into account these possibilities, we expected that the attitude of liking bicycling and the variable, Car Ownership, measuring the availability of a car, would affect bicycling indirectly through their effect on bicycle ownership. We also hypothesized a direct influence of bicycle ownership on bicycling behavior, independent of liking bicycling and car ownership, to account for cases where an individual owns a bicycle by chance.

Figure 3. 1 Basic Hypothesized Conceptual Model



Attitudes toward driving, bicycling, walking, or transit affect auto and bicycle ownership directly as does the community environment. Undoubtedly, the attitudes toward driving (like driving and limit driving) and bicycling influence bicycle ownership. Attitudes toward other modes, such as transit, may also affect the ownership of bicycles because of substitutive relations between them for relatively longer distances.

Community environment plays a direct role in an individual's car ownership: in transit-accessible or communities with mixed land uses, people may choose not to own cars. Some studies (Bhat and Guo, 2007; Cao et al., 2007) provide support for the contribution of the built environment to auto ownership. Although evidence is lacking, we hypothesize that people are more likely to own bicycles if they live in a "bikeable" community.

It is plausible to expect that people who chose their residential locations in part because of a supportive bicycling environment are probably already bicyclists or at least intend to bicycle. Consequently, they tend to own bicycles. Therefore, owning a bicycle is also driven by residential self-selection for bicycling.

3.4.2 Exogenous variable categories

Two exogenous variable categories are illustrated in the conceptual model. Exogenous variables include socio-demographics and travel constraint variables. The former contains age, gender, educational background, household size, annual household income in thousands of dollars, residential tenure, and race; the latter category includes driving constraints and biking constraints, e.g. physical limitations on bicycling and responsibilities for travel assistance for child/children or elder/elders. All endogenous categories may be influenced by the socio-demographics and travel constraint variables. The observed exogenous variables, including gender, educational level, and household ownership, could influence an individual's attitudes, mode ownership, and travel behaviors.

With a broad set of measured factors, the potential quantitative impacts and interactions among attitudes, physical and social environment, residential preference for bicycling, mode ownership, and bicycling behavior, which are briefly summarized above, are to be explored.

3.5. Missing Data

Missing data are a very common problem in data analysis. The main concern raised by the incompleteness of data is that it may decrease statistical power or lead to biases which result in inaccurate parameter estimation (Roth, 1994). Three types of missing data are summarized by Little and Ruin (1987): "Missing Completely at Random" (MCAR), "Missing at Random"(MAR), indicating the data are not MCAR but that some clues as to why the data are missing can be measured, and "Non-Ignorable", also known as "Missing Not at Random" (MNAR) or "Not Missing at Random" (NMAR), implying the data are not MAR but the pattern of incompleteness is not understood or measured. There are a variety of simple statistical techniques to solve the problem of missing data. For example, strategies popularly used include: deletion, including listwise and pairwise deletion, where the former deletes all incomplete cases and the latter eliminates the information "from those statistics that need the information" (Roth 1994, p. 540); weighting, using sample weights to adjust for any known sample biases; imputation, such as mean imputation and regression imputation, using sample information to estimate values for the “missing” data; multiple imputation, creating multiple estimates of the incomplete data to obtain a more realistic view of data; and likelihood-based estimation, using all available data to estimate the parameters of a model predicting the values of the missing data. Specifically, assuming a sample follows the multivariate normal distribution, the parameters of the prediction model are estimated by using the Maximum Likelihood method with all available data. Based on these parameters, the missing data are thus estimated (Roth, 1994).

According to the research of Raymond and Roberts (1987), parameter estimates do not differ much, i.e. the accuracy of the estimates may not be jeopardized, if less than 10% of data is missing in a random pattern. However, missing more than 10% requires the employment of one of the above techniques. In deciding how to address missing data in this analysis, we first looked closely at patterns of missing data in the total data set. Listwise deletion, in which any cases that have missing data for one or more variables in a statistical analysis are discarded resulting in a data set with complete data on every individual case, may be appropriate for data MCAR. Although this method may decrease statistical power because of a smaller sample size and lead to bias if the missing data are not MCAR, the advantage of its simplicity, clarity, and ease of use makes it a popular strategy for handling missing data in many statistical packages.

However, most missing data collected in the survey falls into the category of MAR. For example, incomplete data for agreement that “The city has a network of off-street bike paths” and “The bike route network have big gaps” may be considered as MAR because the cause of the missing data may be dependent on whether the respondent bicycled or not (people who did not bicycle may not be clear about the bicycle network and thus were less likely to respond to the survey question). In other words, the missing data are dependent on the observed data (Bicycled or not) but must be independent of the corresponding values of other cases in the sample. As a matter of fact, the shares of missing data on the two variables are as high as 10.9% and 26.1%. We employed the mean imputation method to fill in missing data in each city with the mean for each aspect of perceived bicycle infrastructure in that city, based on the assumption that perceptions of bicycling infrastructure in a certain city would be similar across all residents. The variables for which this imputation was done are “Bike Lane”, “Wide Street”, “Bike Rack”, “Bike Light”, “Push Button”, “Bike Network”,” Free Obstacle”, and “Bike Gap”.

Other possible data missing at random were handled by the statistical packages used for our models. Specifically, the SPSS package deals with missing data by using the deletion strategy. Therefore, complete cases were analyzed in the ordered logit model (Chapter 4) following listwise deletion of cases with missing data on the variables in the model. By default Mplus, used for structural equation modeling, also employs listwise deletion to deal with missing data, i.e. it will exclude cases with missing values on any of the variables in our analysis, and hence missing data will result in fewer observations being used. However, missing data can be accommodated in Mplus with the Weighted Least Squares estimator, which can be used with the variables defined as categorical. Mplus deals with missing data by allowing it to be a function of the observed covariates but not the observed outcomes (Mplus User’s Guide, p. 7). To achieve as much accuracy in the model estimation as possible, we use this method to fill in the missing data in the four structural equation models (in Chapters 5 and 6).

The datasets for the four SEMs are subsets of the full sample of 965 cases with 356 variables. Before refilling the missing values, we checked the data subsets from two perspectives: how many cases are missing data for a particular variable, and how many variables are missing for a particular case. In the sample subset for the Regular Biking Model, we removed 20 cases that have high item-non response rates (the percent of questions a participant did not answer), ranging from 26% to 69%. In the remaining 945 cases, the maximum number of variables (out of the total of 42) missing for any participant is 10. The highest percent of cases (out of the total of 945) for which any variable has missing values is 9.8%. In the final model, the total share of data missing and filled by Mplus is about 1.8%. In the other three SEMs, out of the total of 44 variables, the highest share of variables missing for any case is 20%; out of the totals of 578, 566, and 567 cases for the three models, the highest share missing for any variable is, correspondingly, 6.4%, 4.4%, and 4.6%. In total, about 1.1% of missing values were filled by Mplus in each of the three models.

Imputation of missing ordinal and continuous data values using Mplus helps to preserve the sample size: it resulted in an effective final sample size of 945 for the model for Regular Bicycling (Chapter 5), compared with a sample of 661 using a listwise deletion method. In the other three models (Chapter 6), final sample sizes of 578 were achieved compared with samples of 446 generated by the listwise deletion method. The method used in Mplus thus reduced the loss of cases due to missing values by about 21-22%.

3.6 Sample Size

Sample size is another concern in this study, especially in the SEM analysis. Although opinions on the recommended sample size for SEM have not converged on a consensus (Sivo et al., 2006), it is commonly agreed that larger sample sizes result in less sampling error and decreased standard errors of parameter estimates than smaller samples (Kline, 2005, p. 110; Lei and Lomax, 2005). Some researchers have proposed a relatively loose "critical sample size" of 200 and have suggested a sample size greater than that to provide statistical power for SEM data analysis (Hoelter, 1983; Garver and Mentzer, 1999). Others recommend a ratio of the sample size to the number of estimated parameters of greater than 10 (Schreiber et al., 2006). MacCallum et al. (1996) found that a relatively better model fit can be achieved for a sample size greater than 500 and degrees of freedom over 30 for a SEM analysis. However, Muthén and Muthén (2002) indicate that there is no rule of thumb in deciding on sample size for SEM analyses. The required sample size depends on many factors such as the distributions of the variables, amount of missing data, reliability of the variables, and strength of the relationships among the variables.

The sample sizes of the SEM analyses in this dissertation are all greater than 500. The sample size of the model in Chapter 5 (exploring contributions of the factors to regular bicycling) is 945 and 578 for the three models in Chapter 6 (exploring contributions of the factors to balance of bicycling for transportation and recreation, transportation bicycling distance, and frequency). Further, a study found that parameter estimates are more influenced by non-normality than by sample size (Lei, M. and Lomax, R. G. (2005). Ory (2007) also suggests that deviations across estimation techniques are more evident when sample sizes are relatively small. Since some variables, especially some important outputs, in this study are categorical variables and have non-normal distributions, the final estimation method employed a weighted least squares approach in the Mplus package, a logical choice and one recommended by Ory (2007), given the relatively small sample sizes in this study.

4. WHY DO PEOPLE LIKE BICYCLING?

4.1 Introduction

To encourage bicycling, a significant proportion of federal resources has been allocated by states and metropolitan areas for improving the bicycling system over the last two decades (Handy et al., 2009). Even so, bicycling accounts for only 1.1 % of all trips for all purposes according to 2009 National Household Travel Survey (NHTS) data, a much lower rate than in many European countries (Pucher and Buehler, 2008). Clearly, while supportive bicycling infrastructure enhances the opportunity to bicycle, its use is not guaranteed. At the same time, in spite of a lack of good facilities, some people still bicycle regularly simply because they like bicycling (Gatersleben and Appleton, 2007).

Attitudes toward bicycling are an important factor in explaining bicycling behavior. Empirical studies show that the attitude of liking bicycling is the most important factor to explaining bicycle ownership and regular use, at least in communities with good bicycle infrastructure to begin with (Handy et al., 2010). The attitude of liking bicycling is also strongly associated with bicycling distances and choice of bicycle commuting (Xing et al., 2010; Handy and Xing, 2010). Attitudes also help to explain bicycling frequency (Heinen et al., 2011). Differences in the extent to which people favor bicycling may help to partly explain bicycling shares of travel in some European countries far higher than that in the US. Numerous empirical studies have found that attitude, particularly affect, is significantly correlated with travel behavior more generally (Dobson and Tischer, 1976; Dobson et al., 1978), and at least one study showed that attitudinal variables have the greatest direct impacts on travel behavior among all explanatory variables (Bagley and Mokhtarian, 2002).

What factors contribute to differences in attitudes is not entirely clear. Many Dutch, Danish, and German cities have programs to stimulate interest and enthusiasm for cycling among all age groups (Pucher and Buehler, 2008). While such programs are rare in the US, communities where bicycling is more common, such as Davis, CA, Boulder, CO, and Portland, OR, have a shared culture of bicycling (Buehler, 2007; Pucher, et al., 2010). Given the significant role of individual attitudes in explaining bicycling behavior, an understanding of the formation of attitudes toward bicycling is important: Where do bicycling attitudes come from? And why do some people like bicycling and others don't? However, research on the determinants of bicycling attitudes, especially whether an individual likes or dislikes bicycling – affect toward bicycling – is lacking.

This study aims to fill this gap by exploring factors that may influence individuals' affect for bicycling, the core of attitude toward bicycling. It reviews previous travel behavior studies and relevant theory to develop a conceptual model of factors influencing bicycling affect, categorized as individual, social environment, and physical environment factors. Data from a cross-sectional survey of residents of Davis and five comparison cities are analyzed using an ordered logit model to explore factors which may stimulate affection for bicycling.

4.2 Literature Review and Conceptual Basis

The concept of attitude refers to the mental evaluation of an object or concept. Some researchers define attitude narrowly as affect for an object or concept, summarized by Fishbein and Ajzen (1975). A more widely accepted definition is that attitude has three elements: cognition, affect, and conation (Day, 1972). The cognitive element denotes a person's perception, specifically, knowledge, opinions, beliefs, and thoughts about the object (Fishbein and Ajzen, 1975). It also includes normative beliefs, what a person or society thinks should be done (e.g. Fishbein and Ajzen, 1975). Normative beliefs differ from general cognitive beliefs in this way: the former refer to social or personal judgments with respect to the object, whereas the latter are perceptions of properties inherent to the object (often tangible aspects). The affective or feeling element reflects whether an individual likes or dislikes an object or concept (Day, 1972). The conative element refers to a person's intention: "The respondent's willingness or intention to do something with regard to the object of the attitude" (Sudman and Bradburn, 1982, p. 123). The intention precedes the behavior but differs from it because an individual may intend to take an action but does not do it.

Among the three elements, affect is regarded by most theorists as the core of the attitude concept and derived from the cognitive element (Day, 1972). A relationship between these two attitudinal elements has been postulated in previous studies although measures of the affect and cognitive elements have differed. The traveler's liking for a mode stems from his awareness and perceptions of the mode's attributes (Hartgen, 1974). Dobson et al (1978) suggested that perceptions lead to affect and affect leads to behavior: that is, perceptions have influences on behavior through affect. In addition, travel liking is believed to be a mediating factor through which the influences of personality and life style act on mobility behavior (Collantes and Mokhtarian, 2002; Ory and Mokhtarian, 2009).

Both theories and empirical evidence suggest the importance of attitude in explaining behavior. Bandura's social cognitive theory emphasizes the role that personal factors in the form of cognition and affect play in the development of human behavior—"what people think, believe, and feel affects how they behave" (Bandura, 1986, p. 25). It emphasizes the importance of attitude by according a central role to it in human behavior change (Pajares, 2002). Further, this theory describes the reciprocal determinism between personal attitude (in the form of cognition and affect), behavior, and environment. For example, personal attitude informs and alters behavior and environments, which, in turn, reinforce or discourage attitude.

The notion that travel can have positive utility also supports the importance of attitude in explaining travel behavior (Salomon and Mokhtarian, 1998; Mokhtarian et al., 2001). It corrects the usual exclusive emphasis on the disutility (negative cost such as distance or time) of travel and acknowledges positive benefits such as adventure seeking and enjoyment of independence as contributing to the value of mobility. The positive-utility premise helps to explain why people bicycle in spite of the inferior convenience of bicycling compared to driving under most conditions in the US. It suggests that in addition to its value as a way to get to activities, bicycling may have value for its own sake, such as when riders experience enjoyment of bicycling.

While many studies have documented the important role that attitudes play in explaining travel behavior in general and bicycling in particular, factors associated with attitude toward bicycling have rarely been explored. However, potential factors contributing to bicycling affect may be drawn from explorations of the nature of factors contributing to affect for other modes in previous travel behavior studies. For example, Tardiff (1977) found attitude, measured by the overall comparative satisfaction with bus or car (a sum of cognition and affect), to be influenced by socio-economic status, auto availability, distance, and modal selection behavior. Dobson et al. (1978) estimated a model suggesting that affect for bus is a function of socio-demographics (number of driver's licenses in a household), cognition (perception of attributes and availability of bus), and behavior (taking the bus). Collantes and Mokhtarian (2002) presented their conceptual model in which affinity for travel, or travel liking, is influenced by objective mobility (measured in terms of frequency of trips, average trip distance, total distance traveled, and total travel time) through subjective mobility (people's subjective assessments of their actual mobility), personality and lifestyle, travel constraints, and other travel attitudes. A related study modeling affect toward travel showed that attitudes and personality are more important determinants of travel liking than objective travel amounts (Ory and Mokhtarian, 2005). Ory and Mokhtarian (2009) further investigated the structural relationships among travel amounts and attitude and found that favoring environmental solutions and amounts of utilitarian travel both affect travel liking, whereas recreational travel amounts do not. This study showed that attitudes and behavior have a reciprocal relationship.

The conceptual model for this study is developed based on but not limited to the relationships shown in previous modeling efforts. We preliminarily hypothesized that the affective element of attitude toward bicycling is influenced by socio-demographics as well as travel constraints, individual cognitions including perceptions and normative beliefs, and behavior as suggested by many studies on attitudes. In addition to the hypothesis that current bicycling behavior can strengthen bicycling affection, we also proposed that the experience of regular bicycling behavior when young may help to form a positive attitude toward bicycling after growing up. Past bicycling experience may reinforce the feeling of liking bicycling. Meanwhile, affect toward other modes may impact bicycling affect due to their possibly competitive or substitutive relations with bicycling. It is also possible that liking physical exercise correlates with affect toward bicycling, a form of physical activity. Further, borrowing from social cognitive theory, we expanded the set of factors hypothesized to influence affect to include the physical and social environments. The physical environment refers to land-use patterns, transportation infrastructure, and the natural environment; the social environment includes the cultural norms of the community, as evidenced by the collective behaviors of its residents. Another factor tested here is an individual's exposure to a bicycling-supportive environment, which was measured by the variable for living in a bicycling-oriented city, such as Davis, for more than five years. (We also tested the influence of a shorter time period living in a bicycling city, i.e. for more than 2 years, but found it insignificant with $p=.247$ in the model.)

This study uses this conceptual model to explore factors related to the affect toward bicycling. Our analysis aims to assess the relative effects of a comprehensive set of variables, drawn from the conceptual model, on affect toward bicycling. It thus contributes to a better understanding of determinants of a positive attitude toward bicycling, which has not drawn much attention from researchers although its salient influence on bicycling behavior has been supported by both theory and empirical findings.

4.3 Methodology

4.3.1 Data

The data employed in this study are from the online survey conducted in the six small western U.S. cities in the year 2006, which was described in detail in Chapter 3.

4.3.2 Variables

Variables were selected for the analysis from the dataset, consistent with the conceptual model (Table 4.1). For several variables, indexes were created from a set of survey questions through averaging; others are responses to original survey questions. The dependent variable and all explanatory variables tested in the models are included in Table 4.1, including those that were not statistically significant.

Table 4. 1 Description of Variables in Model

Variable name	#Items [Range]	Mean (s.d.) or Percent %)[a]	Description
Dependent Variable			
Affect toward Biking	1 [1,3]	28.3%: 45.4%: 26.4%	1:=Strongly disagree or disagree or neutral on the statement that "I like riding a bike", labeled "Disliking Bicycling"; 2=Agree on this statement, labeled "Liking Bicycling"; 3=Strongly agree on this statement, labeled "Strongly Liking Bicycling".
Explanatory Variables			
Socio-demographics			
Age	1 [17,73]	49.29 (15.15)	Age in years
Female	1 [0,1]	44.0%	1=Female, 0=Male
Education Level	1 [1,6]	4.45 (1.86)	The highest level of education. 1=Grade school or high school, 2=High school diploma, 3= College or technical school, 4=Four-year degree or technical school certificate, 5=Some graduate school, 6=Completed graduate degree(s)
Household Size	1 [1,6]	2.41 (1.19)	The number of persons living in the household.
Income	1 [5,125]	71.05 (37.68)	The total annual household income. Continuous, in thousands of dollars.
Car Ownership	1 [0,1]	96.7%	Car ownership. 0=Have no cars, 1=Have one or more cars
Home Own	1 [0,1]	75.5%	Own or rent the current residence. 0=Rent, 1=Own.
White	1 [0,1]	82.0%	1=White, not of Hispanic origin, 0=All others.
Travel constraint			
Limit Biking	1 [0,1]	88.7%: 11.3%	1=Have any physical or mental conditions that limit or prevent sb. from riding a bike, 0=Do not have.
Good Health	1 [1,5]	3.91 (0.99)	Agreement that "I am in good health" on 5-point scale[b]
Travel Assistance	1 [0,1]	87.8%: 12.6%	1=There is / are child/children or elder/elders in one household that needs assistance to travel outside of the home, 0=No such assistance is needed.
Cognition			
Biking Comfort	6 [1,3]	2.40 (0.39)	Average comfort biking on an off-street path or quiet street, two-lane-local-street with or without bike lane, four-lane-street with or without bike lane, on 3-point scale where 1=Uncomfortable and I wouldn't ride on it, 2=Uncomfortable but I'd ride on it, 3=Comfortable.
Safety Concern	5 [1,3]	1.66 (0.43)	Average concern of being hit by a car, being hit by another bicyclist while biking, being bitten by a dog, being mugged or attacked, or crashing because of road hazards on 3-point scale where 1=Not at all concerned, 2=Somewhat concerned, 3=Very concerned.
Normative beliefs			
Environmental Concern	1 [1,5]	3.36 (1.10)	Agreement that "I try to limit my driving to help improve air quality" on 5-point scale[b]
Get Exercise	1[1,5]	4.50 (0.86)	Agreement that "It is important to get regular physical exercise" on 5-point scale[b]
Affect toward other modes and physical exercise			
Like Driving	1 [1,5]	3.68 (1.05)	Agreement that "I like driving" on 5-point scale[b]
Need Car	1 [1,5]	4.13 (0.87)	Agreement that "I need a car to do many of the things I like to do" on 5-point scale[b]

Variable name	#Items [Range]	Mean (s.d.) or Percent %)[a]	Description
Limit Driving	1 [1,5]	3.41 (1.05)	Agreement that "I try to limit driving as much as possible" on 5-point scale[b]
Like Walking	1 [1,5]	4.00 (0.85)	Agreement that "I like walking" on 5-point scale[b]
Like Transit	1 [1,5]	2.61 (1.10)	Agreement that "I like taking transit" on 5-point scale[b]
Enjoy Exercise	1 [1,5]	4.00 (1.03)	Agreement that "I enjoy physical exercise" on 5-point scale[b]
Physical environment factors			
Bike Infrastructure	8 [1,4]	2.85 (0.60)	Average perception that "Major streets have bike lanes", "Streets without bike lanes are generally wide enough to bike on", "Stores and other destinations have bike racks", "Streets and bike paths are well lighted", "Intersections have push-buttons or sensors for bicycles or pedestrians", "The city has a network of off-street bike paths", "Bike lanes are free of obstacles", "The bike route network [does not] have big gaps"[c] on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true.
Hilly Topography	1 [1,4]	1.17 (0.49)	Perception that "The area is too hilly for easy bicycling" on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true.
Distances	6 [1,4]	2.39 (0.57)	Average perception of distances from home to "your usual grocery store", "the nearest post office", "a restaurant you like", "a bike repair shop", "your workplace", "the local elementary school" on 4-point scale where 1=Less than a mile, 2=1-2 miles, 3=2-4 miles, 4=More than 4 miles
Social environment factors			
Good Driver Attitude	4 [1,5]	2.81 (0.63)	Average agreement that "Most drivers [do not] seem oblivious to bicyclists" [c], "Most drivers yield to bicyclists", "Most drivers watch for bicyclists at intersections", "Most people [do not] drive faster than the speed limit"[c] on 5-point scale[b]
Biking is Normal	2 [1,5]	2.76 (0.97)	Average agreement that "Bicycling is a normal mode of transportation for adults in this community" and "It is [not] rare for people to shop for groceries on a bike"[c] on 5-point scale[b]
Kids Bike	1 [1,5]	3.47 (0.96)	Agreement that "Kids often ride their bikes around my neighborhood for fun" on 5-point scale[b]
Bikers Poor	1 [1,5]	2.03 (0.89)	Agreement that "Most bicyclists look like they are too poor to own a car" on 5-point scale[b]
Bikers Spend	1 [1,5]	2.85 (0.85)	Agreement that "Most bicyclists look like they spend a lot of money on their bikes" on 5-point scale[b]
Bikers Not Concerned with Safety	1 [1,5]	2.91 (1.10)	Agreement that "Many bicyclists appear to have little regard for their personal safety" on 5-point scale[b]
Bike City Years	1[0,1]	48.1%	Derived from the responses to the original survey question "How long have you lived in this city?" on a 6-point scale (1=Less than 2 years; 2=2-5 years; 3=6-10 years; 4=11-20 years; 5=21-30 years; 6=more than 30 years.); 1=have lived in either of the three bike cities, Davis, Eugene, or Boulder, for more than 5 years; else 0.
Bicycling			
Regular Biking When	5[1,5]	75.0%	It takes the value of 1 if any response of the 5 survey questions that "How often did you bike to school,

Variable name	#Items [Range]	Mean (s.d.) or Percent %)[a]	Description
Young			convenience store, friends' houses, roaming/exploring, or library" when 12 years old on 5-point scale (1=never; 2=occasionally; 3=about once a week; 4=several times a week; 5=daily) is greater than 3; else 0.
Regular Biking	1 [0,1]	40.2%	1=Bicycled during the last 7 days, 0=Did not.

Note: [a] Mean (s.d.) for continuous variables and percent for discrete variables. For binary variables, the percentage of the variable taking the value of 1 is shown.
[b] 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree.
[c] indicates that the scale of the survey question was reversed in creating the index.

Dependent variable

The dependent variable—respondents' affect toward bicycling—was based on respondents' agreement with the statement "I like riding a bike." A five-point agreement scale was used, from "strongly disagree" to "strongly agree". Respondents who said that they "strongly disagree", "disagree", or are "neutral" were labeled "disliking bicycling" (though technically this category is "not liking biking" since it includes respondents who are neutral about bicycling); those who chose "agree" fall into the group "liking bicycling"; and those who chose "strongly agree" were categorized as "strongly liking bicycling". Three categories were used rather than two because of the significantly higher level of bicycling among those who "strongly agree" than those who just "agree," as shown in previous analyses with these data (Handy et al., 2010; Handy and Xing, 2010). Given the general wording of the question, we assume this variable reflects an individual's unconditional affect for bicycling in general, rather than his enjoyment of bicycling given a certain time and place.

Explanatory variables

Explanatory variables fall into three categories: individual factors, environmental factors, and bicycling behavior.

- Individual factors

Individual factors include socio-demographics, travel constraints, cognitions, normative beliefs, and affect toward other modes and toward physical exercise. Socio-demographics include gender, age, annual household income, education level, residence ownership, and race. Constraints mainly reflect the transportation constraints an individual confronts: whether an individual has any physical or mental conditions that seriously limit or prevent him/her from bicycling; whether there is anyone (child/children or elder/elders) in family that needs assistance to travel outside of the home. Respondents also indicated their level of health.

Cognitions include bicycling comfort and safety concern. Respondents were asked about their comfort levels on a three-point scale when bicycling on six different types of streets. Bicycling comfort, reflecting confidence in one's ability to engage in bicycling, was measured by averaging the scores of these items for each respondent. Respondents also reported their level of concern regarding several safety issues when bicycling; these scores were also averaged.

Normative beliefs measured here are the expectations that limiting driving will benefit the environment and that getting regular exercise will improve health. Finally, the survey contains six statements relating to the respondents' affect toward other travel modes, such as driving, walking, and taking transit. Affect toward physical activity was also measured.

- Environmental factors

Environmental factors include both physical and social environment factors. Physical environment factors depend on the nature of transportation infrastructure, land-use patterns, and the natural environment. A measure of perceptions of bicycling infrastructure in the respondent's current city was created by averaging responses to eight survey questions asking about different aspects of bicycling infrastructure. Perceived distances from home to selected destinations were averaged to create a measure of accessibility, reflecting the land-use mix in a community. Topography is measured by original responses indicating how true the statement, "The area is too hilly for easy bicycling," is for their community, on a four-point scale.

Social environment factors reflect the social norms of the community, as created by the individuals in the community through their social interactions. On the other hand, social norms further regulate people's interactions by establishing accepted ways of behavior and appearance in a particular group, i.e. a reference group. For example, they provide guidance on whether or not behaviors are approved of through perceptions of how other people are actually behaving, as well as expectations as to how an individual should behave (Perkins 2002). In this study, social environment was measured by perceptions of other people bicycling in the community, as well as perceptions of drivers' attitudes toward bicyclists.

Finally, a variable for living more than five years in a city with a reputation for being a bicycling-oriented city was also tested in the model. We expected that the supportive bicycling environment in these cities (Davis, Boulder, and Eugene) could increase enthusiasm toward bicycling for a resident who lives there for some time. Unfortunately, the cross-sectional survey does not enable a direct test of whether the environment can lead to changes in bicycling affect.

- Bicycling behavior

To reflect bicycling experience when the respondent was 12 years old, we created a dichotomous variable, where the value of 1 indicates that the respondent bicycled more than once per week to one of five destinations listed in the survey. In addition, a variable representing current bicycling behavior was included. Respondents who indicated having bicycled at least once in the last 7 days were labeled "regular bicyclist".

4.3.3 Model choice and procedure

We employed an ordered logit model because the dependent variable is formed by categorizing theoretically continuous responses but with unequal distances between the three response categories. A proportional odds test for the discernable ordinal scale of the three categories supported this approach.

The explanatory variables were entered into the model in steps as sets defined according to the conceptual model. At each step, only the statistically significant ($p<0.1$) variables were retained. The order in which sets of variables were entered into the model was consistent with the previous findings and related theories. We first entered individual factors including socio-demographic variables, travel constraints, and cognitions, which have been widely explored in previous attitude studies. Few previous studies have tested the effect of environmental factors on affect toward bicycling, so we next entered these factors to test whether they explain additional variation once individual factors have been accounted for. Bicycling behavior was entered as the last set into the model to check its association with affect.

However, this study is limited by its cross-sectional methods. Affect for bicycling is not only influenced by the “snapshot” of current factors but also individual and environmental factors in the past. For example, if an individual lives in an environment with a strong bicycle culture and good bicycle infrastructure, her preference for bicycling may increase over time. Testing for these possibilities requires a longitudinal approach to measure changes in each of the variables and test for associations between these changes. Additionally, potential endogeneities among the factors were also ignored in this analysis. For example, though bi-directional causalities may exist between affect and the behavior, as well as affect and environment through advocating for environmental change, here we only investigate a single direction of causality, specifically, from each of these factors to bicycling affect.

4.4 Results

The best-fitting ordered logit models are shown in Table 4.2. Model I contains only individual factors associated with the affect; Model II adds environmental factors to the individual factors; Model III tested associations between bicycling behavior and affect, controlling for individual and environmental factors. We fail to reject the null hypothesis at 95% significance that the slope coefficients are the same across the three categories of the dependent variable based on the significance of chi-square statistics for the proportional odds test of the three models, indicating that the applications of the ordered logit model are valid. As an analogue to the OLS R-square, the McFadden pseudo-R square measures the goodness-of-fit of the model. The results of the three models show that individual, environmental and behavioral factors correlate with affect toward bicycling. The coefficients in Table 4.2 indicate the change in the log-odds of being in a higher affect category, holding other variables constant, resulting from a one unit change in the explanatory variable. Note that although the magnitudes of the coefficients change as each additional set of variables is added to the model and two variables become statistically insignificant, the results of the three models are relatively robust as to the key factors associated with bicycling affect.

4.4.1 Individual factors

Two variables in this category were significant in the first two models but not the third. The first two models show that a higher education level has a positive influence on affect for bicycling, though it is insignificant in Model III, which includes the variable for regular bicycling. Survey data shows that education level is tied to regular bicycling in this sample (the Pearson Chi-Square test is 45.796 (p=0.000), indicating a significant relationship between the two categorical variables), which is drawn predominantly from college towns: those with higher levels of education are more likely to be university employees, who are more likely than others to bicycle to their jobs on campus. A negative affect toward driving, measured as agreement that one tries to limit driving, also has a positive influence in Models I and II but becomes insignificant in Model III. As with education level, this variable is strongly correlated with regular bicycling (Chi-square = 35.266, p=0.000). The impacts of both education level and driving affect on affect for bicycling were thus suppressed by the variable "Regular Bicycling" in Model III.

Among other socio-demographic characteristics, only age and race were significant. Older age reduces the likelihood of being in a higher affect category, holding other variables constant. People of white race are more likely to be in a higher affect category than the other races, all else equal. Not surprisingly, a physical limitation on bicycling exerts a strong negative impact on bicycling affect. Other cognitions are also associated with the level of affect for bicycling. The respondent's comfort with bicycling plays a relatively important role in explaining bicycling liking. The models also show that a normative belief that limiting driving benefits the environment influences bicycling affect.

Additionally, transit liking and enjoyment of physical exercise positively correlate with bicycling affect. It is possible that transit and bicycling are synergetic for longer trips, e.g. bicycling to the transit station, leading to the close relationship between affect toward bicycling and transit. It is also possible that bicycling and transit affect are correlated because they are both alternative choices to driving for non-motorized travel advocates.

4.4.2 Environmental factors

Perceived bicycle infrastructure is not related to affect toward bicycling, nor are topography or average distances from home to selected destinations. The finding that affect toward bicycling is independent of the physical environment in the current community supports our assumption that our measure of affect for bicycling is a pure measure of affect independent of place. However, this finding does not preclude the possibility that current affect for bicycling is impacted by experiences with bicycle infrastructure in the past and that current bicycle infrastructure is in the process of shaping future affect. In this cross-sectional analysis, it appears that the physical environment influences bicycling behavior directly or indirectly through other factors rather than indirectly through bicycling affect; in other words, bicycling affect is not shown to be a mediator between physical environment and bicycling behavior.

In contrast, social environmental factors are found to be associated with affect for bicycling. Higher levels of agreement both that "Most bicyclists look like they spend a lot of money on their bikes" and that "Many bicyclists appear to have little regard for their personal safety" decrease the probabilities of having higher affection for bicycling, controlling for other variables. The negative effects of these factors suggest that that they are seen as negative qualities of bicycling in a community.

Living in bicycling cities for more than five years does not correlate with bicycling affect. This result suggests that a bicycling supportive community does not necessarily trigger bicycling affect over time.

4.4.3 Bicycling behavior

The strongest association is between regular bicycling and affect. This strong association may be caused by the reciprocal causalities between them. Although few studies examine the causal relationships between affect for bicycling and bicycling behavior, causalities between travel liking and travel amounts (by vehicle, airplane, or other) hold in both directions as found by Ory (2007). However, it is also possible that bicycling affect directly influences bicycling behaviors, while bicycling behaviors impact bicycling affect indirectly through bicycling comfort or other factors. With cross-sectional data and a single equation model, it is not possible to be certain about the directions and pathways of the causal relationships. Nevertheless, this model has merit in providing support for the construction of a more complex model. It is notable that most other explanatory variables remain significant with little change in the magnitude of coefficients with the addition of bicycling behavior.

Unexpectedly, regular bicycling when young did not show an influence on current bicycling affect. While this suggests that bicycling when young does not contribute to the development of liking bicycling as an adult, it is also possible that the variable used in the study fails to capture critical dimensions of prior bicycling experience that do influence bicycling affect.

Table 4. 2 Ordered Logit Models of Affect toward Bicycling

Variable Name	Model I Coefficient		Model II Coefficient		Model III Coefficient	
Thresholds						
Threshold 1	-0.114	***	3.700	***	2.571	***
Threshold 2	2.284	***	6.382	***	5.655	***
Individual Factors: socio-demographics						
Education Level	0.159	**	0.132	**		
Age	-0.026	***	-0.024	***	-0.018	***
White Race	0.360	*	0.425	**	0.375	*
Bike Limit	-1.444	***	-1.506	***	-1.026	***
Attitudinal Factors: cognitions, affect toward other modes and physical exercise						
Biking Comfort	1.364	***	1.230	***	0.894	***
Environmental Concern	0.245	***	0.268	***	0.277	***
Like Transit	0.131	*	0.138	**	0.158	***
Limit Drive	0.169	**	0.153	*		
Enjoy Exercise	0.507	***	0.512	***	0.437	***
Environmental Factors						
Bikers Spend			-0.272	***	-0.256	***
Bikers Not Concerned with Safety			-0.226	***	-0.207	***
Bicycling Behavior						
Regular Bicycling					1.843	***
Significance of Chi-square statistic for Proportional Odds Test	0.129		0.208		0.095	
Valid N in three categories respectively	228, 364, and 200		228, 362, and 200		229, 365, and 202	
LL(C)	-841.441		-840.577		-846.213	
LL ($\hat{\beta}$)	-698.459		-684.242		-635.582	
McFadden Pseudo- R^2	0.170		0.186		0.249	

Note: *10% significance level, ** 5% significance level, *** 1% significance level.
A blank indicates the corresponding variable was not included in the model.

4.5 Discussion and Conclusions

This chapter supplies a preliminary examination of individual, environmental, and bicycling behavior factors associated with affect toward bicycling. Using cross-sectional data, ordered logit models were applied to test the influences of a wide range of individual, environmental, and behavioral factors. Results show that bicycling behavior has the strongest relationship with liking or disliking bicycling. Bicycling constraint follows it as the second most important factor associated with affect toward bicycling. People's cognitions (Biking Comfort), normative beliefs (Environmental Concern), as well as affect toward transit and physical exercise, also play important roles in predicting affect for bicycling. Social environment factors also influence liking of bicycling, although physical environment factors were not associated with it.

It is notable that the Chi-square statistic testing the parallel proportional odds hypothesis is borderline significant for Model III ($p=0.095$), in contrast to the other two models where it is more decisively insignificant. This possibly results from the endogeneity of the variable "Regular Bicycling" with both the dependent variable and with some explanatory variables in this model. For example, affection for bicycling may lead to regular bicycling behavior. It is also possible that the respondent's comfort in bicycling encourages an individual to bicycle regularly.

The results offer meaningful insights into ways to increase bicycling level. Planners usually focus on tangible strategies, such as improving bicycle facilities, to promote bicycling. Changing attitudes toward modes has not traditionally fallen within the realm of the transportation planner. This study, however, points to the importance of better understanding the factors that influence bicycling affect in order to identify other potential ways to get more people on bicycles. The application of social marketing strategies to travel behavior is increasing, and planners can draw on the experiences of the public health community in bringing about attitude change. Although limited, the available evidence suggests that these “soft” strategies can have a measurable impact on bicycling (Pucher et al., 2010).

Bicycling planners may draw inspiration from experiences of national tobacco control. Although in tobacco control, the goal is to discourage rather than encourage the behavior, decreasing smoking and increasing bicycling share the common goal of changing people’s attitudes as a way to change their behavior. Thus social marketing strategies applied for tobacco control provide a potential model for bicycle planners. Experiences from tobacco control show that individual strategies focusing on changing attitude may not be effective on their own. Rather, measurable changes may be achieved via mixed comprehensive strategies aiming at reducing the attractiveness of tobacco (Shiu et al., 2009). Mixed public policies have been applied widely on tobacco control from economic policies such as increasing tobacco tax, legal bans on tobacco use in many public places, to “anti-tobacco” programs or events held by government, including funding anti-smoking advertisements through all kinds of media, education about the hazards of smoking, and grants for researchers to demonstrate effectiveness of tobacco-control programs. Additionally, numerous organizations have formed a broad consensus all over the country on the issue of tobacco and work in conjunction with each other to reduce smoking. As a result, after decades of work, the public attitude toward tobacco has remarkably turned from general acceptance to wide unacceptance (Kluger, 1996).

Although not as comprehensively as in the public health field, transportation planners have employed a wide variety of interventions in an attempt to improve attitudes toward bicycling, including promotional programs such as "bike to work day," providing guidance on bicycling routes, or even providing financial incentives. Such programs have reportedly had some lasting effect on bicycling (Bunde, 1997; Rose and Marfurt, 2007; Bauman et al., 2008). Given sufficiently supportive bicycle infrastructure, bicycling comfort can be enhanced through training for bicyclists, for adults as well as children, leading to increases in bicycling (Telfer, 2006). Other kinds of efforts might also help. A supportive social environment can be fostered through multi-media advertisements publicizing the benefits of bicycling and featuring high-profile individuals who bicycle. Working with local communities and governments, scientific institutions and sports clubs can play synergetic roles in advocating bicycling as an environmentally beneficial physical exercise to build a shared positive image of bicycling. Such interventions are most effective when combined in an integrated package with infrastructure provision and supportive land use patterns (Pucher, et al., 2010); "one-off" strategies are unlikely to achieve the desired goal, as affection for bicycling is likely formed over longer time periods. Sustained campaigns are needed to increase affection for bicycling.

This study provides new and potentially important insights into factors associated with bicycling affect. Some issues cannot be resolved without further study, such as endogeneities among bicycling affect and bicycling behavior as well as the effect over time of some factors on bicycling affect. The former requires the application of more advanced techniques like structural equation modeling, while longitudinal data is essential for resolving effects over time. Qualitative methods could be a useful next step in understanding the factors that have contributed to an individual's affection for bicycling.   Nevertheless, this study offers an initial understanding of potential determinants of bicycling affect that helps to support the formation of policies directed toward getting more people on bicycles.

5. WHY DO SOME PEOPLE BICYCLE REGULARLY?

5.1 Introduction

Bicycling, a relatively clean, cheap, small, energy-saving, and physically active transportation mode, is widely embraced in many countries as an effective strategy to reduce driving, mitigate air pollution and greenhouse gas emissions, calm urban traffic, and decrease health care costs. However, bicycling accounts for only 1.1 percent of all trips for all purposes in the US, according to the 2009 *National Household Travel Survey* (NHTS) data. Levels of bicycling in European countries are anywhere from 4 times (in the U.K., France, Italy) to 28 times (in the Netherlands) the level of bicycling in the US (Pucher and Dijkstra, 2003).

Studies show that the physical and social environments in European countries are different in important ways from the environment in the US. (Pucher and Dijkstra, 2000; Pucher and Buehler, 2006; Pucher and Buehler, 2008). European countries have more compact land-use patterns with higher average urban densities and consequently shorter average trip lengths than those of the US. Many cities in the US lack appropriate facilities for cycling compared with those in European countries. The extent of the car-dependent culture and lifestyle also makes the US different from other countries. More pro-bicycling policies and programs as well as restrictions on driving in European countries have reinforced wider social support for bicycling. These factors apparently help to explain much higher levels of bicycling in Europe than the US (Pucher and Buehler, 2008). In addition, while incomes and auto-ownership are comparable between the US and Europe, it is possible that individuals are simply more favorably inclined towards bicycling in Europe.

However, empirical findings of the influences of physical and social environments on bicycling behavior are still limited. Most bicycling studies use single equation models to establish associations between the environment and behavior, ignoring potential relationships among the explanatory variables. For example, few studies examine the possibility of a self-selection effect, in which a preference for bicycling leads individuals to choose to live in communities that are conducive to bicycling. Consequently, the importance of physical and social environments, relative to each other and to individual factors as well, in explaining bicycling behavior is still unknown, given the lack of accounting for potential interactions among these factors.

This paper explores the relative importance of physical and social environments as well as individual attitudes on bicycling behavior. We use structural equations modeling to map out the direct and indirect effects of all three sets of factors. The purpose of this study is to provide a stronger empirical basis for policy decisions promoting bicycling by contributing to an improved understanding of the influences of physical and social environments as well as individual attitudes on bicycling.

5.2 Literature Review

This chapter attempts to understand bicycling behavior in terms of interactions between bicycling and its explanatory factors, as well as relationships among the factors influencing bicycling. We start with a review of previous bicycling studies. However, given the limited empirical methods used in these studies, we then review more general travel behavior studies to construct a broader set of hypothesized factors associated with bicycling and postulate more realistic causal relationships between these factors and bicycling.

5.2.1 Factors associated with bicycling

Previous research on bicycling provides evidence of individual factors associated with bicycling behavior. Socio-demographics play important roles in explaining bicycling: bicycle ownership or number of bicycles in the household (Moudon et al., 2005; Cervero and Duncan, 2003; Krizek and Johnson, 2006), gender (Williams, 1996; Stinson and Bhat, 2004; Wardman, 2007), age (Plaut, 2005; Wardman et al., 2007), car ownership (Stinson and Bhat, 2004; Plaut, 2005), race (Plaut, 2005; Moudon et al., 2005), education (Plaut, 2005), and health condition (Moudon et al., 2005) are all related to bicycling. Another set of potentially important individual factors are constraints. For example, physical limitations owing to age or other causes may constrain the ability to bicycle, though previous bicycling studies have not examined these factors.

Attitudes refer to an individual’s specific opinions, intentions, affections, and beliefs about an object or idea. Given the importance of attitudes in explaining driving behavior (Ory, 2007), it seems likely that attitudes also influence choices about bicycling. However, few studies have examined this possibility. Gatersleben and Appleton (2007), using stated preference methods, found that people who like bicycling would bicycle commute under most circumstances. Another study of bicycling among a working population found that people who have external self-efficacy (as indicated by the willingness to cycle even if the weather is bad) and ecological-economic awareness (agreement that cycling is cheaper, better for the environment, etc.) are more likely to bicycle for transport (Geus et al., 2007). Further, few studies of bicycling have explored the possibility of "self-selection" for bicycling, the possibility that an individual's preference for bicycling leads him to choose to live in a community with an environment supportive of bicycling of one type or the other (Handy et al., 2006). Pinjari et al. (2008) found a residential self-selection effect on bicycle ownership. However, they measured self-selection for a bicycle-friendly neighborhood by categorizing individuals who now live in bicycle-friendly neighborhood as self-selectors, despite the fact that those individuals may have moved there for reasons other than bicycling. Another recent study (Xing et al., 2010) found an important influence of self-selection on the proportion as well as the distance of transportation bicycling.

Physical- and social-environment factors are also associated with bicycling. Previous studies have identified various characteristics of the physical environment, including built (man-made) and natural features, associated with bicycling. Several studies show an association at the city level between bicycle and bicycle infrastructure, including miles of bicycle pathways per 100,000 residents (Nelson and Allen, 1997), number of bicycle lanes per square mile (Dill and Carr, 2003), and proportion of separated bicycle paths (Parkin et al., 2008). In addition, the perceived presence of bicycle lanes and trails in the neighborhood, as well as the availability of bicycle facilities (bike racks or lockers), are associated with bicycling (Moudon et al., 2005; Stinson and Bhat, 2004). Studies have also found that land use patterns, measured by presence of destinations (grocery stores and schools) in the neighborhood, land-use mix (land areas occupied by more residential and commercial uses) or land-use diversity (jobs balanced across the retail/service, office and manufacturing/trade/other sectors at the origin or destination) are positively associated with bicycling (Moudon et al., 2005; Cervero and Duncan, 2003). Natural features such as hilliness (Parkin et al., 2008), darkness (Cervero and Duncan, 2003), rain (Dill and Carr, 2003; Parkin et al., 2008), and temperature (Parkin et al., 2008) are also determinants of bicycling.

Few studies have explored the influence of the social environment, though it emerged as important at least in one study (Geus et al., 2007): people with relatives who cycle and give social support by cycling with them are more likely to bicycle for transport. However, the social support for cycling in the neighborhood as measured in another study (Moudon et al., 2005) did not add explanatory power in models of bicycling behavior.

5.2.2 Causal relationships between travel behavior and its associated factors

Although no studies of bicycling behavior have used structural equations modeling to examine the potentially complex web of relationships between explanatory factors, results from such studies of other aspects of travel behavior provide potentially useful insights. For example, the causal link from vehicle ownership to vehicle use has been hypothesized and examined in a number of travel behavior studies. The strongest link from car ownership to trips is shown in Golob's study (1989). Similarly, Simma and

Axhausen (2001), employing structural equation modeling, confirm that car ownership leads to car usage.

The role of attitudes, perceptions, or intentions has also been studied using structural equation modeling. Tardiff (1976) confirms a stronger link from behavior to attitudes than vice versa by using path analysis, a special case of structural equation modeling. Another study found mutual causal links between attitudes and behavior (Dobson et al., 1978). Attitudinal variables have the greatest direct impacts on travel behavior of all the variables in a study by Bagley and Mokhtarian (2002). A more recent study shows that specific attitudes, such as the enjoyment of travel (Travel Liking), lead directly to travel behavior, but also vice versa (Ory, 2007). The study by Cao et al. (2007) found that residential self-selection for walking neighborhoods has a direct influence on travel behavior.

Some studies have used structural equation modeling to explore the causal relationship between the built environment and travel behavior. The study by Bagley and Mokhtarian (2002) is the first disaggregate structural equation model employed to test whether the built environment has a causal effect on travel behavior. They found that residential location had little influence on travel behavior. However, using a quasi-longitudinal study design, Cao et al. (2007) found a causal relationship between the built environment (specifically, close proximity to destinations) and both driving and walking behavior. Social-environment factors are rarely examined in travel behavior studies.

Overall, although previous bicycling studies provide important insights into factors associated with bicycling, they provide limited insights into the causal connections between environment and bicycling. In most bicycling studies, explanatory variables are treated as exogenous variables in single equation models, ignoring all possible endogenous relationships between them and accordingly yielding incomplete and potentially invalid results. Travel behavior studies employing structural equations modeling shed light on potential relationships between environment and bicycling. By capturing the interactions among factors and bicycling behavior, a structural equations model can help us to better understand the complex relationships between the variables.

5.3 Methodology

5.3.1 Data and key variables

Data are from a survey conducted in six communities in the Western US (see details in Chapter 3) and were selected for the study based on several factors. The survey variables used in this study can be categorized into three general groups: measurements of bicycling, individual factors, and physical and social environment factors. Some are original variables from the survey (e.g. most socio-demographics) and are fully documented in the Appendix. Some variables were created through simple mathematical computation such as averaging (e.g. Biking Comfort). The others are latent factors identified through that Common Factor Analysis (CFA) method. The constructs of the latent factors, demonstrating the relationships between the latent factors and the factor indicators explored by CFA, are shown in Table 5.1 as a guide to the measurement models (defined later) appearing in the structural equation modeling.

Factor analysis is widely used to express covariation among observed (manifest) variables through fewer unobserved (latent) dimensions, i.e. latent factors. Specifically, Common Factor Analysis (CFA), in which a variable has a part common to other relevant variables (communality, also known as the amount of variance each variable in the analysis shares with other variables) and a unique part (uniqueness) uncorrelated with other variables, was employed to find the common vector space, i.e. the latent factors, captured by all variables in each category introduced above. Oblique rotation was selected based on the assumption that the extracted factors are correlated with one another. The percentage of the total variance in the relevant survey items accounted for by each extracted factor is greater than 30%, except that one factor, "Non-Motorized," explains only 28% of the total variance. The variance explained by this set of factors combined falls within the typical acceptable range of 30%-50% for CFA (Widaman, 1993). This step also contributes to the development of the measurement models in structural equations modeling introduced later in this chapter by providing empirical support for them.

Table 5.1 presents all latent factors appearing in the factor constructs for the measurement models in the final structural equation modeling together with their factor loadings (the correlation coefficients between the variables and latent factors) and communalities explored by CFA. All the variables documented here were tested in the SEM and only significant ones were kept to achieve the most parsimonious model.

Measurements of bicycling

In this study, bicycling is defined with respect to both bicycle ownership and regular bicycling. Bicycle ownership was measured as a dichotomous variable from a survey question: “Do you own or have regular access to a bicycle (in working condition)?” Regular bicycling is a dichotomous variable indicating whether or not respondents bicycled during the last seven days.

Individual factors

Individual factors consist of socio-demographics, constraints, and attitudinal factors. Socio-demographics include gender, age, annual household income, education level, home ownership, and race. Constraints mainly reflect the transportation constraints an individual confronts: whether an individual has any physical or mental conditions that seriously limit or prevent him or her from bicycling, or whether there is anyone (child/children or elder/elders) in the family that needs assistance to travel outside of the home. It is notable that the variances of both the variables Age (229.541) and Household Income (1419.719) exceed the value of 10, which may lead to convergence problems in Structural Equation Modeling, particularly with combinations of categorical and continuous endogenous variable (Mplus User’s Guide, p. 382). Therefore, those two variables were standardized to present similar scales with other factors in the model. We expect that socio-demographic characteristics and transportation constraints influence bicycling directly and we will control for them when testing a more comprehensive set of variables.

Attitudinal factors were measured in various ways. Respondents were asked about their comfort level on a three-point scale when bicycling on six different types of streets (an off-street bicycle path, a quiet residential street, a two-lane local street with a bicycle lane, a narrow two-lane local street without a bicycle lane, a four-lane street with a bicycle lane or without a bicycle lane) in daylight and good weather. Individual bicycling comfort, reflecting confidence in one's ability to engage in bicycling, was measured by simply averaging the scores of these items. The attitude of liking bicycling was dichotomously categorized by "strongly agree[ing]" or "agree[ing]" versus "strongly disagree[ing]", "disagree[ing]", or "neutral" on the statement, "I like riding a bike". The importance to respondents of "A good community for bicycling" when they were deciding where to live was measured on a four-point scale from ''not at all important'' (1) to ''extremely important'' (4); we named it "Residential Preference for Biking".

Two sets of attitudes were also measured in the survey. One set contains eight statements, which were designed to capture respondents' preferences with respect to travel mode and the environment. The other set includes three statements, which were designed to capture individuals' attitudes toward physical exercise. Because each variable in the two categories is significantly correlated with the others within the same at a 0.05 significance level, the underlying constructs of the attitudes represented by them were explored using common factor analysis (CFA). The results of the CFA were used to guide the specification of the measurement models of the structural equation model, as described below.

From the first set of eight variables reflecting attitudes toward travel mode and environment, two latent factors were extracted empirically based on the eigenvalue-one criterion. Based on the factor loadings, the two manifest variables reflecting responses to the statements “When choosing travel modes, how important is the consideration of environmental benefits in your decision” and “I try to limit driving as much as possible” are heavily loaded on the first factor (0.813 and 0.657 respectively); “I like driving” and “I need a car to do many of the things” have the greatest loadings on the second factor (0.453 and 0.318). The first factor may represent “Environmental Concern” and the second may be labeled as “Pro-driving.” However, the variable “I like driving” also loaded heavily but negatively on the first factor (with factor loading of -0.380). Possibly the high negative loading for this variable captures environmental concern as well as the attitude of disliking driving. Although the eigenvalues suggested a 2-factor solution, the balanced factor loadings of some variables on both factors suggests some confusion in the factors. Additionally, the second factor contributes almost nothing to the capturing of variance though it has an eigenvalue of 1.09. To make the analysis parsimonious, i.e. explaining the variance with as few variables as possible, we kept only the first factor. Empirically, we set the number of factors to 1 rather than strictly following the eigenvalues rule. Based on the factor loadings of the variables (Table 5.1), we named the factor “Non-Motorized.” This factor explains 28% of the total variance in the eight statements.

Table 5. 1 Factor Constructs Appearing in the Final SEM (N=965)

Factor	Description of Indicators	Factor Loading	Communality
Attitudinal Factors			
Non-Motorized	Agreement that "I like driving" on 5-point scale*	-.349	.122
	Agreement that "I need a car to do many of the things I like to do" on 5-point scale*	-.400	.160
	Agreement that "I try to limit driving as much as possible" on 5-point scale*	.616	.379
	Agreement that "I like walking" on 5-point scale*	.398	.159
	Agreement that "I like taking transit" on 5-point scale*	.464	.215
	"When choosing travel modes, how important is the consideration of environmental benefits in your decision", on 4-point scale where 1=Not at all important, 2=Somewhat important, 3=Important, 4=Extremely important.	.665	.442
	Opinions on stricter environmental laws and regulation. 0= "[They] cost too many jobs and hurt the economy", 1= "[They] are worth the cost".	.406	.165
	Agreement that "I try to limit my driving to help improve air quality" on 5-point scale*	.765	.585
Pro-Exercise	Agreement that "It is important for me to get regular physical exercise" on 5-point scale*	.712	.507
	Agreement that "I enjoy physical exercise" on 5-point scale*	.873	.762
	Agreement that "I am in good health" on 5-point scale*	.752	.566
Physical Environment Factor			
Supportive Infrastructure	Agreement that "Major streets have bike lanes" on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true.	.664	.441
	Agreement that "Streets without bike lanes are generally wide enough to bike on" on 4-point scale same as above.	.611	.374
	Agreement that "Stores and other destinations have bike racks" on 4-point scale same as above.	.666	.443
	Agreement that "Streets and bike paths are well lighted" on 4-point scale same as above.	.659	.434
	Agreement that "Intersections have push- buttons or sensors for bicycles or pedestrians" on 4-point scale same as above.	.510	.261
	Agreement that "The city has a network of off-street bike paths" on 4-point scale same as above.	.689	.474
	Agreement that "Bike lanes are free of obstacles" on 4-point scale same as above.	.592	.351
	Agreement that "The bike route network has big gaps" on 4-point scale same as above.	-.556	.310
Social Environment Factor			
Popular Culture	Agreement that "It is rare for people to shop for groceries on a bike" on 5-point scale*	-.603	.363
	Agreement that "Bicycling is a normal mode of transportation for adults in this community" on 5-point scale*	.771	.594
	Agreement that "Most bicyclists look like they are too	-.357	.128

Factor	Description of Indicators	Factor Loading	Communality
	poor to own a car" on 5-point scale*		
Good Driver Attitude	Agreement that "Most drivers seem oblivious to bicyclists" on 5-point scale*	-.702	.493
	Agreement that "Most drivers yield to bicyclists" on 5-point scale*	.806	.649
	Agreement that "Most drivers watch for bicyclists at intersection" on 5-point scale*	.797	.636
Biking Supportive Community			
Biking Supportive Community	Supportive Infrastructure (see above)	.845	.714
	Popular Culture (see above)	.554	.307
	Good Driver Attitude (see above)	.464	.216

*Where 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree.

One factor emerged empirically and accounts for 61% of the total variance in the set of three statements. The pattern matrix of the obliquely rotated factor loadings for the factor analysis solution is presented in Table 5.1. All the variables heavily load on the factor (all factor loadings are greater than 0.70). This factor was labeled as "Pro-Exercise."

We hypothesize that bicycling is directly impacted by multiple attitudes, such as confidence in one's ability to engage in bicycling, affect for bicycling, residential preference for bicycling, and attitudes toward non-motorized travel and physical exercise. A reciprocal causal relationship is expected between the attitude of liking bicycling and bicycling behavior, based on the findings of previous travel behavior studies and Chapter 4 of this dissertation. It is reasonable to hypothesize that residential preference for bicycling is driven by the attitude of liking bicycling. Additionally, we expect to find a direct link from residential preference for bicycling to bicycling behavior.

Environmental factors

Environmental factors include both physical and social environment factors, as well as a second-level factor that reflects a composite of these factors—Biking Supportive Community (Table 5.1). Physical environment factors depend on the nature of transportation infrastructure, land-use patterns, and the natural environment. Following the same CFA method used to identify the two attitudinal factors, "Non-Motorized" and "Pro-Exercise," one latent factor, "Supportive Infrastructure," was derived from a group of responses to eight statements describing the bicycling system. This factor structure was also employed later in the structural equation modeling. The factor loadings for the factor analysis solution are presented in Table 5.1. This factor solution explains 38% of the total variance in the eight statements. Perceived distances from home to selected destinations (usual grocery store, nearest post office, the favorite restaurant, bike repair shop, the workplace, and the local elementary school) were averaged to create a measure of accessibility, reflecting the land-use mix in a community. The topography is measured by original responses indicating how true the statement, "The area is too hilly for easy bicycling," is for their community, on a four-point scale.

Social environment factors reflect the cultural norms of the community, as created by the individuals in the community through their social interactions and as evidenced by the collective behaviors of its residents. In this study, two different aspects of the perceived social culture were identified by two latent factors by employing CFA method: Popular Culture and Good Driver Attitude. The former factor captures a popular bicycling culture (especially transportation bicycling) through a set of three manifest variables reflecting a community where it is not rare for people to bicycle to buy groceries, where bicycling is a normal transportation mode, and where bicyclists are not viewed as being too poor to own a car. In total 36% of the variance in the three statements was explained by this factor. The latter factor was identified as drivers' positive attitudes toward bicyclists, constructed with responses to three relevant statements reflecting a community where drivers are aware of bicyclists, yield to them, and watch for them at intersections. This factor accounted for 59% of the total variance in the group of statements. These factor constructs were used as a guide to the measurement models in the structural equation modeling.

The Biking Supportive Community factor was designed for the purposes of examining the role of residential preference for biking. Residential self-selectors for bicycling may not be attracted by extensive bicycle lanes or popular bicycling culture alone. For example, the City of Woodland has relatively good bicycle infrastructure: it has 61.10 miles of bike lanes and paths per 50,000 residents and 5.83 miles of bike lanes and paths per square city mile, compared to 78.62 and 9.89 for Davis. However, Woodland is not known for its bicycling culture. A community like Woodland is not as seductive city to those individuals seeking to live in a good community for bicycling as is Davis. Therefore, we assume that supportive bicycle infrastructure and bicycling culture work together to attract residents with a preference for a bicycling community. The factor Biking Supportive Community was constructed using CFA as the underlying common dimension of the three first-order variables Supportive Infrastructure, Popular Culture, and Good Driver Attitude. This factor explained 41% of the total variance in the three first-order factors.

We hypothesize that the physical environment (Average Distance, Hilly Topography, Supportive Infrastructure), as well as the social environment factors (Popular Culture and Good Driver Attitude) impact bicycling directly. They also have indirect influences on bicycling through mediating variables—Biking Comfort and Like Biking. Residential preference for bicycling manifests itself as influences on Biking Supportive Community, Average Distances, and Hilly Topography, which then have an impact on bicycle ownership and bicycling.

5.3.2 Hypothesized model

The hypothesized conceptual model of regular bicycling developed from the conceptual model of general bicycling behavior (Figure 3.1) described in Chapter 3, which is derived from travel and physical activity behavior theories as well as empirical studies. Using this conceptual model, we hypothesize a multilevel array of factors that potentially influence bicycling behavior.

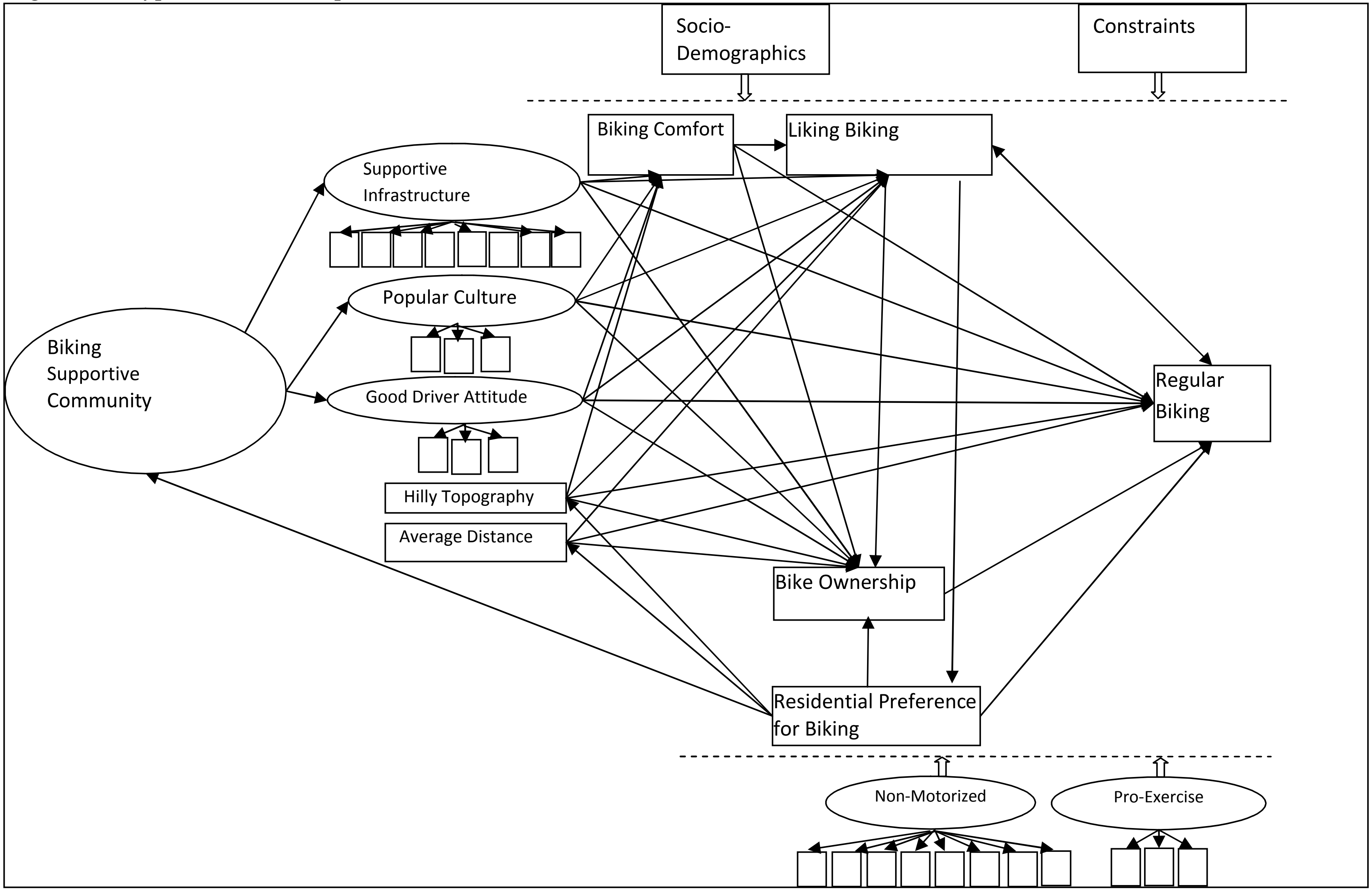
Specifically, drawing on factors shown to be associated with bicycling and causal relationships confirmed in previous travel behavior studies, we developed the hypothesized conceptual model, which includes all the hypothesized links mentioned above (Figure 5.1).

In the figure, an observed variable is shown as a solid rectangle; while a factor is represented by an ellipse. The variables are separated into exogenous variables (independent variables with no prior causal variable) and endogenous variables (effects of other variables, i.e. those that receive the end of one or more arrows). Exogenous variables are separated from endogenous variables by the dashed lines in Figure 5.1. One-way arrows indicate one direction of causality; two-way arrows refer to reciprocal causality between two connected variables.

Limited by cross-sectional data, the model does not show reciprocal relationships between the environment and bicycling behavior, specifically the effect of bicycling on the environment, even though both social cognitive and ecological models suggest they are reciprocal for the reasons documented in Chapter 2. Additionally, we ignore possible causal links from attitudes to the physical and social environment. It is possible that in the long run strong enthusiasm and support from residents can lead to changes in bicycle infrastructure and social norms. Furthermore, the interactions between attitudes toward travel modes and the environment (measured by the factor Non-Motorized) and physical exercise (measured by Pro-Exercise), i.e. how they affect each other, were not explored. They were treated as unobserved exogenous factors in the model. Similarly, we did not model the possible relationships between land use patterns, topography and bicycle infrastructure or bicycling culture. Theoretically, it is possible that these impacts occur over time rather than instantly; practically, we simplify the model by leaving out these potential relationships in order to avoid the problem of statistical under-identification, i.e. a set of parameters in a model cannot be uniquely determined depending on the number of observations and the structure of the model. However, we compensated for this omission to some extent by allowing unanalyzed associations, i.e. two variables are assumed to covary, but the reasons why they covary, whether they affect each other or have common causes, are unknown (Kline, 2005, p. 97), between them in the model. Specifically, two types of unanalyzed associations are allowed in the model. One type is unanalyzed associations between exogenous variables, such as Household Income and Education Level or Household Size. The other unanalyzed associations are those between pairs of disturbances, representing all omitted causes of the corresponding endogenous variables, e.g. unanalyzed association may exist between the second-order factor representing the environment, Biking Supportive Community, and Regular Biking. Biking Supportive Community may also have unanalyzed associations with the attitude of Liking Biking and Biking Comfort respectively. Additionally, the factors Non-Motorized and Pro-Exercise are hypothesized to covary.

All links in this model were tested empirically. This model contains two parts: measurement models and a structural model. The former describes the relationships between latent factors and observed dependent indicators. In this model, they include all the factor constructs shown in Table 5.1. The latter specifies three types of relationships: the relationships among latent factors; the relationships among observed variables; and the relationships among latent factors and variables that are not factor indicators (in factor analysis, latent variables are referred to as factors; observed variables used to define the latent variables are called factor indicators) (Muthén and Muthén, 2007, p.50). Note that all factor indicators in the model are ordinal variables except that of the continuous second-order factor, Biking Supportive Community.

Figure 5. 1 Hypothesized Conceptual Model



5.3.3 Modeling approach

This study employed structural equations modeling (SEM) to determine the direct and indirect relationships among individual factors, environmental factors, and bicycling behavior. SEM is generally viewed as a more powerful alternative to ordinary regression because it captures the multiple directions of interactions among the endogenous and exogenous variables. The analysis procedure involves five basic steps: model specification, i.e. "the researcher's hypotheses are expressed in the form of a structural equation model" (Kline, 2005, p. 63). Second, model identification, which refers to whether it is theoretically possible that all unknown model parameters are uniquely estimated in a SEM. Third, model estimation, in which one or more different methods, all of which are based on a general approach called covariance structure analysis, are employed to find the "best" set of parameters in a SEM (Mokhtarian and Ory, 2008). Fourth, model fit evaluation and parameter interpretation, measuring the goodness of fit of a SEM. At last, if the estimated model-implied covariance matrix does not adequately fit the population covariance matrix (as estimated by the sample covariance matrix), hypotheses can be adjusted and the model needs to be retested. Specifically, model structure, estimation methods, and measures of goodness of fit for a SEM are introduced in the following discussion.

Ory (2007) summarized the matrix notation used in Jöreskog et al. (1999) and expressed a generic structural equations model as having the following form:

$$\eta = \alpha + B\eta + \Gamma\xi + \varsigma$$

where,

α = is a column vector (N_η x 1) of intercept terms,

η = ($N\eta$ x 1) column vector of endogenous variables ($N\eta$ = number of endogenous variables),

ξ = (N_ξ x 1) column vector of exogenous variables (N_ξ = number of exogenous variables),

B = ($N\eta$ x $N\eta$) matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables,

Γ = (N_ξ x N_ξ) matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and,

ς = ($N\eta$ x 1) column vector of errors.

More generally, the endogenous or exogenous variables could be latent factors manifested by other endogenous and exogenous variables. Assuming y denotes endogenous and x stands for exogenous factor indicators, the matrix notation is expressed as follows:

$$y = \tau_y + \Lambda_y \eta + \varepsilon$$

$$x = \tau_x + \Lambda_x \xi + \delta$$

where the error terms ε and δ are assumed to be uncorrelated with η and ξ,; Λ_y and Λ_x are coefficients; τ_y and τ_x are intercepts.

A general approach, covariance structure analysis, is usually applied to identify a specific SEM. In this approach, α, B and Γ, as well as the true population variances and covariances of the exogenous variables X, denoted by the matrix ϕ (N_ξ x N_ξ), and of the error terms ς, denoted by ψ ($N\eta$ x $N\eta$), have unknown (free) parameters to be determined. So do τ_y , Λ_y , τ_x , Λ_x , the covariance matrices of ε and δ, denoted by Θ_ε and Θ_δ respectively, the covariance matrix of the error terms $\Theta_{\delta\varepsilon}$ in the latent factor equations. The model-implied (estimated) covariance matrix can be obtained by fitting all the unknown parameters to minimize the difference (also known as the residual matrix) between the model-estimated population covariance matrix and the sample-estimated population covariance matrix (an unbiased estimator of the population matrix).

Some of the most commonly used methods to estimate SEMs are generalized least squares (GLS), maximum likelihood (ML), and asymptotically distribution-free (ADF) (Mokhtarian and Ory, 2008). When the observed variables are multivariate normally (MVN)-distributed, the former two methods are more appropriate; ADF needs no distributional assumptions, but requires a relatively large sample size. A recently developed method is the Mplus technique, which employs a weighted least squares approach that is similar to ADF but respects the specific nature of ordinal variables when they are present (Muthén and Muthén, 2007). Because many of the variables as well as some factor indicators in this study are ordinal or binary (e.g. Residential Preference for Biking, Regular Biking, and the indicators of Pro-Exercise) rather than continuous and are thus not multivariate normally distributed, we used the estimation technique of the Mplus software package. This technique, which uses a weighted least squares approach to deal with categorical endogenous variables, is a good choice for our categorical factor analysis, as supported by the findings of Ory and Mokhtarian (2010).

All methods mentioned above yield a fitting function, which is the difference between the estimated (model-implied) population covariance matrix, Σ, and the sample-estimated population covariance matrix, S, as the result of the estimation process. Then the natural question is: how close is the estimated model-implied covariance matrix to the true population matrix? Measures of model fit for a SEM vary according to different concepts. The most commonly reported measures are χ^2, χ^2/d.f., RMSEA, and CFI (Mokhtarian and Ory, 2008). The basic measure is the model chi-square statistic (χ^2), which is expressed as (N-1) FML , where N is the sample size and FML is the fitting function (i.e. the discrepancy between observed and model-implied variance-covariance matrices). Higher values of the chi-square statistic imply a rejection of the null hypothesis that there is no difference between the two matrices. Thus lower values are indicators of better goodness of fit. However, this measure greatly depends on the sample size. A larger sample size more easily leads to a rejection of the null hypothesis. Another measure of model fit, the ratio of chi-square to its degrees of freedom (χ^2/d.f.), helps reduce the sensitivity of chi-square to sample size. Similarly, large values of this measure indicate bad goodness of fit. Root Mean Square Error of Approximation (RMSEA) refers to the amount of error of approximation per model degree of freedom, and is widely used to evaluate model fit: a value of less than 0.05 suggests a good fit and a value of less than 0.08 indicates an acceptable fit (McNeill et al., 2006). It measures the discrepancy between the sample model and the estimated model per degree of freedom and thus corrects for sample size and penalizes model complexity. A value greater than 0.9 of the Comparative Fit Index (CFI), which compares the fit of the estimated model to that of a baseline or null model, indicates a good model fit.

The final SEM model includes eight equations and therefore eight endogenous variables. Some are linear regression equations with continuous dependent observed variables or factors: *Bike Comfort* (explanatory variables in this equation are Female, Household Size, Household Income, Education Level, White Race, Supportive Infrastructure, and Hilly Topography), *Average Distance, Hilly Topography*, and *Biking Supportive Environment* (with the same single explanatory variable in each of the three equations: Residential Preference for Bicycling). Others are probit regression equations for binary or ordered categorical dependent variables—*Regular Biking* (explanatory variables in this equation are Home Ownership, Biking Limit, Bike Ownership, Popular Culture, and Like Biking), *Biking Ownership* (explanatory variables include Household Size, Home Ownership, Biking Limit, Biking Comfort, and Like Biking), *Residential Preference for Biking* (explanatory variables are: Education Level, Like Biking, and Non-Motorized), and *Like Biking* (explanatory variables are Age, Household Income, White Race, Biking Comfort, Non-Motorized, and Pro-Exercise).

It is important to note that we allow some latent factor indicators (Supportive Infrastructure, Popular Culture, and Good Driver Attitude) to have a direct influence on variables, e.g. Biking Comfort, other than the second-order latent factor, Biking Supportive Community. It is unconventional to use a variable as both a factor indicator for a latent variable and as a regular variable with a direct influence on other variables is unusual, but we do so specifically for measuring the direct effects of supportive bicycling infrastructure and bicycling culture on bicycling, beyond their indirect contribution to a bicycling supportive environment in general. This model design achieved a better model fit and more reasonable results than a conventional one in which the latent factor indicators were not hypothesized to affect other variables directly.

5.4 Model Results

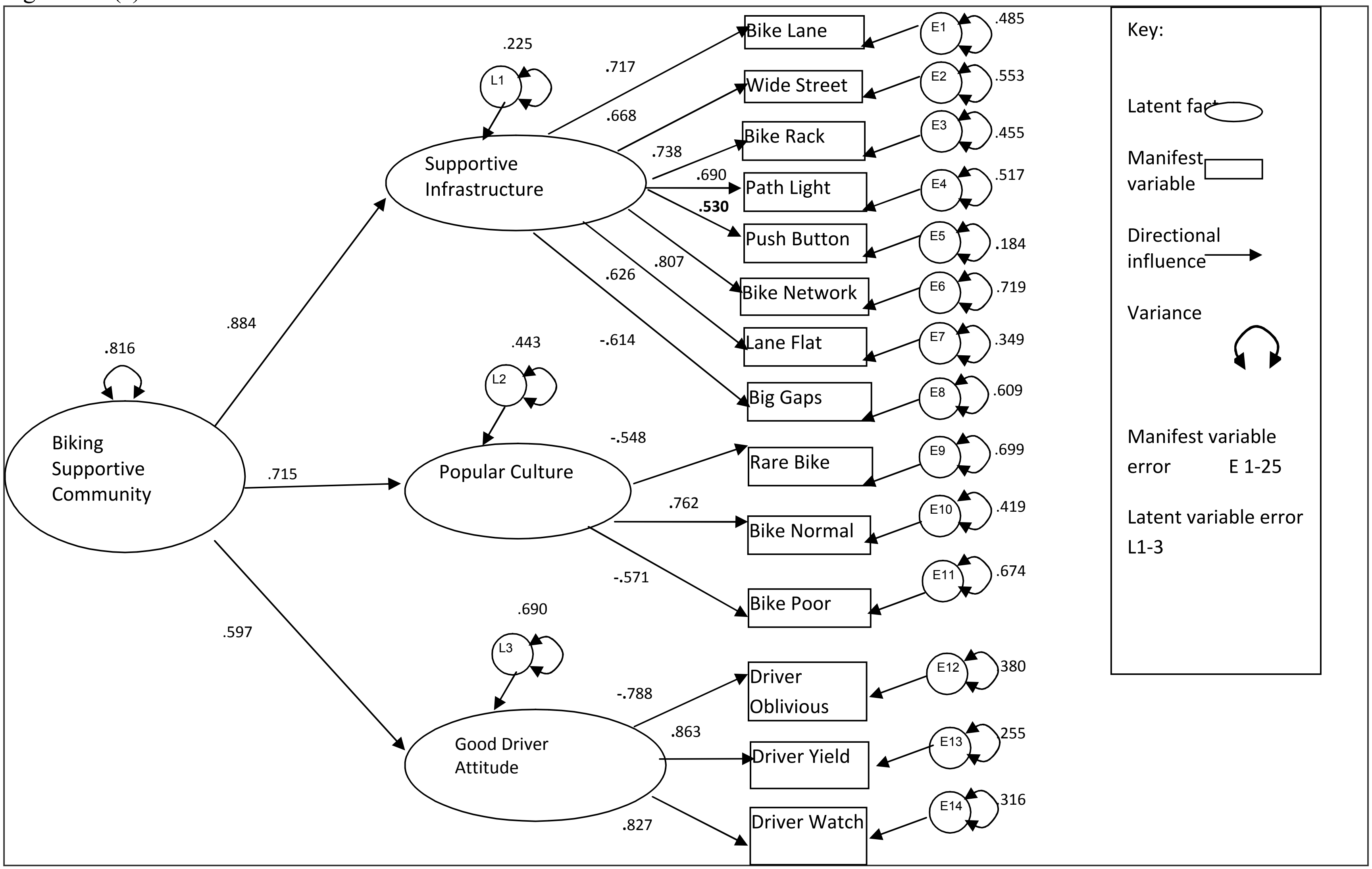
The final estimated results are shown in Figure 5.2 (a) and (b) (the measurement model), 5.3 (the structural model), and Table 5.2 (total effects). Although total effects (the sum of the direct and all the indirect effects through mediating variables) are our focus, presenting all direct links (Figure 5.3) helps to show the pathways by which important variables influence bicycling. Note that blanks in Table 5.2 represent coefficients constrained to be zero in the model, either as hypothesized or because of empirical insignificance (at the 0.1 significance level). Overall, most indexes to evaluate the goodness of model fit indicate a good model fit. The exception is CFI, which is less than but close to 0.90. However, it still falls within the range of [0.88, 1.00], the acceptable range in applications of structural equation modeling in operations management research (Shah and Goldstein, 2005).

Figure 5.2 (a) and (b) depict the measurement model including a hierarchical model of environmental factors and a two-factor model of relations between the two attitudinal factors: Non-Motorized and Pro-Exercise. “Hierarchical model” refers to a model construct that includes at least one second-order factor, which is not directly measured by any indicator (Kline 2005, p. 168). This model was guided by the factors developed using common factor analysis. In this model, the second-order factor, the common direct cause of the three first-order factors, is assumed to explain the correlations among them. The estimates for the errors indicate the proportion of unique, i.e. unexplained, variance of the corresponding indicators or the first-order factors. Although unexplained variances are greater than 0.50 for a total of six out of fourteen indicators, statistical estimates of the direct effects from the factors to their indicators, i.e. factor loadings, are significant at the .001 level and substantial in magnitude (from .530 to .884). The results of the two factor model of Non-Motorized and Pro-Exercise show that the estimated factor correlation (0.387) is small, which confirms discriminate validity, i.e. that the two constructs differ.

The empirical results show the relative importance of individual, physical environment, and social environment factors in explaining bicycling behavior. Not surprisingly, the estimated standardized total effects of various factors on bicycling show that the attitude of liking bicycling plays a relatively important role in encouraging both bicycle ownership and regular bicycling. Note that the hypothesis of a reciprocal causal relationship between Like Biking and Regular Biking was not confirmed: only the direct link from Like Biking to Regular Biking exists, while the other link was removed due to its insignificance ($p=0.191$). Other important determinants of bicycling include the constraint of physical or mental limitations on bicycling, attitude toward travel and environment, and attitude toward physical exercise. Socio-demographics also strongly impact bicycling: older age decreases the probability of owning a bicycle and bicycling regularly; females are less likely to have a bicycle and to bicycle compared with males; the number of members in a household, education level, and white race are positively related to bicycling. Both higher annual household income and owning one's residence increase the probability of bicycle ownership; however, home ownership decreases the likelihood of regular bicycling. Bicycling comfort, a measure of bicycling self-efficacy, has strong positive impacts on bicycling. Although residential preference for a bicycling community has no direct effect on bicycling, it shows significant indirect impacts on regular bicycling and bicycle ownership through its influences on Biking Supportive Community, Average Distances, and Hilly Topography, implying a self-selection effect on bicycling.

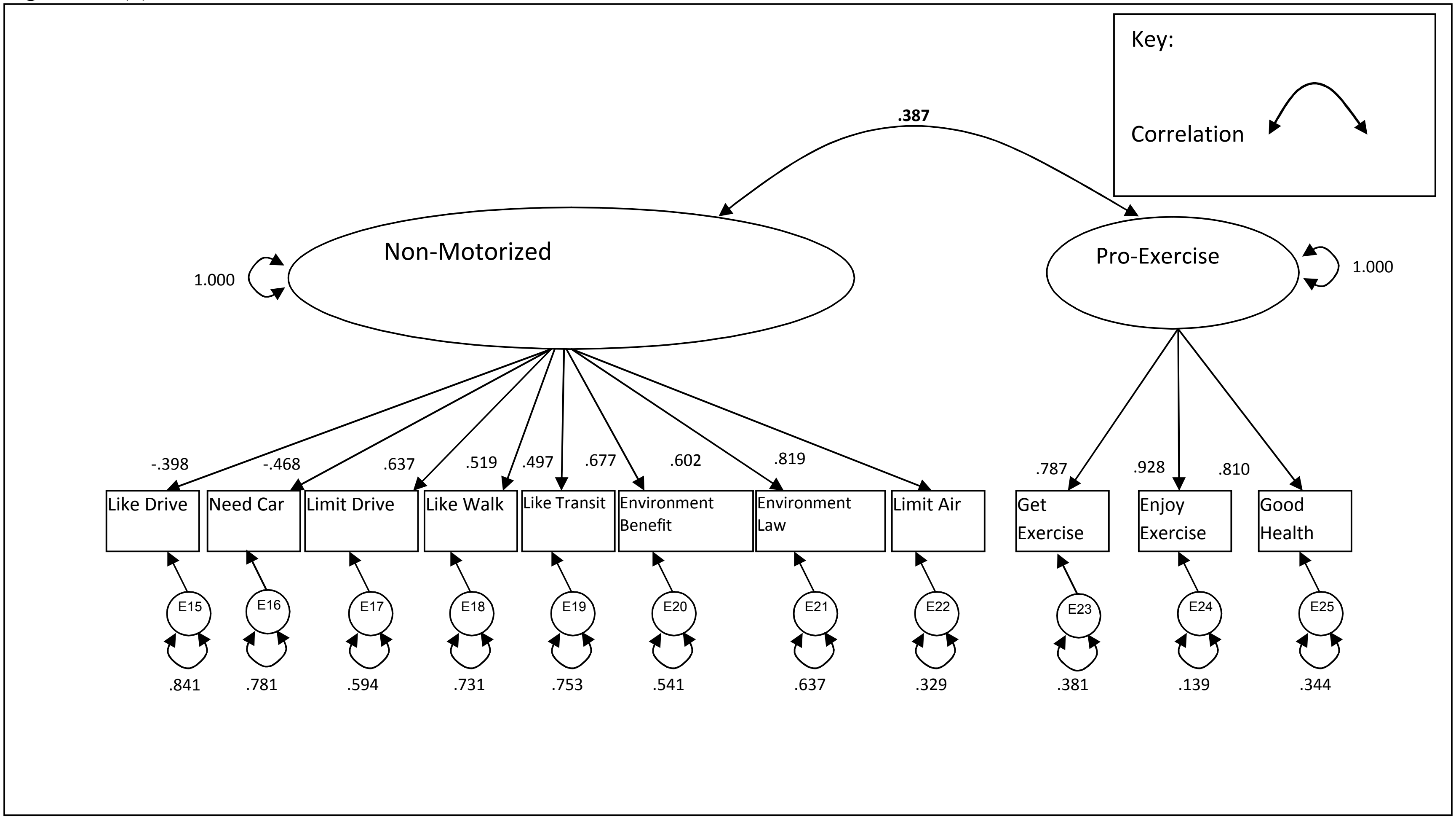
The results show that both physical and social environment factors impact bicycling. All the effects have the expected signs except the measure of land-use mix (Average Distances), which is not significant. Bicycle infrastructure has no direct effect but does have indirect effects on bicycling through biking comfort. So does hilly topography, which decreases the likelihood of bicycle ownership and regular bicycling. Popular culture, a measure of the social environment, has the strongest influence on regular bicycling among all of the environmental variables.

Figure 5.2 (a) Standardized Estimates for the Measurement Model: Hierarchical Model of Environmental Factors



Note: Estimates for the measurement errors are proportions of unexplained variance. All estimates are statistically significant at the .001 level.

Figure 5.2 (b) Standardized Estimates for the Measurement Model: Two-factor Model of Non-Motorized and Pro-Exercise



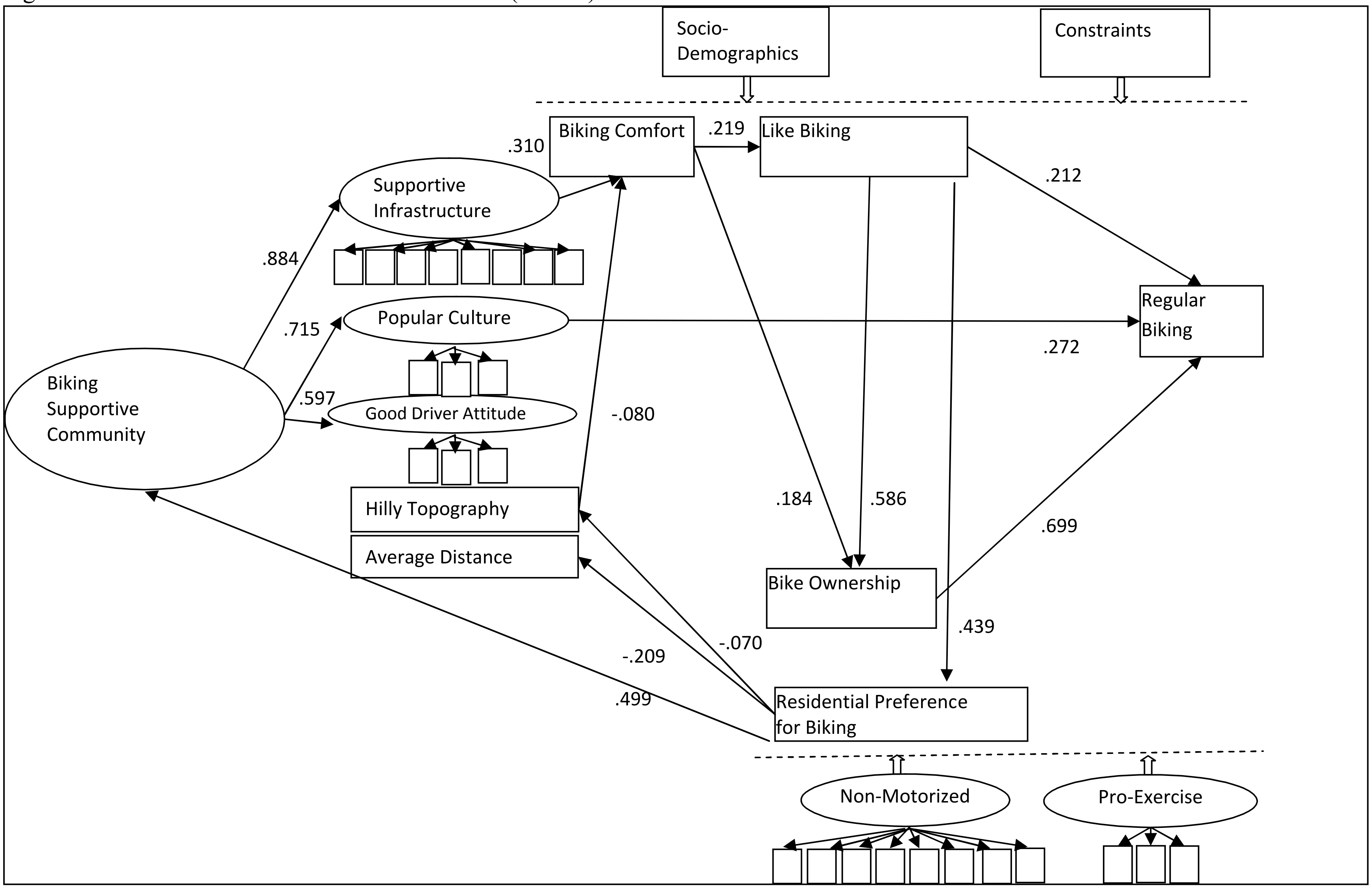
Note: Estimates for the measurement errors are proportions of unexplained variance. All estimates are statistically significant at the .001 level.

Table 5. 2 Standardized Total Effects for SEM (N=945)

Endogenous variable	Attitudes			Community Environment			Biking	
Explanatory variable	Biking Comfort	Like Biking	Residential Preference for Biking	Biking Supportive Community	Average Distance	Hilly Topo-graphy	Bike Ownership	Regular Biking
Socio-demographics								
Age	-0.230	-0.407	-0.179				-0.281	-0.136
Female	-0.252	-0.055	-0.024				-0.079	-0.069
Household Size							0.119	0.083
Household Income	0.020	0.314	0.138				0.188	-0.023[2]
Education Level	0.168	0.037	0.143				0.052	0.164
White Race	0.104	0.117	0.052				0.088	0.091
Constraints								
Biking Limit							-0.206	-0.400
Attitudes								
Biking Comfort[1]		0.222					0.317	0.278
Like Biking [1]	0.063		0.445				0.606	0.682
Residential Preference for Biking[1]	0.144			0.506	-0.212	-0.071	0.045	0.137
Non-Motorized	0.058	0.307	0.409				0.098	0.238
Pro-Exercise	0.010	0.164	0.072				0.087	0.110
Physical environment								
Average Distance[1]								
Hilly Topography[1]	-0.081	-0.018					-0.025	-0.022
Supportive Infrastructure	0.314	0.069					0.098	0.086
Social Environment								
Popular Culture								0.272
Biking								
Bike Ownership[1]								0.699
Measures of fit								
Degrees of freedom (d.f.)								204
Chi-square: Discrepancy between observed and model-implied variance-covariance matrices; low values are better.								998.571
Chi-square/d.f.: Reduces the sensitivity of Chi-square to sample size; recommended values <5[3]								4.895
Comparative Fit Index (CFI):Assumes a non-central χ^2distribution for the baseline model discrepancy; recommended values > 0.9[3]								0.891
Root Mean Square Error Of Approximation (RMSEA): Amount of error of approximation per model degree of freedom, correcting for sample size and penalizing model complexity; recommended values <0.08[3]								0.064

[1] Endogenous variable; [2] The total effects are insignificant. [3]Source: Mokhtarian and Ory (2008)

Figure 5. 3 Estimated Standardized Direct Effects (N=945)



5.5 Summary and Conclusions

This study developed a structural equation model based on findings of previous bicycling and travel behavior studies. It distinguishes direct, indirect, one-directional, and bi-directional relationships among individual, physical and social environment variables as well as the magnitudes of the effects of these variables on bicycling. Additionally, the model controls for a self-selection effect to test the true relationships between physical and social environment variables and bicycling. Using this relatively sophisticated methodology, this study yields more robust results than previous bicycling studies. The empirical findings show that individual attitudes, especially the attitude of liking bicycling, have the greatest impact on bicycling behavior. The social environment emerges as the second most important factor. Physical environment variables also influence bicycling after accounting for residential self-selection.

However, the study is still limited by its cross-sectional design, which cannot account for relationships between variables that occur over time. It is possible, for example, that residents' enthusiasm for bicycling leads them to advocate for public investments in bicycle facilities in a community over a period of time. Nor can we estimate the feedback loops from bicycling to the environment, though it is likely that the more regularly people bicycle, the more likely the city would be to invest in improved infrastructure. Although we include the effect of environment on attitudes towards bicycling, it is possible that it takes some time living in such an environment before a measurable shift in attitudes occurs. Another limitation of the study is that the physical environment was measured subjectively, e.g. the perception of the topography, distances to destinations, and bicycle facilities. In theory, perceptions of the environment operate as mediators between the objective environment and bicycling behavior. Ideally, we would have tested both subjective and objective measures, but we did not have the resources to develop respondent-specific measures of physical environment for the six cities.

Nevertheless, the study yields meaningful results showing that individual attitudes, especially the attitude of liking bicycling, have the greatest influences on bicycling behavior, compared with physical and social environment factors. This is consistent with the findings in at least one previous travel behavior study that attitudes play the most important role in explaining travel behavior (Bagley and Mokhtarian, 2002). Attitudes toward travel mode and the environment and characteristics of the physical environment also influence bicycling, though their effects are more limited than the effect of liking bicycling. Biking comfort not only has important total effects on bicycling but also acts as an essential mediator: physical environment variables exert indirect influences on bicycling through biking comfort. The model shows a significant self-selection effect: residential preference for bicycling has a direct influence on the choice to live in a bicycling supportive community which then exerts an effect on both bicycle ownership and regular bicycling, after controlling for other factors.

Following the attitude of liking bicycling, the social environment emerged as the second most important factor. This finding suggests that cultivating a popular bicycling culture may be more important in encouraging bicycling than investments in bicycle infrastructure (at least given a community with reasonably good bicycle infrastructure to begin with, as is the case for four of the cities studied here). Physical environment variables are not unimportant: they do influence bicycling after accounting for residential self-selection. The result that land-use mix (measured as distances to destinations) does not influence bicycling may stem from the inclusion of both transportation bicycling (for which distances to destinations matter) and recreational bicycling (for which distances to destinations may not matter) in the measure of regular bicycling use. Nevertheless, land-use mix still has an effect as one of the attractive conditions for residential self-selectors, who, as shown by the model, are more likely to bicycle regularly.

The results are useful to planners in their efforts to increase bicycling. They suggest, first, that programs should aim to foster supportive attitudes toward bicycling. Promotional programs such as Bike to Work Day and other events have reportedly had some lasting effect on bicycling (Bunde 1997; Rose and Marfurt 2007; Bauman et al., 2008). Such events can also help create a supportive social environment. Bicycling comfort, another important factor, can be enhanced through improving bicycling facilities in addition to training for bicyclists, for adults as well as children (Telfer 2006). The self-selection effect suggests that communities can increase bicycling by attracting more bicycle-oriented residents as well as by changing the behavior of existing residents. A good bicycle transportation system, including a network of bicycle lanes and paths as well as bike racks and other facilities, helps to attract bicycle-oriented residents and further encourages bicycling by increasing individuals' comfort with bicycling and contributing to the attitude of liking bicycling.

To increase bicycling to the largest extent, planners need to consider comprehensive programs that affect factors on all three levels—individual, social environment, and physical environment. This study shows that all three levels work together to influence bicycling: many factors have indirect impacts on bicycling through factors at the other levels, implying synergistic effects of the three levels on bicycling. Indeed, some cities have substantially increased bicycling by employing a comprehensive package of interventions targeting all three levels (Pucher, et al., 2010). Copenhagen, for example, achieved a 70% increase in bicycle trips between 1970 and 2006, with the share of trips by bicycle increasing from 25% to 38%. In Portland, OR, the number of bicyclists crossing the four bridges into downtown increased 369% from 1992 to 2008. This study helps to illuminate the causal factors underlying these success stories and, by highlighting critical factors to target, provides a basis for the development of new programs.

6. WHY DO SOME PEOPLE BICYCLE MORE FOR TRANSPORTATION?

6.1 Introduction

Bicycle is a traditional transportation mode as well as a good form of exercise, and thus generally, there are three primary bicycling purposes: utility, recreation, and sport. Utilitarian bicycling refers to bicycling for transportation purposes, that is, for the purpose of getting from one place to another. Recreational bicycling is primarily for fun, pleasure, or adventure. Bicycling for sport is for athleticism, competition, or health. Loosely speaking, utilitarian and recreational or sport bicycling may sometimes overlap: people bicycle to get somewhere as well as for fun or fitness. However, the main purpose of utilitarian bicycling is still to reach a destination rather than for pleasure or health. Utilitarian bicycling also differs from the other two purposes in that it more often occurs on main roads accompanied by higher traffic volumes on weekdays, whereas recreational and sport bicycling more often occur away from traffic, e.g. on off-street paths, on weekends or during vacations.

However, even though bicycles were invented as an important means of transportation, today they have lost this traditional role in the U.S. In fact, the share of transportation bicycling is very low in the U.S. In the U.S., the vast majority of bicycling – over two-thirds of bike trips - is for recreation or sport rather than transportation. However, some European countries have much higher shares of transportation bicycling. With shares of urban trips by bicycling that are much higher than in the U.S., shares of all bicycle trips that are for commuting in The Netherlands and Germany are more than twice that in the

U.S. - 24% and 20%, respectively, compared to only 9% in the U.S.; trips to school are 17% and 15% of bicycle trips in the Netherlands and Germany, compared to 9% in the US; shopping trips are 19% and 26% compared to 13% (Pucher and Dijkstra, 2000).

Despite the dominance of recreational and sport cycling, communities in the US may have significant potential to achieve a higher level of transportation bicycling, particularly bicycle commuting. Recently, utilitarian bicycling has been given increased priority by many communities through spending on bicycle projects, motivated by rising obesity levels, volatile gas prices, traffic congestion, and environmental problems. Indeed, although the overall level of bicycle commuting in the U.S. is low –according to the 2009 American Community Survey (ACS), only 0.6% of workers usually commute by bicycle – there is a significant amount of commuting by bicycle at least in some parts of the US: the share of workers usually bicycling to work was 21.4% in Davis, CA, 10.8% in Boulder, CO, and 7.7% in Eugene, OR[1]. According to the Bike Friendly America Yearbook for 2010[2], the higher share of transportation bicycling and other non-motorized modes has reduced the growth in vehicular miles traveled in Boulder to approximately 1 percent annually since 1990, far less than for the U.S. as a whole.

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[1] http://factfinder.census.gov/servlet/STTable?_bm=y&-state=st&-context=st&-qr_name=ACS_2009_1YR_G00_S0801&-ds_name=ACS_2009_1YR_G00_&-tree_id=309&-keyword=Davis,%20CA&-redoLog=false&-geo_id=01000US&-format=&-_lang=en. Accessed on 12/29/2010.

2 http://www.bikeleague.org/programs/bicyclefriendlyamerica/bicyclefriendlyyearbook/index.php, Accessed on 12/28/2010.

How have these cities achieved such high shares of bicycle commuting, and can other cities follow their example to achieve the same? Relatively small city size, relatively flat topography, moderate weather year-round, and the presence of a university may contribute to higher levels of transportation bicycling in these cities. Extensive networks of bicycle facilities and bicycle promotional programs may enable bicycling to compete with driving by making bicycling safer and more comfortable. Additionally, the strong bicycling culture in these communities might also help to explain their high levels of transportation bicycling (Buehler and Handy, 2008).

However, what specific factors influence an individual's choice to bicycle more for transportation than recreational are comparatively unknown, as well as their relative importance. Existing studies have examined factors associated with bicycling purpose, but have not accounted for the interactions between them. As a result, the true impacts of the factors have not been rigorously assessed. Additionally, the range of factors examined has been relatively limited, omitting for example bicycling culture and individual attitudes. Building on the analysis of the determinants of regular bicycling presented in Chapter 5, we take a closer look specifically at transportation bicycling in this chapter. The purpose of this analysis is to provide a stronger empirical basis for the development of strategies to promote transportation bicycling by contributing to an improved understanding of factors influencing the three decisions to bicycle (1) mostly, (2) longer, and (3) with a higher daily bicycling probability, for transportation.

6.2 Literature Review

Previous studies show that individual socio-demographical factors such as age, gender, education, race, and car ownership influence the choice to bicycle for transportation, specifically, to bicycle commute (Williams and Larson, 1996; Stinson and Bhat, 2004; Wardman et al., 2007; Plaut, 2005; Parkin et al., 2007). Studies have also found that attitudinal factors are associated with bicycling for transportation. One recent study of bicycling among a working population found that people with external self-efficacy and ecological-economic awareness are more likely to commute by bicycle (Geus et al., 2007). Gatersleben and Appleton (2007) found that people who like bicycling would bicycle commute under most circumstances (as discussed in Chapter 2). One recent study shows that attitudes and other psychological factors influence bicycle commuting choice as well as its frequency (Heinen et al., 2011). By employing factor analysis and a binary logit model, this study found that benefits such as time-saving and comfort were associated with bicycle commuting trips of all distances as well as the decision to bicycle commute, whereas awareness of environmental and health benefits from bicycling correlated only with long-distance bicycle commutes. The perception of societal support and traffic safety were important in the choice of shorter-distance bicycling trips. Having a cycling habit increased the likelihood of cycling and having a higher frequency of cycling. The perceived opinion of others was found only to be associated with short-distance bicycling. Daley and Rissel (2011) looked at the influence of public images of cycling on the choice to bicycle and found that the perception of lower status and lack of public acceptability worked as a barrier to utility and commute bicycling.

Characteristics of the physical environment are of particular interest, given the influence that planners and engineers have over these characteristics. Studies show that various characteristics of the physical environment influence transportation bicycling, especially bicycle commuting, though neither the characteristics examined nor the results are entirely consistent across studies (see Table 2.1 in Chapter 2). Bicycle infrastructure, including the number of separated bicycle paths and on-street bike lanes per mile, and the proportion of off-road routes seem to have a significant effect on bicycling (Parkin et al., 2008), though one study did not find any association (Geus et al., 2007). Facilities such as bike racks or lockers have also been found to influence transportation bicycling (Stinson and Bhat, 2004). Dangerous traffic conditions or larger traffic volumes were found to be determinants of not bicycling for transportation (Parkin et al., 2008), though Geus et al. (2007) failed to find this association. Land use patterns, such as population density and accessibility to the workplace or transit, were associated with bicycling to work Stinson and Bhat (2004), but the relationship was unclear in Geus et al. (2007). Parkin et al. (2007) found a significant effect of natural environment factors such as hilliness and weather.

However, even fewer studies look directly at the differences between transportation and recreation bicycling. A study by Xing et al. (2010) showed that bicycling comfort and an aversion to driving were associated with more transportation bicycling compared with recreational bicycling. A culture of utilitarian bicycling and short distances to destinations were also key factors for transportation-oriented bicycling. Bicycle infrastructure appeared to play an indirect role in encouraging transportation-oriented riders through its effect on perceived bicycling safety and through the self-selection effect, by attracting bicycling-inclined people to bicycling-supportive communities. Other studies are mostly from the physical activity literature. Perceived accessibility to bike lanes, for example, was associated with engagement in any transportation-oriented bicycling versus non-transportation bicycling in Hoehner et al. (2005), while Troped et al. (2003) concluded that streetlights, enjoyable scenery, sidewalks, and distance to a community rail-trail significantly affect weekly minutes for transportation-motivated physical activities (including walking and bicycling) but have no impact on weekly minutes for recreational activities. Similarly, studies on walking show that physical-environment factors are more important in explaining walking for transportation than for recreation (Saelens and Handy, 2008), a pattern that might hold for bicycling as well.

Thus, empirical knowledge about factors related to transportation bicycling for individuals is still limited. The influence on bicycling purpose of “self-selection” is not clear. If individuals who prefer bicycling as a mode of transportation also favor a supportive environment for transportation bicycling when deciding where to live, the effect of bicycle infrastructure or land use patterns on transportation bicycling found in previous studies could be spurious. Even if these factors have true influences on transportation bicycling, it is still unclear what characteristics of the physical environment are most important unless the endogeneities between factors are controlled for. Most previous studies have not explored the interactions between these factors and transportation bicycling. Our analysis thus aims to assess the relative effects of a more comprehensive set of variables drawn from each level of the conceptual model described in Chapter 2.

6.3 Methodology

The research employs a cross-sectional research design to determine the relative influence of individual factors, physical-environment factors, and social-environment factors on transportation-oriented bicycling. The unit of analysis for the study is the individual, and the sample is drawn from six small cities. Details of sampling and administration were fully documented in Chapter 2. Structural equations modeling was employed to account for the multiple interactions between factors associated with transportation bicycling. The three factors used as indicators of transportation bicycling (balance between transportation and recreational bicycling, transportation bicycling miles, and daily transportation bicycling probability, as described in 3.3.1) are significantly and strongly correlated, with correlation coefficients ranging from 0.405 to 0.719. Although ideally we would use one comprehensive model to determine factors influencing the three aspects of transportation-oriented bicycling, putting all three closely associated aspects of transportation bicycling into one structural equation model led to model underidentification owing to model complexity. We therefore constructed three separate models to explore factors influencing the three aspects of transportation bicycling. This approach enables an assessment of the potential relationships between explanatory variables and transportation-oriented bicycling, transportation bicycling distance, and daily transportation bicycling probability.

6.3.1 Data and key variables

Data are from a survey conducted in six communities in the US in 2006 (see details in Chapter 3); variables from this data set were selected for this analysis based on the conceptual framework and literature review. The variables used in this study fall into three general groups: measurements of transportation bicycling, individual factors, and environmental factors including both the physical and social environments. Some are original variables from the survey (e.g. most socio-demographics) and are fully documented in Table 4.1 (Chapter 4). Some variables were created through simple mathematical computation such as averaging (e.g. Biking Comfort). The construct of the measurement models in the three SEMs is the same as that in the model of Regular Biking (Chapter 5). Both the significance and magnitudes of the parameters, such as factor loadings, are similar in the four SEMs. All the variables documented here were tested in the SEM and only statistically significant variables were retained to achieve the most parsimonious model.

Measurements of transportation bicycling

The measure of balance between bicycling for transportation versus recreation or sport comes from a survey question that asked the respondents who bicycled at least once within the last year about their portion of bicycling for transportation and recreation purposes, in this way: “What portion of your bike rides are for transportation (commuting, shopping, visiting people) and what portion are for recreation (exercise, pleasure rides, adventure)? By ‘bike ride’ we mean a time you ride a bicycle for five minutes or more.” Five choices were offered: 1. All bike rides for transportation. 2. Most bike rides for transportation. 3. About half and half for each. 4. Most bike rides for recreation. 5. All bike rides for recreation. It is notable here that recreational bicycling loosely includes bicycling for recreation or sport. The distribution by category is shown in Table 6.1. In this sample, more people bicycle completely or mostly for recreation (48.7%) than do people for transportation (34.4%), consistent with the finding of Pucher and Dijkstra (2000) that recreational bicycling is more popular than transportation cycling in the US.

Using the responses to the survey question on portions of bicycling for transportation and recreation purposes, we generated new variables representing the proportions of bicycling for each purpose (Table 6.1). The proportion of transportation bicycling – "Imputed Transportation Proportion" – was created as follows: "All bike rides for transportation" was recoded as 100%, "Most bike rides for transportation" was recoded as 75%, "About half and half for each" was recoded as 50%, "Most bike rides for recreation" was recoded as 25%, and "All bike rides for recreation" was recoded as 0%. Note that the variable reverses the order from the original survey question.

The final sample size is 578 given responses to this survey question and employing the missing data technique in the Mplus statistical package (three cases were deleted from the total 581 cases due to more than one fourth loss of variables in each case). This sample is relatively small but still efficient as discussed in Chapter 3.

Table 6. 1 Distribution of Respondents by Portion of Bicycling Purpose

Biking Purpose	Imputed Transportation Proportion (%)	Number	Share (%)
1: All bike rides for recreation	0	156	26.8
2: Most bike rides for recreation	25	127	21.9
3: About half and half for each	50	98	16.9
4: Most bike rides for transportation	75	142	24.4
5: All bike rides for transportation	100	58	10.0
Total		581	100.0

This variable was then used to create two more measures of transportation bicycling—transportation bicycling miles and daily transportation bicycling probability. Weekly miles of transportation bicycling miles was derived by multiplying "Imputed Transportation Proportion" (Table 6.1) and another survey question that asked respondents to report their weekly bicycling miles. Although some respondents who had ridden a bicycle within the last year reported their portions of bicycling by purpose, their reported weekly miles were zero, presumably because their bicycling is irregular. To meet the assumption of normality of residuals, we took the natural log of the values of weekly miles of bicycling. To all zero scores (for bicyclists who reported their weekly bicycling miles are 0 or whose bike rides all for recreation) we added a very small constant of 0.001 mile before the logarithmic transformation to avoid taking the log of zero.

The third measure, Daily Transportation Biking Probability, was created from the combination of three variables: "During the last seven days, on how many days did you: ride a bicycle?" with answers from 0 to 7 days; "When did you last go for a ride on a bicycle?" with six answers offered: 1. I have never ridden a bicycle; 2. Over 10 years ago; 3. Between 1 and 10 years ago; 4. Between 1 month and 1 year ago; 5. Between 1 week and 1 month ago; 6. Within the last week.; and the third question—"Imputed Transportation Proportion.". We first combined the variable measuring regular bicycling and Last Bike Ride to get an estimate of the daily probability of bicycling for any purpose: the bicycling frequency of individuals who have never ridden a bicycle or over 10 years ago was coded as "0"; that of individuals whose last bike rides were between 1 and 10 years was "1/(365*5)", assuming 365 days a year and bicycling once per 5 years; if the last bike rides occurred between 1 month and 1 year ago, "1/(365/2)", assuming bicycling once per half a year; if the last bike rides were between 1 week and 1 month ago, "1/15", assuming bicycling once per half month; if the last bike rides were within the last week, then combined with the variable measuring days bicycled during the last seven day and divided by 7, i.e. 7 days a week, to get the probability of having bicycled on a given day. For instance, for an individual bicycled 4 days during the last seven days, the corresponding daily bicycling probability would be 4/7.

However, in the two survey questions, "the last week" overlaps "the last seven days" but may not have been interpreted exactly the same. In the survey, 18 individuals gave inconsistent responses to these two questions. In these cases, we assigned a daily bicycling probability of 1/7. After coding the bicycling probability, we then calculated the product of the Imputed Transportation Proportion and the bicycling probability to estimate the daily probability of transportation bicycling, which is treated as taking continuous values from 0 to 1.

It is important to note that each rider in this sample owned or had access to a bicycle. Therefore, owning or having access to a bicycle cannot help to explain the choice between transportation- and recreation-oriented bicycling, the choice of transportation bicycling distance, or the daily transportation bicycling probability. Bicycle ownership was thus not included in the models.

Individual factors and environmental factors

The same sets of factors used in the SEM model in Chapter 5 were used in this analysis: individual factors consisting of socio-demographics, constraints, and attitudinal factors; and environmental factors, including physical and social environmental factors, and a second-level factor that reflects a composite of these factors—Biking Supportive Community.

6.3.2 Hypothesized model

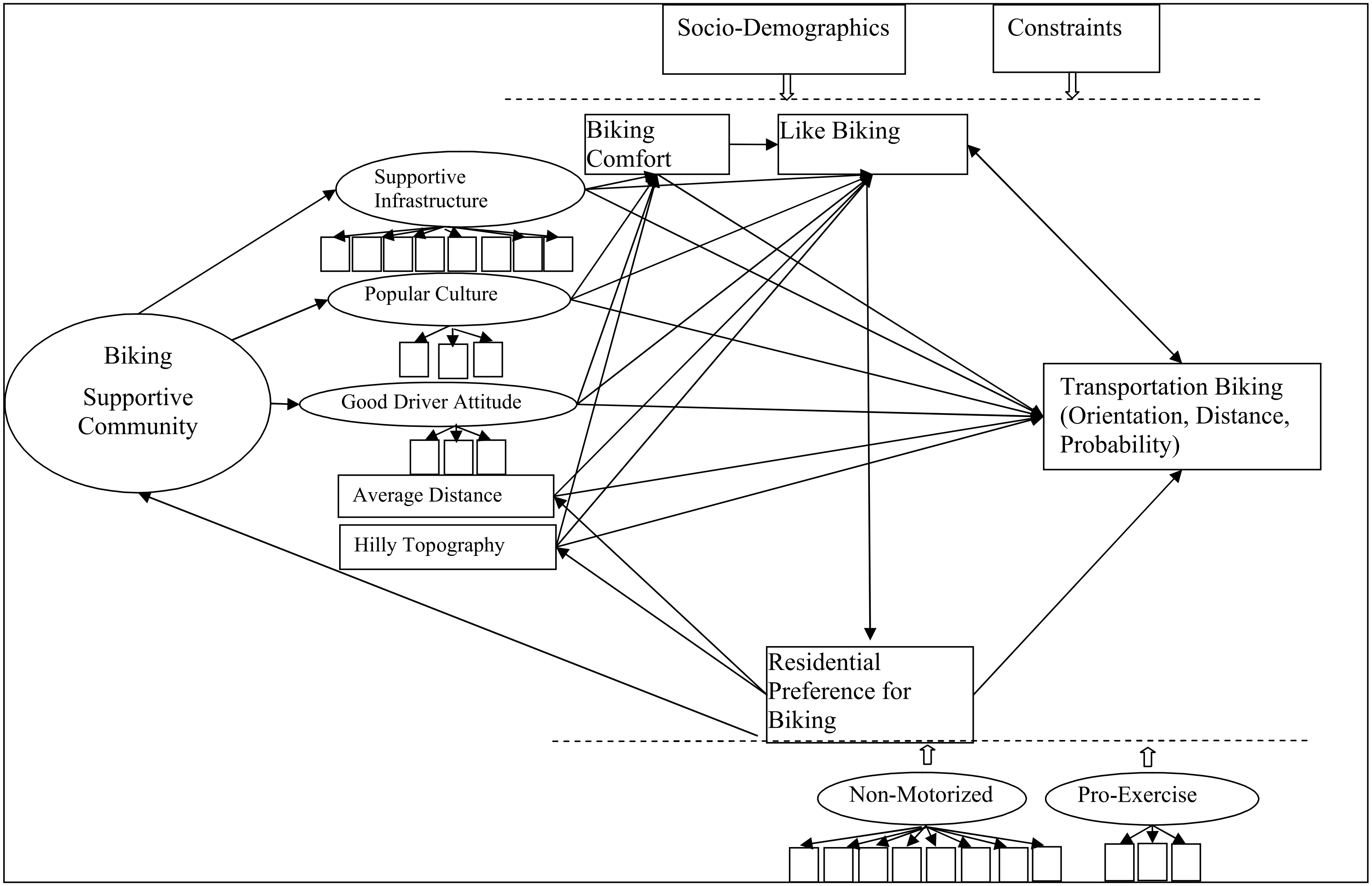
Our conceptual model (Figure 3.1 in Chapter 3) was developed based on the theories and empirical studies reviewed in Chapter 2. Based on this conceptual model, we hypothesized that three levels of factors, individual, physical and social environments, directly impact the balance of bicycling for transportation and recreation, transportation bicycling miles, and daily transportation bicycling probability. However, because the sample for this analysis comes from the population of bicyclists rather than the general population, some hypotheses differ from those in the hypothesized conceptual model in Chapter 5. Specifically, bike ownership was omitted from the model, for the reasons described earlier. In Chapter 5, the results suggest that confidence in one's ability to engage in bicycling (Biking Comfort), and affection for bicycling (Like Biking), increase the likelihood of bicycling regularly. In this chapter, we hypothesize that the two factors also have a positive effect on transportation-oriented bicycling. We expect the two factors to help explain bicycling longer distances for transportation and higher probabilities of daily transportation bicycling as well. Furthermore, it is possible that the more a rider bicycles for transportation, his or her affection for bicycling may increase. Thus a reciprocal causal relationship is expected between Like Biking and all three measures of transportation biking. Additionally, a preference for non-motorized modes may lead an individual to bicycle more for transportation. The attitude of "Pro-Exercise" may drive a rider to bicycle longer distances for transportation and have a higher daily probability of bicycling for transportation, but we expect it to increase recreational bicycling even more, so that the likelihood of being a transportation-oriented bicyclist declines. We also expect to find a self-selection effect—those with a residential preference for a bicycling community would bicycle longer distances, have a higher probability of daily transportation bicycling, or be more of a transportation-oriented bicyclist. This effect may be realized through the decision to live in a community that has both physical and social environments supportive for bicycling, as well as shorter average distances and less hilly topography.

The physical environment factors, Average Distance, Hilly Topography, and Supportive Infrastructure, as well as the social environment factors, Popular Culture and Good Driver Attitude, are hypothesized to exert direct impacts on transportation bicycling. Specifically, we hypothesize that Supportive Infrastructure, Popular Culture and Good

Driver Attitude differentiate transportation- from recreational-oriented bicycling because these conditions may favor transportation bicycling; we also expect these factors to positively affect transportation distance and daily probability of transportation bicycling. We expect that greater values of Average Distance and Hilly Topography decrease the likelihood of being transportation-oriented and discourages bicycling longer and more frequently for transportation. Further, we hypothesize that all these physical environment factors influence transportation bicycling indirectly through the mediating factors—Bike Comfort and Like Biking. Specifically, Supportive Infrastructure, Popular Culture, and Good Driver Attitude increase bicycling comfort and liking bicycling, whereas Average Distance and Hilly Topography reduce bicycling comfort and liking bicycling.

For the same reasons as in the analysis in previous chapter (see Chapter 5), we ignored possible reciprocal causal links between attitudes, the environment, and transportation bicycling. Potential bi-directional interactions among average distances, topography, bicycle infrastructure, and bicycling social culture (Popular Culture and Good Driver Attitude) were also neglected due to the limits of our cross-sectional design. Instead, associations between these factors were allowed to obtain a more realistic model.

Figure 6. 1 Hypothesized Conceptual Model



6.3.3 Modeling approach

Given the hypothetical model depicted in Figure 6.1, this study employed structural equations modeling (SEM) to determine what factors influence transportation bicycling (Orientation, Distance, Probability) and their relative importance. As mentioned in Chapter 5, SEM offers advantages over traditional analysis techniques, particularly with respect to modeling complex multivariate relations, including direct or mediated effects, between factors simultaneously and helping to correct for measurement error by allowing analysis of latent variables (Kline, 2005, pp. 72-73).To estimate models with categorical endogenous variables, the Mplus software package was used. The Mplus method for handling missing data by treating missingness as a function of the observed covariates produced a sample size of 578 in the final three models. In each model, six basic analysis steps were followed: model specification, model identification, model estimation, model fit evaluation and parameter interpretation, and model respecification when necessary. This process enables us to find an appropriate hypothesized model that fits the sample data.

The three final models each include six equations and therefore six endogenous variables. The model for Transportation-Oriented Bicycling has a mix of linear regression equations for the continuous dependent observed variables or factors (Bike Comfort, Average Distance, and Biking Supportive Environment) and probit regression equations for binary or ordered categorical dependent variables (Transportation-oriented Biking, Residential Preference for Biking, and Like Biking). Note that the hypothesized link from Transportation-Oriented Biking to Like Biking was insignificant and thus removed in the final model but the link from Like Biking to Transportation-Oriented Biking was retained.

There are also six equations in the models of Transportation Bicycling Miles and Daily Probability of Transportation Bicycling: four are linear regression equations with continuous dependent observed variables or factors (Bike Comfort, Average Distance, Biking Supportive Environment, and natural log of Transportation Biking Miles in the former model or Daily Probability of Transportation Bicycling in the latter). The others are probit regression equations for binary or ordered categorical dependent variables (Like Biking and Residential Preference for Biking). In both models, the hypothesis of the link from Like Biking to the natural log of Transportation Biking Miles or Daily Probability of Transportation Biking was insignificant and thus removed in the final model, with only the link from natural log of Transportation Biking Miles or Daily Probability of Transportation Biking to Like Biking retained.

6.4 Model Results

The measurements of model fit, the ratio of model Chi-square to the degrees of freedom, CFI (comparative fit index), and RMSEA (root mean square error of approximation), fall in the accepted range for model fit. The final versions of the three models are shown in Tables 6.2, 6.3, and 6.4, presenting the standardized total effects, and Figures 6.2, 6.3, 6.4, showing the interactions between the factors and the standardized direct effects. Both direct effects and total effects are presented to show the working mechanisms by which the factors exert effects on transportation bicycling. Note that variables shown in the tables with blanks had coefficients constrained to be zero in the model, either as hypothesized or because of empirical insignificance (at the 0.1 significance level).

It is notable that some standardized values in the results of models are greater than 1 in magnitude, e.g. in the model for Transportation-Oriented Bicycling, the factor loading of the first-order factor, Bike Infrastructure, on the second-order factor, Biking Supportive Community, is 1.062. A standardized coefficient greater than 1 sometimes can be valid. Joreskog (1999) discussed how large an estimated standardized coefficient in a measurement or structural relationship can be and indicated that if the factors are correlated (oblique), the factor loadings are regression coefficients rather than correlations and as such they can be greater than 1.

6.4.1 Factors influencing transportation-oriented bicycling

Individual factors influencing transportation-oriented bicycling

The empirical results show the relative importance of individual, physical environment, and social environment factors in explaining transportation-oriented bicycling. Individual factors contribute most to transportation-oriented bicycling: the estimated standardized total effects of various factors on transportation-oriented bicycling show that respondents with higher education levels are more likely to make a higher portion of bike rides for transportation than recreation, as might be expected in college towns. For example, in a college town like Davis, Boulder, or Eugene, professors as well as graduate students, more educated than the average resident, can often be seen bicycling to campus. Higher annual household income discourages transportation-oriented bicycling, which may reflect a higher value of time. Older age decreases the likelihood of being transportation-

Table 6. 2 Total Effects for SEM in Model of Transportation-oriented Bicycling (N=578)

Endogenous variable	Attitudes		Community Environment			Biking
Explanatory variable	Biking Comfort	Like Biking	Residential Preference for Biking	Biking Supportive Community	Average Distance	Transportation-Oriented Biking
Socio-demographics						
Age						-0.102
Female	-0.220					-0.038
Household Income	-0.252	-0.838	-0.759			-0.385
Education Level	0.314	1.044	0.946			0.479
White	0.062					0.011
Attitudes						
Biking Comfortr[1]						0.172
Like Biking[1]	0.224		0.675			0.342
Residential Preference for Biking[1]	0.247			0.620	-0.467	0.246
Pro-Exercise						-0.107
Non-Motorized						0.269
Physical environment						
Average Distance[1]	0.135	0.449				-0.068[2]
Supportive Infrastructure	0.375					0.064
Hilly Topography						-0.103
Social Environment						
Popular Culture						0.208
Measures of fit						
Degrees of freedom (d.f.)*						154
Chi-square: Discrepancy between observed and model-implied variance-covariance matrices; low values are better.						516.800
Chi-square/d.f.: Reduces the sensitivity of Chi-square to sample size; recommended values <5[3]						3.356
Comparative Fit Index (CFI):Assumes a non-central χ^2distribution for the baseline model discrepancy; recommended values > 0.9[3]						0.908
Root Mean Square Error of Approximation (RMSEA): Amount of error of approximation per model degree of freedom, correcting for sample size and penalizing model complexity; recommended values <0.08[3]						0.064

[1] Endogenous variable; [2] the corresponding total effect is insignificant; [3]Source: Mokhtarian and Ory (2008).

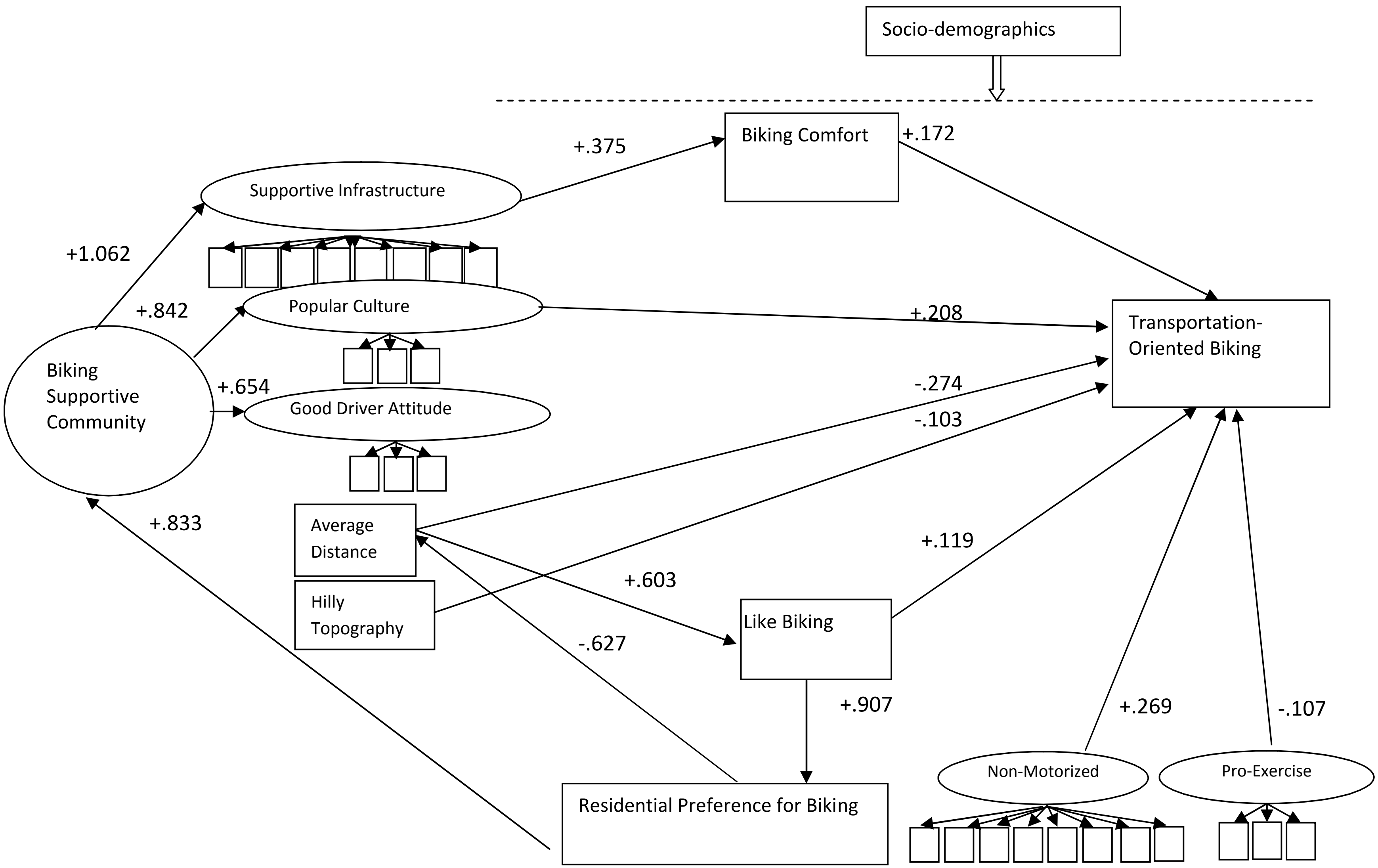
* The Mplus software corrects the degrees of freedom to account for the explicit treatment of ordinal variables (Appendix 4 in Muthén, 2004).

A blank cell indicates neither direct nor indirect link from column variable to row variable exists, so the total effect is zero.

oriented riders. It is possible that the elderly have more safety concerns or health limitations regarding bicycling, or simply that older people do not need to commute after their retirement. Females are less likely to be transportation-oriented riders. White race is also a significant predictor of being more transportation-oriented, though it exerts a smaller influence.

The attitude of liking bicycling works as the strongest attitudinal facilitator of having a higher portion of transportation bicycling. It is notable that more than half of the total effect of liking bicycling on Transportation-Oriented Biking is an indirect effect through the mediating factor—Residential Preference for Biking. In other words, affection for bicycling leads an individual to be more likely to have a residential preference for bicycling, which then leads to the choice to live in a bicycling supportive community, which then influences transportation-oriented bicycling (introduced self-selection effect, as will be discussed below). However, the result that people who like bicycling are more likely to be transportation-oriented is unexpected because we did not find that liking bicycling differentiated the balance of bicycling for transportation and recreation in the previous single-equation analysis (Xing et al., 2010). It is possible that part of the influence of affection for bicycling on transportation-oriented bicycling is caused by a high share of bicyclists who like bicycling and are transportation-oriented in Davis (50.0% of bicyclists who reported liking bicycling are transportation-oriented vs. 29.6% recreational-oriented, with the remainder splitting their bicycle rides into about half for each purpose).

Figure 6. 2 Direct Effects in Model of Transportation-oriented Bicycling (N=578)



In addition, people who have more concern for the environment and prefer non-motorized travel modes tend to be transportation-oriented riders. Bicycling comfort, a measure of the comfort with bicycling on different types of facilities, works as another facilitator of a higher portion of transportation bicycling. A possible explanation is that transportation bicycling requires riders to use a wider range of facility types, including high-traffic streets, whereas recreational bicycling can be confined to quieter streets and off-street bicycle paths. In addition, bicyclists who have a positive attitude toward physical exercise and enjoy it tend to be more recreation- rather than transportation-oriented.

The model also shows a significant self-selection effect on bicycling for transportation purposes as evidenced by an indirect impact of Residential Preference for Biking on Transportation-Oriented Biking through the choice of a Biking Supportive Community; that is, people with a preference for a bicycling-oriented community tend to choose communities with a supportive bicycling environment and they do a greater share of their bicycling for transportation. As shown in Figure 6.2, a supportive bicycling environment increases the share of transportation bicycling through good bicycle infrastructure, a popular bicycling culture, and short average distances. It appears that bicycling for transportation is more dependent on these characteristics than recreational bicycling is. In addition, recreational bicyclists, at least those who are experienced and well equipped, may be less sensitive to the physical environment than the average transportation bicyclist.

Physical and social environment factors influencing transportation-oriented bicycling

As noted above, the results show that both physical and social environment factors influence the balance between bicycling for transportation and recreation. Popular Culture, a measure of the social environment that reflects a more acceptable image of utilitarian bicycling, influences transportation-oriented bicycling directly and is the most important environmental factor explaining transportation-oriented bicycling.

Average Distance to destinations, which depends on land use, has a direct negative influence on the balance between transportation and recreational bicycling: short distances act to encourage or facilitate transportation-oriented bicycling. However, the direct negative effect is offset by its positive influence through bicycling affection on transportation-oriented bicycling, so that the total effect is not significant. Hilly topography has a negative impact on the share of transportation-oriented bicycling; conversely, it increases the share of bicycling for sport or exercise, perhaps because of the physical challenge it poses. Bicycle infrastructure indirectly influences transportation-oriented bicycling through the factor Biking Comfort, though it is less important than some factors such as affect for bicycling. Because Supportive Bike Infrastructure might also facilitate recreational bicycling, it could have a smaller influence on the balance between transportation and recreational bicycling than it does on the amount of each type of bicycling.

Interactions between factors influencing transportation-oriented bicycling

The results provide evidence on the relationships between the factors influencing transportation-oriented bicycling as well. Factors influencing the attitude of liking bicycling include socio-demographic factors and one physical environment factor. People with higher education levels tend to like bicycling, a result which could be tied to the presence of a university, as noted earlier. Lower household income reduces the likelihood of liking bicycling. The unexpected finding that Average Distance exerts a positive direct influence on the attitude of liking bicycling may capture the characteristic of the sample that more bicyclists bicycle for recreation than for transportation. "Average Distance" is a reflection of the land use pattern, e.g. longer average distances to some utilitarian destinations results from relatively segregated land uses, which may also produce longer distances to areas suitable for recreational bicycle riding. For this specific sample containing more recreational bicyclists than transportation bicyclists, the respondents who live in areas with less mixing of land uses may enjoy bicycling tours over longer distances, leading to a positive link from Average Distance to the attitude of liking bicycling.

Several individual factors influence Biking Comfort: women have lower bicycling comfort; higher education levels are associated with higher bicycling comfort; higher incomes are associated with lower bicycling comfort. Attitudes are also associated with bicycling comfort: residential preference for bicycling increases bicycling comfort, as does the attitude of liking bicycling. As noted earlier, the physical environment also contributes to bicycling comfort: good bicycle facilities increase comfort. However, unexpectedly, greater Average Distance to destinations tends to indirectly increase Bike

Comfort. Figure 6.3 shows how this works: Average Distance has a positive direct effect on the attitude of liking bicycling, while the latter has an effect on residential self selection for a biking supportive community, and then supportive bicycle infrastructure helps to improve bicycling comfort. Similar to the interpretation of the positive effect of Average Distance on Like Biking, described above, this result may reflect the preference of recreational bicyclists for communities with longer distances to destinations as well as supportive bicycle infrastructure.

Additionally, people with higher education levels, lower household income, and who like bicycling tend to have higher levels of residential preference for bicycling. It is notable that average distances and bicycling supportive community work as two attractive elements for those with a residential preference for bicycling in their decisions to move to an environment supportive for bicycling.

6.4.2 Factors influencing weekly bicycling miles for transportation

Individual factors influencing weekly bicycling miles for transportation

The empirical results show the relative importance of individual, physical environment, and social environment factors influencing bicycling distance for transportation. Individual factors, specifically attitudes, are the most important factors in explaining bicycling longer for transportation purposes. Socio-demographic factors are important but less so than attitudes. Females are less likely to bicycle longer for transportation, white race works as the second most important socio-demographic predictor of bicycling longer for transportation. People with higher incomes also tend to bicycle longer for transportation, though the influence is very small.

The latent factor, Non-Motorized, capturing the attitudes of having more environmental concern and preference for non-motorized travel modes, exerts the greatest influence on bicycling distance for transportation. A higher level of bicycling comfort also works as an facilitator of longer distances of transportation bicycling.

Similarly to the model of Transportation-Oriented Bicycling, this model also shows a significant self-selection effect on bicycling distance for transportation purposes: Residential Preference for Biking has an indirect impact on transportation bicycling distance through choosing a bicycling-friendly community with supportive bicycle infrastructure and mixed land-use patterns. This mechanism is shown in Figure 6.3, which indicates that it is tied to the importance of bicycle infrastructure and relatively short distances to destinations in supporting transportation bicycling, which may be more sensitive to the physical environment than recreational bicycling. Additionally, the attitude of liking bicycling has a relatively smaller indirect influence on weekly miles of transportation bicycling through residential preference for bicycling, implying that affection for bicycling drives residential self-selectors to bicycle longer miles for transportation after moving to a community supportive of transportation bicycling.

Physical and social environment factors influencing weekly bicycling miles for transportation

The results show that physical environment factors influence weekly bicycling miles for transportation, but the social influence of a positive utilitarian bicycling culture on transportation bicycling distance is not shown. Supportive bicycling infrastructure encourages bicycling longer for transportation through the important mediator Biking Comfort. Good bicycle infrastructure helps to increase an individual's confidence with respect to bicycling which then exerts a positive influence on bicycling distance for transportation. Average Distance, which reflects land-use mix, also has an effect on weekly miles of transportation bicycling. Longer distances from home to utilitarian destinations require bicyclists to ride longer for transportation than those living in a community with mix of land uses and thus shorter distances.

Interactions between factors influencing weekly bicycling miles for transportation

The relationships between the factors influencing weekly bicycling miles for transportation are shown in the model results. Most of the relationships are similar to those in the model of Transportation-Oriented Bicycling, but there are also some differences due to the focus on a different aspect of transportation bicycling. The results show an opposite influence of household income on Biking Comfort compared with that in the model of Transportation-Oriented Bicycling: controlling for weekly bicycling miles for transportation, people with higher incomes are more likely to have higher bicycling comfort levels. In addition to the contributions of residential preference for bicycling and the attitude of liking bicycling, the attitude of environmental concern and preference for non-motorized travel (represented by the latent factor, Non-Motorized) also helps to explain higher bicycling comfort levels. Supportive bicycling infrastructure increases the level of bicycling self-efficacy as well. As in the findings of the model for Transportation-Oriented Bicycling, segregated land use patterns, measured by longer average distances to selected utilitarian destinations, also positively influence the attitude of liking bicycling directly and positively affects bicycling comfort level indirectly through the mediator Like Biking. This may be for the same reason as for the positive influence of Average Distance on Like Biking and Bike Comfort in the model for Transportation-Oriented Bicycling, i.e. the two unexpected results may reflect the fact that the sample contains more recreational- than transportation-bicyclists..

Socio-demographic, attitudinal, and physical environmental factors are found to influence the attitude of liking bicycling, controlling for all other interactions between the factors. Females are less likely to like bicycling. In contrast to the finding of the model for Transportation-Orientation Bicycling that higher household income decreases affection for bicycling, this model shows that people with higher incomes tend to like bicycling, controlling for weekly bicycling distance for transportation. It is reasonable that among people with the same share of transportation-orientation bicycling, e.g. people for whom most of their bicycle rides are for transportation, higher incomes decrease the likelihood of liking bicycling because of the value of time. However, among people who bicycle similar distances for transportation, the wealthier people with a greater range of transportation choices, e .g. driving, are more likely like bicycling compared to poorer people with more constrained alternatives to bicycling. The latent factor, Non-Motorized, reflecting preference for non-motorized travel mode as well as environmental concern, is the most important individual factor in explaining bicycling longer for transportation purposes. Having a higher bicycling comfort level also increases the likelihood of liking bicycling. Finally, the model shows that the farther an individual bicycles for transportation, the more likely s/he is to like bicycling.

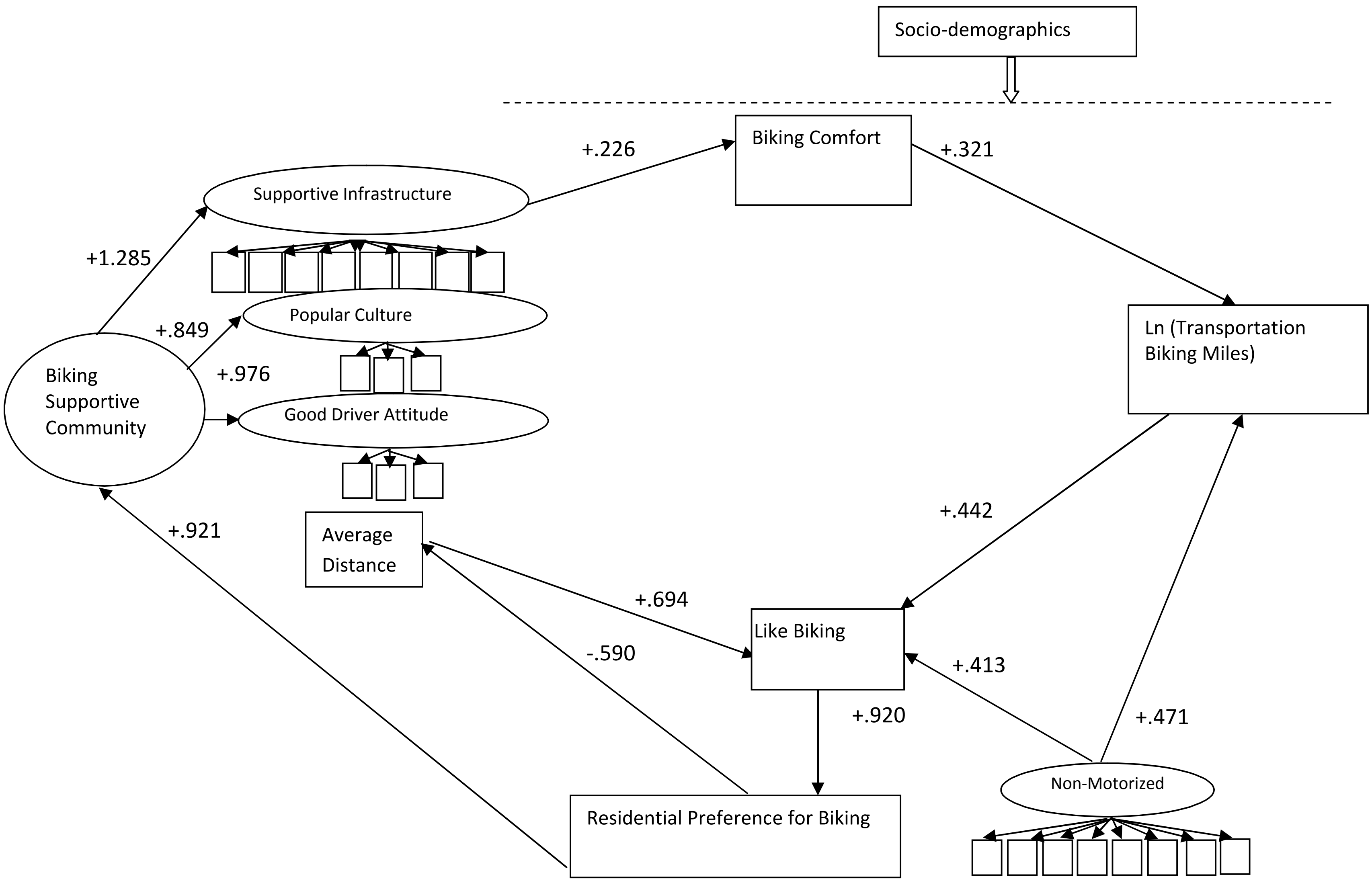
Several individual factors are found to impact residential preference for bicycling: females are less likely to have a residential preference for bicycling; being white shows a positive, though very small, influence on residential preference for bicycling; preference for non-motorized travel mode together with environmental concern (represented by the latent factor, Non-Motorized) encourage an individual to look for a residential community supportive of bicycling. Note that these findings of the models are consistent in showing that mixed land-use patterns (and thus short distances to destinations) and having a bicycling-supportive community work as two attractive elements for residential self-selectors in their decisions to move to an environment supportive for bicycling.

Table 6. 3 Total Effects for SEM in Model of Transportation Bicycling Miles (N=578)

Endogenous variable	Attitudes			Community Environment		Biking
Explanatory variable	Biking Comfort	Like Biking	Residential Preference for Biking	Biking Supportive Community	Average Distance	Ln (Transportation Biking Miles)
Socio-demographics						
Age						
Female	-0.228	-0.025	-0.023			-0.073
Household Income	0.051	0.209	0.192			0.016
White	0.073	0.008[2]	0.007[2]			0.023
Attitudes						
Biking Comfortr[1]		0.112				0.330
Like Biking[1]	0.194		0.725			0.062
Residential Preference for Biking[1]	0.210			0.726	-0.465	0.068
Pro-Exercise						
Non-Motorized	0.120	0.489	0.450			0.509
Physical environment						
Average Distance[1]	0.108	0.441				0.035
Supportive Infrastructure	0.232	0.025				0.075
Hilly Topography						
Social Environment						
Popular Culture						
Ln (Transportation Biking Miles)		0.349				
Measures of fit						
Degrees of freedom (d.f.)*						150
Chi-square: Discrepancy between observed and model-implied variance-covariance matrices; low values are better.						490.751
Chi-square/d.f.: Reduces the sensitivity of Chi-square to sample size; recommended values <5[3]						3.272
Comparative Fit Index (CFI):Assumes a non-central χ^2 distribution for the baseline model discrepancy; recommended values > 0.9[3]						0.908
Root Mean Square Error of Approximation (RMSEA): Amount of error of approximation per model degree of freedom, correcting for sample size and penalizing model complexity; recommended values <0.08[3]						0.063

[1] Endogenous variable.
[2] The total effect is insignificant in the model.
[3] Source: Mokhtarian and Ory (2008).
* The Mplus software corrects the degrees of freedom to account for the explicit treatment of ordinal variables (Appendix 4 in Muthén, 2004).
A blank cell indicates neither direct nor indirect link from column variable to row variable exists, so the total effect is zero.

Figure 6. 3 Direct Effects in Model of Transportation Bicycling Miles (N=578)



6.4.3 Factors influencing daily transportation bicycling probability

Individual factors influencing daily transportation bicycling probability

The results show that daily transportation bicycling probability is heavily influenced by individual, especially attitudinal, factors. Socio-demographics such as household income and white race impact transportation bicycling probability positively, but females and older people are less likely to bicycle for transportation on any given day.

The attitude of preference for non-motorized travel mode as well as environmental concern (represented by the factor Non-Motorized) is the most important factor in explaining transportation bicycling probability. Higher bicycling comfort levels encourage more frequent transportation bicycling. Similarly to the findings of the models of Transportation-oriented Bicycling and Transportation Bicycling Miles, a significant self-selection effect on probability of bicycling for transportation purposes is shown: Residential Preference for Biking has an indirect influence on daily transportation bicycling probability through choosing a bicycling-friendly community with supportive bicycle infrastructure and mixed land-use patterns. The same mechanism as that in the model of Transportation Bicycling Miles is shown: good bicycle infrastructure and relatively mixed land-use pattern (short distances to destinations) support transportation bicycling. An affection for bicycling increases the probability of transportation bicycling, though indirectly through residential preference for bicycling and it less important.

Physical and social environment factors influencing daily transportation bicycling probability

The physical environment factor, Supportive Infrastructure, adds power in explaining frequent transportation bicycling but positive utilitarian bicycling culture does not show an influence. Supportive bicycling infrastructure works as a facilitator of daily transportation bicycling probability through the mediator Biking Comfort but is less important. Longer average distance to utilitarian destinations, which reflects more segregated land use pattern, shows a negative though insignificant influence on transportation bicycling probability.

Interactions between factors influencing daily transportation bicycling probability

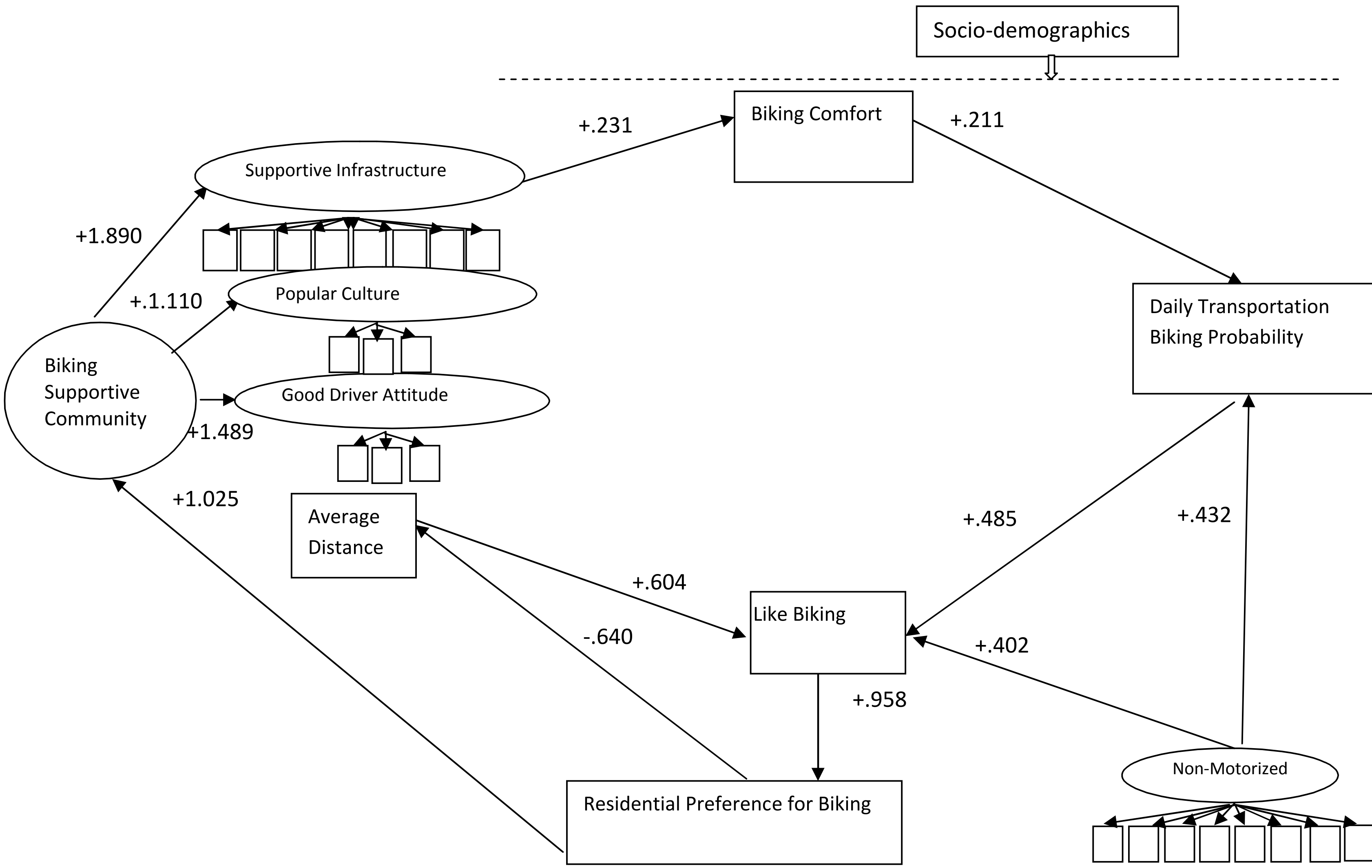
The relationships between the factors influencing daily transportation bicycling probability are very similar to those in the model of Transportation Bicycling Miles. One difference is that age, is shown to influence Biking Comfort, Like Biking, and Residential Preference for Biking: older age decreases the likelihood of having a higher level of bicycling comfort, liking bicycling, and having a higher residential preference for bicycling. Another difference is that education level does not impact the three attitudinal factors significantly in this model, but does so in the model of Transportation-Orientated Biking. Aside from these few differences, the relative consistency of the interactions between the factors may suggest the robustness of the models.

Table 6. 4 Total Effects for SEM in Model of Daily Transportation Bicycling Probability (N=578)

Endogenous variable	Attitudes			Community Environment		Biking
Explanatory variable	Biking Comfort	Like Biking	Residential Preference for Biking	Biking Supportive Community	Average Distance	Daily Transportation Biking Probability
Socio-demographics						
Age	-0.027	-0.063	-0.061			-0.179
Female	-0.231	-0.071	-0.068			-0.200
Household Income	0.065	0.150	0.144			0.014
White	0.074	0.006	0.005			0.016
Attitudes						
Biking Comfortr[1]		0.077				0.218
Like Biking[1]	0.323		0.722			0.068
Residential Preference for Biking[1]	0.337			0.772	-0.482	0.071
Non-Motorized	0.198	0.461	0.442			0.474
Physical environment						
Average Distance[1]	0.195	0.455				0.041
Supportive Infrastructure	0.239	0.018				0.050
Hilly Topography						
Social Environment						
Popular Culture						
Transportation Biking Frequency		0.366				
Measures of fit						
Degrees of freedom (d.f.)*						150
Chi-square: Discrepancy between observed and model-implied variance-covariance matrices; low values are better.						481.206
Chi-square/d.f.: Reduces the sensitivity of Chi-square to sample size; recommended values <5[2]						3.208
Comparative Fit Index (CFI):Assumes a non-central χ^2 distribution for the baseline model discrepancy; recommended values > 0.9[2]						0.915
Root Mean Square Error of Approximation (RMSEA): Amount of error of approximation per model degree of freedom, correcting for sample size and penalizing model complexity; recommended values <0.08[2]						0.062

[1] Endogenous variable;
[2] Source: Mokhtarian and Ory (2008).
* The Mplus software corrects the degrees of freedom to account for the explicit treatment of ordinal variables (Appendix 4 in Muthén, 2004).
A blank cell indicates neither direct nor indirect link from column variable to row variable exists, so the total effect is zero.

Figure 6. 4 Direct Effects in Model of Daily Transportation Bicycling Probability (N=578)



6.5 Summary and Conclusions

Structural equations modeling is employed to explore the interactions between factors associated with transportation bicycling found in previous studies. This method is used to model direct, indirect, one-directional, and bi-directional relationships among individual, physical and social environment variables, and three aspects of transportation bicycling (share of bicycling that is transportation-oriented, transportation bicycling distance, and daily transportation bicycling probability), as well as the relative importance of these variables to transportation bicycling. Using this relatively sophisticated methodology, this study yields more robust results than previous bicycling studies.

However, the study is still limited by its cross-sectional design, which cannot account for relationships between variables that occur over time. For example, we have measured the effect of the environment on *current* attitudes towards bicycling, but we do not know how an individual's affection for bicycling changes *over time* if living in such an environment. Neither can we estimate the change in the environment over time due to changes of attitude, i.e. residents' growing enthusiasm for bicycling may lead them to advocate for public investments in bicycle facilities in a community over a period of time. Another limitation of the study is that the physical environment was measured subjectively, e.g. perception of topography, distances to destinations, and bicycle facilities. In theory, perceptions of the environment operate as mediators between the objective environment and bicycling behavior. Ideally, we would have tested both subjective and objective measures, but we did not have the resources to develop respondent-specific measures of physical environment for the six cities. Additionally, separated measurement of bicycle facilities for transportation and recreation respectively is needed for further research on the effects of specific bicycle infrastructure elements on transportation bicycling.

Overall, the study yields meaningful results showing that individuals' attitudes play the most important role in explaining transportation bicycling orientation, distance, and daily probability. The attitude of environmental concern and preference for non-motorized travel modes increases the likelihood of bicycling longer and more frequently for transportation purposes, as well as transportation-oriented bicycling. Self-efficacy—measured by bicycling comfort on different types of bicycle facilities—has a great influence on the balance between bicycling for transportation and recreation, distance, and probability of transportation bicycling. Additionally, it works as an important mediator of factors such as bicycle infrastructure which exert an indirect influence on transportation bicycling through bicycling comfort. The models show a significant self-selection effect on transportation bicycling: residential preference for bicycling leads an individual to be more transportation-oriented, and to bicycle longer and more frequently after moving to a bicycling supportive community. Further, people with positive attitudes toward physical exercise are more likely to be recreational-oriented riders but also to bicycle longer for transportation. Affection for bicycling leads to more transportation- than recreational-oriented bicycling; a great part of its influence works through residential preference for bicycling, which represents a self-selection effect on transportation-oriented bicycling. Reciprocal influences of the attitude of liking bicycling and transportation bicycling distance and probability are shown: people who bicycle longer and more frequently for transportation are more likely to like bicycling; affection for bicycling encourages people to bicycle longer and more frequently for transportation though indirectly and with a smaller magnitude.

Environmental factors influence transportation bicycling as well, controlling for individual factors. Mixed land-use patterns, measured by a shorter average distance to selected utilitarian destinations, increases the likelihood of transportation-oriented bicycling but results in shorter weekly bicycling miles for transportation. A supportive bicycling infrastructure system tends influence people to be transportation- rather than recreational-oriented, and to bicycle longer and more frequently for transportation, but its influence works through bicycling comfort. Hilly topography acts as a barrier to the choice of bicycling mostly for transportation. Although the social environment factor—Popular Culture—does not show a significant influence on transportation bicycling distance and probability, it impacts the choice of balance between transportation and recreation bicycling: a social environment in which transportation bicycling is a part of the community culture is the most important environmental factor encouraging transportation-oriented bicycling.

Transport planners aiming to increase transportation bicycling, whether as a strategy for achieving sustainable community goals or for other reasons, may be inspired by this research if they want to build on current levels of higher recreational bicycling. Altogether, the results suggest, most importantly, that programs aiming to change people's attitudes toward bicycling will be essential to increasing transportation bicycling, even in communities with good bicycle infrastructure to begin with. More positive attitudes toward bicycling could be encouraged through promotional programs, such as Bike to Work Day and other events; such programs have reportedly had some lasting effect on bicycling (Bunde, 1997; Rose and Marfurt, 2007; Bauman et al., 2008). Additionally, public programs and events to arouse environmental concern, promote non-motorized transportation, and reduce driving will also influence residents' choices of transportation bicycling. Another possible effective way is to develop self-efficacy in bicycling. Low confidence in bicycling may result from lacking knowledge of riding techniques, bicycle routes in a city, or road rules related to bicycling. Providing training for bicyclists, bicycle map information through traditional media or the internet, and public education on the bicycle-related rules will foster more confident bicycle riders. A supportive bicycle infrastructure helps to increase the level of bicycling comfort and affection as well, suggested by the empirical results of this study. A higher level of transportation bicycling in a community may also be achieved through attracting more residential self-selectors for bicycling, given a sufficiently supportive environment for bicycling in the community.

Further, comprehensive approaches that include improvements to the physical environment as well as programs to enhance the social environment are needed. As a traditional strategy to increase bicycling levels, efforts to improve bicycle infrastructure also help to boost transportation bicycling, this empirical research suggests. We find that cultivating a supportive social environment for transportation bicycling is an efficient way to increase transportation bicycling. Positive social marketing campaigns to change the image of transportation bicycling from a marginal activity to a mainstream transport mode may contribute to a supportive culture for transportation bicycling. Specifically, promotional programs such as training for bicyclists, promotional events, publicizing of high-profile role models, or even financial incentives help to encourage bicycling for transportation. Such programs can also improve individual attitudes toward bicycling, which in turn have a significant effect on transportation bicycling. Mixed land use patterns ensure shorter distances, thus helping to promote bicycling as a mode of transportation.

7. CONCLUSIONS

Previous bicycling studies have found associations between bicycling behavior and the environment, including the bicycle transportation system, land use patterns, topography, and social culture. However, the causal mechanisms behind the associations are unclear in these studies, as are the magnitude and relative importance of the impact of the environment on bicycling. This study provides more robust models than the single equation models used in previous bicycling research, with the aim of contributing to an improved understanding of the influences of physical and social environments, as well as individual factors, on bicycling.

7.1 Summary of the Findings

This dissertation explores the direct and indirect effects of physical environment, social environment, and individual factors on bicycling as well as the interactions between them, based on a survey conducted in six small western U.S. cities in 2006 that yielded a sample size of 965. Bicycling behaviors were measured specifically as bicycle ownership, regular bicycling (bicycling occurred within the last 7 days), transportation- vs. recreational-oriented bicycling (increasing portions of bike rides for transportation vs. decreasing portions for recreation), weekly transportation bicycling miles, and daily probability of transportation bicycling.

The physical environment includes built environment characteristics, such as the bicycling system (a latent variable measured through factor analysis as a composite of bicycle infrastructures such as bicycle lanes, streets, bicycle racks, push buttons for bicycling at intersections, etc.) and land-use mix (measured by the average distance from home to selected utilitarian destinations), as well as natural environment characteristics, such as perceived hilly topography.

Social environment factors reflect the social norms of the community, as created by the individuals in the community through their social interactions. Social norms further coordinate people's interactions by establishing accepted ways of behavior and appearance in a particular group. In this study, utilitarian bicycling culture was measured by perceptions of other people who are bicycling in the community: perceptions that "Bicycling is a normal mode of transportation for adults in this community"; "It is rare for people to shop for groceries on a bike"; and "Most bicyclists look like they are too poor to own a car". Another important social environment factor, Driver Good Attitude, measures drivers' attitudes toward bicycling through agreement with statements such as "Most drivers seem oblivious to bicyclists" and "Most drivers yield to bicyclists".

Individual factors consist of socio-demographics, travel constraints, and attitudes. Socio-demographic characteristics include age, household annual income, gender, and education level. Travel constraints refer to physical or mental limitations on bicycling, having a health condition, and the need to assist in the travel of child/children or elder/elders in the household. The study measured various attitudes, including average comfort bicycling on different facilities, affection for bicycling and other travel modes, concern for the environment, preference for non-motorized travel, attitude toward physical exercise, and residential preference for bicycling.

The established theories in travel behavior and physical activity research and previous empirical findings in travel behavior studies contribute to the identification of possible interactions between the factors and provide a basis for mapping out the direct and indirect influences of the factors on bicycling behavior. Additionally, because attitudes play important roles in explaining travel behavior and because among the three elements of attitude, affect is regarded as the core of the attitude concept (Day, 1972), an ordered logit model was employed to explore factors associated with affect for bicycling. This model provided the basis for hypotheses on the possible paths by which individual, physical and social environment factors affect bicycling through the mediator of bicycling affect. Then we estimated four models to estimate the total effects of individual, physical and social environments on different bicycling behaviors of interest: regular bicycling, transportation- vs. recreational-oriented bicycling, weekly transportation bicycling miles, and daily probability of transportation bicycling, controlling for endogeneities between the factors.

This research provides new and potentially important insights into factors impacting the decision to own a bicycle, to bicycle regularly, to bicycle mostly for transportation rather than recreation, and to bicycle more miles and more frequently for transportation. The summary of the results, shown in Table 7.1, helps to explain many of the findings of associations between individual, physical and social environmental factors and bicycling in previous studies, as summarized in Table 2.1 in Chapter 2. The results demonstrate the contributions of individual factors and physical and social environments, to bicycling in general and transportation bicycling in particular.

7.1.1 Contributions of the environment

Physical environment Supportive Infrastructure, referring to the perception of the bicycle transportation system in the community, exerts a significant influence on both kinds of bicycling. Supportive bicycling infrastructure encourages, though to a smaller extent and indirectly through bicycling comfort, owning a bicycle, regular bicycling, higher portions of bicycle rides for transportation, and bicycling more miles and more frequently for transportation.

The average perceived distance from home to selected destinations—nearest grocery, post office, school, restaurant— as determined by land use patterns, has only a limited impact on transportation-oriented bicycling, but positively influences weekly bicycling miles for transportation and daily transportation bicycling probability: shorter distances to destinations may lead an individual to bicycle mostly for transportation purposes, but they also result in relatively shorter bicycling miles for transportation. The Daily Transportation Biking Probability Model shows that a longer average distance increases affection for bicycling, which further results in a higher daily transportation bicycling probability. The insignificant influence on bicycle ownership, regular bicycling, and transportation bicycling probability may result from insufficient variation in distances in the six cities, given that, by intention, all six cities are relatively small and self-contained.

It is notable that although the influence of Average Distance on bicycling is limited, it works as an important attractive element for residential self-selectors, as suggested by all four structural equation models.

Hilly topography explains bicycling as well. It discourages owning a bicycle and regular bicycling, and decreases the probability of bicycling mostly for transportation but may encourage people to be more recreational-oriented bicyclists.

Social environment A popular culture of transportation bicycling shows stronger influences on bicycling than the physical environment does, controlling for individual factors and residential preference for bicycling as well. It works as a facilitator of regular bicycling and may lead to a higher portion of bicycling for transportation. Additionally, both social environment factors, Popular Culture and Good Driver Attitude, contribute to the creation of a bicycling supportive community which then attracts people who have higher levels of residential preference for bicycling, as an ideal residential location for such people.

In summary, the models provide evidence that both physical and social environments influence bicycling even when we isolate the spurious associations caused by residential preference for bicycling. Popular bicycling culture shows a greater effect on regular and transportation-oriented bicycling than a supportive bicycling system does. Shorter average distances to destinations have only a limited impact on the choice of transportation- rather than recreational-oriented bicycling. Hilly topography negatively impacts bicycle ownership, regular bicycling, and transportation-oriented bicycling. Another effect of physical and social environments is that a good bicycle system, popular culture especially with respect to transportation bicycling, and drivers' positive attitudes toward bicycling work synergistically to shape a supportive bicycling community, which residential self-selectors seek.

7.1.2 Influence of individual factors

Socio-demographics This study helps us understand the characteristics of bicyclists, particularly transportation-oriented bicyclists. Younger, white males who are more highly educated are more likely to own bicycles, bicycle regularly, and bicycle for transportation. Larger household size results in a higher probability of owning a bicycle and bicycling regularly, perhaps for fun, but discourages bicycling more frequently for transportation. Naturally, people with higher incomes are more likely to own a bicycle. An interesting finding is that wealthier people tend to be less transportation-oriented, but bicycle more miles and more frequently for transportation. They may bicycle longer distances and more frequently for recreation as well, though we did not examine this possibility in this study. It is possible that people with higher incomes are more likely to recognize the importance of physical activity for keeping healthy; it is also possible that wealthier people are more confident about their social standing so that they are less likely to care about a negative social image of transportation bicycling as being for people cannot afford to buy a car.

Attitudinal factors The attitudinal factors consistently have larger standardized coefficients in all the models, indicating their strong influences on bicycling behavior. The attitude of liking bicycling is the most important factor in explaining bicycle ownership and regular bicycling. It also leads to a greater likelihood of transportation-oriented bicycling. Additionally, affection for bicycling exerts positive but smaller influences, indirectly, on miles and probability of bicycling for transportation, but the reverse effects, of transportation bicycling on bicycling affection, were much greater. Another important factor significant in all the models, the attitude of environmental concern combined with preference for non-motorized travel mode (represented by the factor, Non-Motorized), strongly impacts bicycling, especially transportation bicycling. Naturally, Biking Comfort, which is related to bicycling self-efficacy, contributes to bicycle ownership and regular bicycling, as well as to transportation bicycling. It also works as an important mediator through which supportive bicycle infrastructure exerts an influence on bicycling. The models show the importance of a positive attitude toward physical exercise in explaining bicycling ownership, regular bicycling, and transportation-oriented bicycling, but does not help to increase weekly miles of transportation bicycling and the daily probability of bicycling for transportation. Note that people who favor physical exercise may bicycle more for recreation over transportation purposes, which leads to a negative influence of this variable on transportation-oriented bicycling.

A self-selection effect is shown in all the bicycling models. The results imply that the people who have a higher level of residential preference for bicycling are more likely to own a bicycle, bicycle regularly, bicycle mostly, more miles, and more frequently for transportation when they live in a bicycling-friendly community, which suggests a longitudinal analysis necessary to further explore this effect.

Constraints on bicycling Having any physical or mental conditions that limits or prevents a person from riding a bicycle significantly discourages bicycle ownership and is especially an obstacle to regular bicycling.

In general, individual factors, especially attitudinal factors, are more important in explaining bicycling than environmental factors. Even the confirmed influences of some environmental factors, such as supportive bicycle infrastructure, on bicycling are exerted through attitudinal factors, particularly Biking Comfort. Affection for bicycling shows a strong effect on bicycling for all purposes. Most importantly, people who bicycle more miles or more frequently for transportation are more likely to like bicycling; the reverse effect also occurs, but to a smaller degree and indirectly. A self-selection effect, in which an individual who chooses a residential location for bicycling is more likely to bicycle, is confirmed by the model results.

Table 7. 1 Summary of Total Effects of the Factors on Bicycling

Explanatory variable	Bicycling: Bike Ownership	Regular Biking	Transportation-oriented Biking	Transportation Biking Miles	Daily Transportation Biking Probability
Socio-demographics					
Age	-0.281	-0.136	-0.102		-0.179
Female	-0.079	-0.069	-0.038	-0.073	-0.200
Household Size	0.119	0.083			
Household Income	0.188	-0.023[1]	-0.385	0.016	0.014
Education Level	0.052	0.164	0.479		
White Race	0.088	0.091	0.011	0.023	0.016
Constraint					
Biking Limit	-0.206	-0.400	n/a	n/a	n/a
Attitudes					
Biking Comfort	0.317	0.278	0.172	0.330	0.218
Like Biking	0.606	0.682	0.342	0.062	0.068
Residential Preference for Biking	0.045	0.137	0.246	0.068	0.071
Non-Motorized	0.098	0.238	0.269	0.509	0.474
Pro-Exercise	0.087	0.110	-0.107		
Physical Environment					
Average Distance			-0.068[1]	0.035	0.041
Hilly Topography	-0.025	-0.022	-0.103		
Supportive Infrastructure	0.098	0.086	0.064	0.075	0.050
Social Environment					
Popular Culture		0.272	0.208		
Biking					
Bike Ownership	n/a	0.699	n/a	n/a	n/a

n/a: the variable was not tested in the model.
A blank cell indicates that neither a direct nor an indirect link from the Explanatory variable to the Bicycling variable exists, so the total effect is zero.
[1] The total effect is insignificant in the model.

7.2 Policy Implications

These findings together suggest that a multifaceted approach to increasing bicycling is needed, that focuses on the physical environment but that also addresses individual factors as well as the social environment. Most notably, they suggest that programs that increase positive attitudes toward bicycling may have a stronger effect on bicycle ownership, regular use, and transportation bicycling, especially in communities with good bicycle infrastructure to begin with. More positive attitudes toward bicycling could be encouraged through promotional programs, such as Bike to Work Day and other events; such programs have reportedly had some lasting effect on bicycling (Bunde, 1997; Rose and Marfurt, 2007; Bauman et al., 2008). Environmental concern and positive attitudes towards non-motorized transportation may be strengthened through a mixture of public policies such as economic policies that increase gas taxes and parking fees to decrease driving, and educational campaigns on climate change, energy security, and traffic congestion. Bicycling comfort can be enhanced through training for bicyclists, for adults as well as children; such programs have been shown to lead to increases in bicycling (Telfer, 2006). A supportive social environment, also important in encouraging bicycling, can be created through promotional events, publicizing of high-profile role models, or even financial incentives to encourage bicycle commuting to make transportation bicycling popular.

Meanwhile, it seems unlikely that such programs would have much of an effect in communities without adequate bicycle infrastructure. Investments in a network of off-street bicycle paths could encourage both transportation and recreational bicycling, particularly for less experienced bicyclists who express a preference for such facilities (Jackson and Ruehr, 1998). Mixed land-use patterns that bring destinations within close distance of residences could help to support transportation bicycling. The self-selection effect, in which residents who choose a community in part because of its bicycle orientation are more likely to own a bicycle, bicycle regularly, and bicycle for transportation, also suggests important roles for a good bicycle system, mixed land-use patterns, and a popular social culture for bicycling. Communities may succeed in increasing all types of bicycling by attracting more bicycle-oriented residents as well as by changing the behavior of existing residents. Transportation planners must think more broadly about the physical environment, as more than just bicycle lanes or paths.

Our results suggest that while strategies targeting any one of the three levels of factors – individual, social environment, physical environment – can help to increase bicycling, an approach that addresses all three levels is likely to be most effective. Indeed, those cities that have succeeded in increasing bicycling have employed a comprehensive package of strategies addressing factors at all three levels (Pucher et al., 2010). For example, Copenhagen invested in a massive expansion of fully separated bicycle paths and cycle tracks (separated by curb from motor vehicle traffic), special intersection modifications, traffic signals specifically timed to bicyclist speed, and guarded bicycling parking facilities. The city conducted an innovative bi-annual survey of cyclists to evaluate bicycling conditions. Promotional programs also include mandatory bicycling education for all schoolchildren. Portland, OR, has also invested heavily in bicycle infrastructure, as well as education and marketing events conducted year-round. In addition to expanding its bikeway network, Portland offers comprehensive promotional, educational, and encouragement strategies. For example, the city undertook a project called "Understanding the barriers to bicycling" in order to understand the economic and social barriers to bicycling and then designed a pilot project to overcome these barriers. In addition, the city provides free, annual training and encouragement programs for bicyclists and for women specifically. In both cases, the results are impressive. Copenhagen achieved a 70% increase on bicycle trips between 1970 and 2006, with the share of trips by bicycle increasing from 25% to 38%. In Portland, the number of bicyclists crossing the four bridges into downtown increased 369% from 1992 to 2008. It seems likely that a package of strategies has synergistic effects, producing more total effect than the sum of the individual effects of each strategy on its own. Although most of these successful cities are found outside the U.S., the experiences of Davis, Boulder, Eugene, and Portland provide hope that a comprehensive approach can succeed in increasing bicycling in communities throughout the U.S.

7.3 Limitations

Although this research provides new and potentially important insights into factors influencing bicycling and their relative importance, it still points to additional research needs. First, it is important to note that this study is fundamentally limited by its cross-sectional design. Although we have controlled the influence of the current environment on attitudes, it is possible that, for example, if an individual lives in a community with a strong bicycle culture and with good bicycle infrastructure, her preferences for bicycling increase over time (alternatively, of course, there could be a *negative* feedback loop, whereby an individual who initially sees cyclists as a minor nuisance come to see them as more annoying over time, *diminishing* their personal preferences for cycling). We also ignore other possible effects that may occur over time, for example, that residents' enthusiasm for bicycling leads them to advocate for public investments in bicycle facilities in a community. Neither can we estimate the feedback loops from bicycling to the environment, though it is likely that the more regularly people bicycle, the more likely the city is to invest in bicycle infrastructure to satisfy people's needs. To address these questions, before-and-after studies are needed.

Second, we use perceptions of bicycle infrastructure rather than objective measures. Studies show that perceptual and objective measures of the built environment are closely correlated (Kirtland et al., 2003; Leslie et al., 2005). Theoretically, perceptions mediate the relationship between the environment and behavior and may have a more direct impact on behavior than objective measures of the environment (Bauman et al., 2002). Ideally, both perceptions and objective measures would be tested in the models (McCormack et al., 2004), and objective measures would reflect the specific residential locations of each respondent rather than general community characteristics. The resources needed to develop such measures were not available for this project.

Third, future studies also need to expand the data set to more efficiently and effectively examine the connection between factors and bicycling, with a larger sample size or more sufficient variation of potential explanatory variables. For example, the insignificant effect of average distances to destinations in some models may result from the fact that all the selected cities are, by intention, relatively similar with respect to geographic size. Additionally, future studies should focus on exploring the impacts of other aspects of bicycling environments, such as landscape and street design, to improve the interpretative power of the models.

7.4 Contributions of this Work

Research on bicycling behavior is limited, particularly in comparison with the recent explosion of studies on walking (Saelens and Handy, 2008) and given the potential of bicycling to fill important gaps in the transportation system (Handy, 2009). This study offers valuable insights into the importance of individual, physical-environment, and social-environment factors in explaining bicycling.

The conclusions and policy implications of the models fully depend on the hypotheses of the specifications of the relationships among individual, physical and social environments, and bicycling. The hypothesized interactions between factors were developed from relevant theories and the empirical findings of previous studies. The conceptual models presenting the hypothesized relationships among the factors may help to guide future studies on bicycling and are thus one of the accomplishments of this research.

The strength of the structural equations modeling technique in distinguishing direct and indirect interactions among factors provides insights into potential causal relationships. We employ the SEM procedure and control for residential self-selection to identify the mechanisms by which physical and social environments influence bicycling, especially transportation bicycling, and to determine their relative importance. The findings provide a better understanding of the role physical and social environments play in bicycling behavior than previous bicycling studies that examined only associations between factors and bicycling. The research is thus an original contribution to the limited literature on bicycling behavior, a topic of increasing interest given growing concerns over climate change and obesity.

Another advantage of this study is the measurement and incorporation of various attitudinal factors in constructing relationships between factors and bicycling through SEM procedures. Attitude can be categorized into three elements: cognition, affect, and conation (details of its definition were documented in Chapter 4). Given the importance of attitudes in explaining driving behavior (e.g., Ory, 2007), it is important to measure and employ attitudinal factors in bicycling studies. However, the attitudinal factors measured and tested in previous empirical studies are limited. This research finds a greater impact of attitude on bicycling behavior by involving a larger range of cognitions (Biking Comfort), normative beliefs (Non-Motorized, Pro-Exercise), and affect toward bicycling (Like Biking), as well as affect toward other travel modes (Liking Driving, Liking Walking) in the models. Attitudinal factors are found to have the strongest total effects on bicycling behavior among all factors in the models.

This dissertation produced many other noteworthy findings. The SEM procedures showed that the self-selection effect, rarely explored in previous studies on bicycling, is significant. Popular social culture plays an important role in regular and transportation-oriented bicycling, but has a limited effect on other aspects of bicycling behavior. Meanwhile, the physical environment influences bicycling as well after both individual factors and residential preference are accounted for: supportive bicycle infrastructure shows a small and indirect effect on bicycling through bicycling comfort. Shorter average distances to destinations exert a positive direct influence on transportation-oriented bicycling but lead to fewer miles of bicycling for transportation. Hilly topography discourages owning a bicycle, bicycling regularly, and bicycling mostly for transportation. By contrast, this research identifies the large and many direct influences of attitudinal factors on all kinds of bicycling behavior, among which bicycling comfort works as a critical mediator through which, for example, bicycling infrastructure impacts bicycling. Another important finding is that reciprocal influences between transportation bicycling, including bicycling miles and probability of transportation bicycling, and affection for bicycling exist, though the effect of affection for bicycling on transportation bicycling is smaller and indirect through residential preference for bicycling.

In summary, this dissertation has improved upon previous approaches to modeling the factors that influence bicycling, thereby contributing to a better understanding of bicycling behavior. We construct more complex conceptual models that specify relationships among individual factors, physical and social environments, and bicycling at a disaggregate analysis level. We determine the relative importance of physical and social environments on encouraging bicycling, especially transportation bicycling, controlling for socio-demographics, attitudes, and residential preference. The results may help transportation planners to better understand the potential facilitators and barriers of bicycling, and improve their ability to design effective strategies to promote bicycling.

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APPENDIX A: Description of Variables Tested in the Model

Variable name	#Items [Range]	Mean (s.d.) or Percent (%)[a]	Description
Bicycling			
Bicycle Ownership	1 [0,1]	71.5%	0=Do not have a bike; 1= Have a bike
Regular Biking	1 [0,1]	40.2%	0=Did not bike within the last 7 days; 1=Biked within the last 7 days.
Biking for Transportation	2[1,5]]	54.0%:13.6%: 10.6%:15.4%: 6.3%	1=All bike rides are for recreation; 2=Bike rides are most for recreation; 3=half for each purpose; 4=Bike rides are most for transportation; 5=All bike rides are for transportation.
Daily Transportation Biking Probability	1[0,1]	0.199(0.260)	Loosely measures bicycling frequency as on the probability of bicycling for transportation on any particular day
Ln(Weekly Transportation Miles)	1[-6.91, 5.73]	-1.318(4.152)	The natural log of weekly bicycling miles for transportation
Regular Biking When Young	5[1,5]	75.0%	It takes the value of 1 if any response of the 5 survey questions that "How often did you bike to school, convenience store, friends' houses, roaming/exploring, or library" when young on 5-point scale (from 1=never; 2=occasionally; 3=about once a week; 4=several times a week; 5=daily) is greater than 3; else 0.
Individual Factors: Socio-Demographics			
Age	1 [17,73]	49.29 (15.15)	Age in years
Female	1 [0,1]	44.0%	1=Female. 0=Male
Education Level	1 [1,6]	4.45 (1.86)	The highest level of education. 1=Grade school or high school, 2=High school diploma, 3= College or technical school, 4=Four-year degree or technical school certificate, 5=Some graduate school, 6=Completed graduate degree(s)
Household Size	1 [1,6]	2.41 (1.19)	The number of persons living in the household.
Income	1 [5,125]	71.05 (37.68)	The total annual household income. Continuous, in thousands of dollars.
Car Ownership	1 [0,1]	96.7%	Car ownership. 0=Have no cars, 1=Have one or more cars
Home Own	1 [0,1]	75.5%	Own or rent the current residence. 0=Rent, 1=Own.
White	1 [0,1]	82.0%	1=white, not of Hispanic origin, 0=all others.
Individual Factors: Constraints			
Limit Biking	1 [0,1]	11.3%	1=Have any physical or mental conditions that limit or prevent sb. From riding a bike, 0=Do not have.
Good Health	1 [1,5]	3.91 (0.99)	Agreement that "I am in good health" on 5-point scale[b]
Travel Assistance	1 [0,1]	12.6%	1=There is / are child/children or elder/elders in one household that needs assistance to travel outside of the home, 0=No such assistance is needed.
Individual Factors: Attitudes			
Biking Comfort	6 [1,3]	2.40 (0.39)	Average comfort biking on an off-street path or quiet street, two-lane-local-street with or without bike lane, four-lane-street with or without bike lane, on 3-point scale where 1=Uncomfortable and I wouldn't ride on it,

Variable name	#Items [Range]	Mean (s.d.) or Percent (%)[a]	Description
			2=Uncomfortable but I'd ride on it, 3=Comfortable.
Good Health	1 [1,5]	3.91 (0.99)	A constraint factor measured by agreement that "I am in good health" on 5-point scale[b]
Biked in Youth	1 [0,1]	97.00%	"Did you ever ride a bicycle when you were about 12 years old", 0=no, 1=yes.
Like Biking_original	1 [1,5]	3.82 (1.05)	Agreement that "I like riding a bike" on 5-point scale[b]
Affect toward Biking	1 [1, 3]	28.3%:45.4% :26.4%:	Derived from Like Biking. 1=Strongly disagree, disagree, or neutral on the statement that "I like riding a bike". 2=Agree on the statement. 3=Strongly agree on the statement.
Like Biking	1 [0, 1]	71.7%	Derived from Like Biking_original. 0=Strongly disagree, disagree, or neutral on the statement that "I like riding a bike". 1=Agree or strongly agree on the statement.
Like Driving	1 [1,5]	3.68 (1.05)	Agreement that "I like driving" on 5-point scale[b]
Need Car	1 [1,5]	4.13 (0.87)	Agreement that "I need a car to do many of the things I like to do" on 5-point scale[b]
Limit Driving	1 [1,5]	3.41 (1.05)	Agreement that "I try to limit driving as much as possible" on 5-point scale[b]
Limit Air	1 [1,5]	3.36 (1.10)	Agreement that "I try to limit my driving to help improve air quality" on 5-point scale[b]
Like Walking	1 [1,5]	4.00 (0.85)	Agreement that "I like walking" on 5-point scale[b]
Like Transit	1 [1,5]	2.61 (1.10)	Agreement that "I like taking transit" on 5-point scale[b]
Environment Benefit	1 [1,4]	3.36 (1.10)	Importance of environmental benefits when choosing mode, on 4-point scale where 1=Not at all important, 2=Somewhat important, 3=Important, 4=Extremely important.
Regular Exercise	1 [1,5]	4.5 (0.86)	Agreement that "It's important to get regular physical exercise" on 5-point scale[b]
Enjoy Exercise	1 [1,5]	4.0 (1.04)	Agreement that "I enjoy physical exercise" on 5-point scale[b]
Residential Preference for Biking	1 [1,4]	1.80 (0.97)	Importance of "a good community for bicycling" when choosing the residential location, on 4-point scale where 1=Not at all important, 2=Somewhat important, 3=Important, 4=Extremely important.
Physical-Environment Factors			
Bike Lane	1 [1,4]	3.01 (0.92)	Perception that "Major streets have bike lanes" on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true.
Wide Street	1 [1,4]	2.65 (0.90)	Perception that "Streets without bike lanes are generally wide enough to bike on" on 4-point scale same as above.
Bike Rack	1 [1,4]	2.85 (0.85)	Perception that "Stores and other destinations have bike racks" on 4-point scale same as above.
Bike Light	1 [1,4]	2.55 (0.85)	Perception that "Streets and bike paths are well lighted" on 4-point scale same as above.
Push Button	1 [1,4]	3.08 (0.80)	Perception that "Intersections have push- buttons or sensors for bicycles or pedestrians" on 4-point scale same as above.
Bike Network	1 [1,4]	3.03 (1.08)	Perception that "The city has a network of off-street bike paths" on 4-point scale same as above.

Variable name	#Items [Range]	Mean (s.d.) or Percent (%)[a]	Description
Free Obstacle	1 [1,4]	2.88 (0.86)	Perception that "Bike lanes are free of obstacles" on 4-point scale same as above.
Bike Gap	1 [1,4]	2.12 (0.95)	Perception that "The bike route network have big gaps" ** on 4-point scale same as above.
Hilly Topography	1 [1,4]	1.17 (0.49)	Perception that "The area is too hilly for easy bicycling" on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true.
Average Distance	6 [1,4]	2.39 (0.57)	Average perception of distances from home to "your usual grocery store", "the nearest post office", "a restaurant you like", "a bike repair shop", "your workplace", "the local elementary school" on 4-point scale where 1=Less than a mile, 2=1-2 miles, 3=2-4 miles, 4=More than 4 miles
Social-Environment Factors			
Driver Oblivious	1 [1,5]	2.69 (0.97)	Average agreement that "Most drivers seem oblivious to bicyclists" [c] on 5-point scale[b]
Driver Yield	1 [1,5]	3.40 (0.90)	Average agreement that "Most drivers yield to bicyclists" on 5-point scale[b]
Driver Watch	1 [1,5]	3.27 (0.91)	Average agreement that "Most drivers watch for bicyclists at intersections" on 5-point scale[b]
Fast Speed	1 [1,5]	4.03 (0.88)	Average agreement that "Most people drive faster than the speed limit" on 5-point scale[b]
Biking Normal	1 [1,5]	2.89 (1.22)	Agreement that "Bicycling is a normal mode of transportation for adults in this community" on 5-point scale[b]
Rare Shop	1 [1,5]	3.38 (1.05)	Agreement that "It is rare for people to shop for groceries on a bike" on 5-point scale[b]
Kids Bike	1 [1,5]	3.47 (0.96)	Agreement that "Kids often ride their bikes around my neighborhood for fun" on 5-point scale[b]
Bikers Poor	1 [1,5]	2.03 (0.89)	Agreement that "Most bicyclists look like they are too poor to own a car" on 5-point scale[b]
Bikers Spend	1 [1,5]	2.85 (0.85)	Agreement that "Most bicyclists look like they spend a lot of money on their bikes" on 5-point scale[b]
Bikers Not Concerned with Safety	1 [1,5]	2.91 (1.10)	Agreement that "Many bicyclists appear to have little regard for their personal safety" on 5-point scale[b]

Note: **[a]** Mean (s.d.) for continuous variables and percent for discrete variables. For binary variables, the percentage of the variable taking the value of 1 is shown.

[b]1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree.

APPENDIX B: Factor Constructs Appearing in the Final SEMs

Factor	Description of Indicators
Attitudinal Factors	
Non-Motorized	Agreement that “I like driving” on 5-point scale* Agreement that “I need a car to do many of the things I like to do” on 5-point scale* Agreement that “I try to limit driving as much as possible” on 5-point scale* Agreement that “I like walking” on 5-point scale* Agreement that “I like taking transit” on 5-point scale* Importance of environmental benefits when choosing mode, on 4-point scale where 1=Not at all important, 2=Somewhat important, 3=Important, 4=Extremely important. Opinions on stricter environmental laws and regulation”. 0=”[They] cost too many jobs and hurt the economy”, 1=”[They] are worth the cost”. Agreement that “I try to limit my driving to help improve air quality” on 5-point scale*
Pro-Exercise	Agreement that “It is important for me to get regular physical exercise” on 5-point scale* Agreement that “I enjoy physical exercise” on 5-point scale* Agreement that “I am in good health” on 5-point scale*
Physical Environment Factor	
Supportive Infrastructure	Agreement that “Major streets have bike lanes” on 4-point scale where 1=Not at all true, 2=Somewhat true, 3=Mostly true, 4=Entirely true. Agreement that “Streets without bike lanes are generally wide enough to bike on” on 4-point scale same as above. Agreement that “Stores and other destinations have bike racks” on 4-point scale same as above. Agreement that “Streets and bike paths are well lighted” on 4-point scale same as above. Agreement that “Intersections have push- buttons or sensors for bicycles or pedestrians” on 4-point scale same as above. Agreement that “The city has a network of off-street bike paths” on 4-point scale same as above. Agreement that “Bike lanes are free of obstacles” on 4-point scale same as above. Agreement that “The bike route network has big gaps” on 4-point scale same as above.
Social Environment Factor	
Popular Culture	Agreement that “It is rare for people to shop for groceries on a bike” on 5-point scale* Agreement that “Bicycling is a normal mode of transportation for adults in this community” on 5-point scale* Agreement that “Most bicyclists look like they are too poor to own a car” on 5-point scale*
Good Driver Attitude	Agreement that "Most drivers seem oblivious to bicyclists" on 5-point scale* Agreement that "Most drivers yield to bicyclists" on 5-point scale* Agreement that "Most drivers watch for bicyclists at intersection" on 5-point scale*
Biking Supportive Community	Supportive Infrastructure (see above) Popular Culture (see above) Good Driver Attitude (see above)

*Where 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree.