Decision making processes, choice behavior, and environmental design : conceptual issues and problems of application

4

Decison-Making Processes, Choice Behavior, and Environmental Design: Conceptual Issues and Problems of Application

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Environmental design is a conscious process in which the environment is shaped to meet certain objectives. In manipulating physical attributes of the environment, the environmental designer influences the aesthetic, functional, economic, and social dimensions of the built environment. Designs will either directly or indirectly exert impacts on the spatial and social behavior of individuals. The architect or urban planner may therefore wish to assess the likely effects of design alternatives on human behaviors when addressing the problem of ex ante evaluation of different design options.

Traditional designers employed rules of thumb and did not spend much time explicitly analyzing and predicting human behavior. However, especially in the field of urban planning, the development of public demands for higher environmental standards, the ever-increasing complexity of urban planning problems, and the process of democratization have all stimulated application of models for predicting the consequences of design alternatives on human behavior. This tendency has perhaps been most strong in the context of spatial behavior. In the Netherlands, for example, it has become common practice, especially in such problem contexts as transportation, retailing, recreation, public facilities, and housing, to base design decisions in part on analyses of human behavior.

The present chapter focuses exclusively on a particular type of decision making and action, namely spatial choice behavior. The extensive research on this type of decision making is not well known to environmental psychologists but there may be a great potential for integrating it with the more traditional research on environmental cognition and assessment. The chapter is organized as follows. First, the problem context is sketched in more depth. A characteristic of research on spatial choice is the development of mathematical–statistical models for predicting choice behavior. The following section outlines a general conceptual framework for the different modeling approaches, which are then briefly explained. A separate section is then devoted to a discussion of the role of the physical environment in spatial choice behavior. The chapter concludes with a discussion of a number of problems research on spatial choice faces. It is contended that the solution to some of these problems may benefit from a broader psychological approach similar to the one taken in environmental psychology.

PROBLEM CONTEXT

As an essential component of environmental design, urban planning is concerned with the location, intensity, and amount of land development for various space-demanding activities. Land use plans are the result of more general planning processes that fulfill certain objectives of economic and social well-being. Research is used to generate the information required to make decisions in the planning process or simply to justify certain policy decisions. Important information in this respect relates to the spatial behavior of individuals. In many cases the design or plan attempts to attract certain groups of individuals, implying insight into the likely reactions of individuals to the plan. Sometimes predictions of the future spatial behavior of individuals are required to assess the feasibility of a project or to assess possible negative external effects of a plan. Finally, predictions of spatial behavior are sometimes required as a necessary link to other evaluation criteria. For example, if design alternatives are to be assessed in terms of the degree of noise that will be created by vehicles as a function of design parameters, the future spatial behavior of individuals needs to be predicted and linked to a model of noise production.

The central problem thus is to predict the spatial choice behavior of individuals: What is the probability that a randomly selected individual will choose a particular choice alternative located at a certain point in space, given its physical attributes, the personal characteristics of the individual, and the location of the individual vis-à-vis the locational pattern of the choice alternatives? This problem was first tackled by developing aggregate models, formulated in analogy to models of physical processes. Models such as the gravity model and the entropy-maximizing model (Wilson, 1974) were not primarily concerned with individual choices but rather with interzonal orientation or interaction patterns, which result by aggregating individual choices across zones. Implicitly these models assumed the existence of perfect information, homogeneity among individuals, identical choice sets, and so on. Surrogate variables were used to define the attractiveness of the choice alternatives. Consequently, the parameters of these models were highly influenced by the chosen zoning system and did not generate much insight into the actual preference structure and decision-making process of individuals. It was this very property that generated considerable criticisms of these aggregate models (Rushton, 1969). The aggregate spatial interaction models merely describe observable interaction patterns rather than producing satisfactory explanations of such patterns. There was a clear need for a cognitive–behavioral approach that seeks to understand the decision-making process of individuals with respect to their environment.

CONCEPTUAL FRAMEWORK

From the 1970s and onward, different types of behavioral choice models have been advanced. All of these models are based on variants of a conceptual model that explicitly relates choice behavior to the environment through consideration of perceptions, cognition, preference formation, and decision making. It is assumed that individuals develop some cognitive representation of the real world. That is, in each decision-making task only a limited number of environmental characteristics are considered because individuals may not perceive or may not remember all of the attributes. These characteristics are implicitly or explicitly evaluated and yield subjective impressions of the different choice alternatives in an individual's choice set. The choice set may include only a subset of the available choice alternatives because individuals may not know all the available choice alternatives. Choices are assumed to be made on the basis of this cognitive representation rather than on characteristics of the environment itself. Individuals are assumed to attach some subjective utility to the attributes defining such a cognitive representation, and combine these utilities into some overall utility according to some combination rule or decision heuristic. This results in a preference structure, which defines the positioning of the choice alternatives in terms of overall utility or preference. Finally, it is assumed that such a preference structure is functionally related to choice behavior. That is, the probability of choosing some alternative is assumed to be systematically related to the overall utilities of the choice alternatives included in an individual's choice set.

Given this conceptual framework, the central problem can be divided into a set of research questions: What are the most important factors influencing the kind of spatial choice behavior under investigation? How do individuals perceive objective attributes of the environment? Are their perceptions related to personal characteristics? What is the functional relationship between the individuals' perceptions and their objective counterparts? How do individuals integrate their part-worth utilities to arrive at some preference structure/choice behavior? What is the functional relationship between individuals' preference structures and subsequent choice behavior?

MODELING APPROACHES

The different approaches used to predict the likely impacts of planning measures may be distinguished into two separate groups. The first set of models is explicitly based on observed behavior. Individuals' behavior in the real world is recorded and *interpreted* in terms of some underlying theory. Choice behavior is seen as the result of some decision-making process by which individuals maximize their utility, choose the alternative with their highest preference, and so on, depending on the theoretical structure that is used by the researcher. Thus, no attempt is made to measure the psychological agents that drive the decision-making process and subsequent choice behavior; revealed behavior is interpreted only in terms of such concepts. In contrast, the second set of models is based on explicit measures of individuals' satisfaction, judgments, or preferences. Space does not allow me to summarize the overwhelming amount of different model structures and advances made with respect to the most popular models (for more information, see, e.g., Timmermans & Borgers, 1986). Rather, a brief summary of the most popular models will be given.

Models Based on Revealed Preferences

These models typically relate observed behavior directly to a set of environmental characteristics. The most popular are the discrete choice models. These models are based on random utility theory and assume stochastic preferences. That is, an individual's utility for a choice alternative is assumed to consist of a deterministic utility component and a random utility component. The deterministic component relates environmental characteristics to behavior, while the random component accounts for heterogeneity, random fluctuations, measurement errors, and so on. In addition, random utility theory assumes a utility-maximizing decision rule. According to such a rule, the probability of choosing some alternative is equal to the probability that the utility associated with that particular choice alternative exceeds that of all other choice alternatives included in the choice set. The actual choice model then depends on the assumptions regarding the distributions of the random utility components. If it is assumed that the random utility components are independently and identically normal distributed with zero mean, the *independent multivariate probit model* results (see Daganzo, 1979). On the other hand, if it is assumed that these random components are independently, identically Type I extreme value distributed, the *multinomial logit model* results (Domencich & McFadden, 1975).

In recent years, various alternative models have been developed that attempt to relax one or more of the rigorous assumptions underlying conventional discrete choice models. The Independence from Irrelevant Alternatives (IIA) assumption imposes the constraint that the ratio of choice probabilities for any two alternatives is invariant with respect to the existence or nonexistence of other choice alternatives. It implies that a new choice alternative will obtain a share by drawing from the existing alternatives in direct proportion to their utilities. This assumption is unrealistic since similar choice alternatives probably compete for their joint market shares. A number of models avoid the IIA property by relaxing the assumption of identically and independently distributed random utility components. Some models allow for different variances of the error terms, others allow for positive correlations between error terms, and still others allow for both (see Borgers & Timmermans, 1988).

Another subclass of non-IIA models circumvents the IIA property by extending the utility specification to account explicitly for similarity between choice alternatives. Finally, a third group of non-IIA models may be distinguished that assumes a hierarchical or sequential decision-making process. Perhaps the best known of these is the nested logit model, in which the alternatives that are supposed to be correlated are grouped together into nests. Each nest is represented by an aggregate alternative with a composite utility consisting of the so-called inclusive value and a parameter to be estimated. To be correctly specified, the inclusive values should lie in the range between 0 and 1, and the values of the parameters should decline from lower levels to higher levels of the hierarchy (McFadden, 1978).

Another approach that avoids the IIA property by assuming a sequential decision structure has been suggested by Tversky (1972a,b). Each choice alternative is assumed to consist of a set of aspects. At each stage of the supposed sequential elimination process, an individual selects one aspect with a probability proportional to the importance of that aspect and eliminates all choice alternatives that do not possess that aspect. This process continues until a single choice alternative remains. Attempts to parameterize this elimination by aspects models include Young, Richardson, Ogden, and Rattray (1982), Young and Ogden (1983), Young and Brown (1983), Young (1984), and Smith and Slater (1981).

Conventional choice models also typically assume that the parameters of the model are invariant with changes in the variation in attribute levels of the choice set. Considerable experimental work has, however, demonstrated that the degree of variability existing among choice alternatives for a particular attribute influences the choice process. The larger the degree of variability, the more important the attribute becomes in the choice process (Eagle, 1984, 1988), implying that the weight attached to a particular attribute shifts to those attributes with the higher degrees of variability. Meyer and Eagle (1982) developed a model that can account for such weight-shifting effects.

Discrete choice models exhibit the regularity property. The introduction of new alternatives in a choice set will never increase the choice probability of any old choice alternative. Yet the introduction of new alternatives might cause an existing choice alternative to become more prominent, implying that the choice probability for this alternative may actually increase. Yu (1978) and Smith and Yu (1982) developed a series of prominence models to account for such effects. The regularity property may also be violated by attraction effects. An attraction effect is the tendency of a new choice alternative to draw choices to alternatives similar to itself (Huber, Payne, & Puto, 1982; Huber & Puto, 1983). Huber (1982) proposed a model that captures such effects.

Almost all spatial choice models are based on the assumption of independence of the spatial structure. The parameters of these models are not influenced by the arrangement of the alternatives in the study area. The models fail to account for competition effects and agglomeration effects. Recently, Fotheringham (1983a,b, 1984, 1985) suggested modifications in traditional spatial interaction models to correct this type of misspecification. Basically, he includes an extra variable, which represents the accessibility of a destination to all other possible destinations. If this parameter is positive, then agglomeration effects are dominant. If the parameter for the accessibility variable is negative, then competition forces between destinations are dominant. Following Fotheringham's general ideas, Borgers and Timmermans (1988) have shown that agglomeration and competition effects can also be included in discrete choice models.

Hanson (1980) criticized discrete choice theory by exploring assumptions that are particularly relevant in modeling destination choice in intraurban travel behavior. Basically, she criticizes conventional choice theory in that no explicit consideration of multistop–multipurpose behavior is given. Conventional disaggregate choice models assume that individuals choose only one alternative within any functional class, and only one at a time. In addition, his or her choices are assumed to be independent, while the utility associated with a choice alternative is not affected by the utility of any other choice alternative. Finally, any systematic variation in utility is denied. In recent years, this type of criticism has led to the development of models of trip chaining and activity patterns.

Finally, considerable progress has been made in extending conventional discrete choice models to the case of dynamic choice behavior. Past behaviors may influence future behaviors. Some authors have shown how the available models may be used to explain certain cases of dynamic choice behavior. Perhaps the most interesting development is the introduction of the beta logistic model, which incorporates the multinomial logit model into a dynamic framework that retains the heterogeneity among individuals (see Dunn & Wrigley, 1985).

There are only a few examples that demonstrate the tendency to incorporate different psychological mechanisms in a discrete choice type of approach to improve the theoretical underpinnings of the model. Undoubtedly, these developments are exciting from a theoretical perspective in that one attempts to integrate more ideas and concepts into some unified modeling framework. Future comparative work should learn whether these more sophisticated models also lead to better predictions of human behaviors. Results obtained in the area of including spatial structure have shown that the improvement in prediction is only minor (Borgers & Timmermans, 1987).

Models Based on Expressed Preferences

Many researchers have argued that overt choice behavior should not be considered as the result of an utility-maximizing decision-making process because overt behavior is also influenced by the constraints imposed by the environment on individual choice behavior. To fully understand individual decision-making and choice processes, one should explicitly measure individual's perceptions and preferences. Several different modeling approaches may be distinguished, but only the decompositional multiattribute preference models will be discussed.

Decompositional multiattribute preference models have in common with the discrete choice models the assumption that individuals cognitively integrate their evaluations of a choice alternative's attributes to derive the utility for a choice alternative. Individuals then arrive at a choice by choosing the alternative with the highest utility. However, unlike discrete choice models, the parameters of the decompositional multiattribute preference models are not derived from real-world data but from contrived experiments.

First, the attributes influencing the choice behavior of interest are categorized. Next, these categories are combined according to an experimental design (full factorial, fractional factorial, or trade-off designs) to yield a set of hypothetical choice alternatives. An individual is then requested to express some measure of preference for each choice alternative. These preference measures are decomposed into the contributions of the categories of the attributes given some prespecified combination rule. Finally, the preference structure is linked to overt choice behavior by specifying some decision rule. A more detailed account of the approach is provided in Timmermans (1984).

Although decompositional multiattribute preference models are not explicitly derived from some formal theory, both strict and random utility theory may be linked with the approach. In addition, Anderson's information integration theory (Anderson, 1974) is associated with this approach. The theory asserts that a response is the result of the integration of information according to simple algebraic rules such as adding, averaging, subtracting, and multiplying.

Whereas the nature of the combination rule has received relatively little attention in the context of discrete choice models, the testing of the most appropriate specification is an important step in decompositional multiattribute preference models. Conjoint measurement and functional measurement have been used to test for the functional form of the utility expression.

Since decompositional multiattribute preference models primarily focus on the formation of preferences, most of these models have assumed a deterministic utility-maximizing decision rule that assumes that the choice alternative with the highest preference score will be selected. More recently, however, different assumptions have led to more complicated specifications involving probabilistic decision rules (Louviere & Meyer, 1979; Timmermans & van der Heijden, 1984).

Although decompositional models have been used in many studies, their practical application has been hindered by a number of unresolved problems and limitations. These models lack an integrated theoretical framework linking preferences to choice behavior, and the form or the parameters of utility or decision functions may vary with differences in choice set composition and may therefore not be context independent. Finally, task demands for individual respondents become more and more onerous as the number of attributes and/or the number of levels of attributes increase. Recently, progress has been made in providing possible solutions to these problems (see Louviere & Timmermans, 1987, for a more extensive discussion).

THE ROLE OF THE PHYSICAL ENVIRONMENT

The general aim of the modeling approaches outlined in the previous discussion is to predict the probability that an individual will choose a particular alternative (shopping center, transport mode, recreation area, residential environment, etc.) from among a set of alternatives. They offer a set of related underlying theoretical considerations that might be applied to many choice situations. The operationalization of the models in terms of the attributes that are assumed to influence the choice behavior of interest will thus be dependent on the field of application.

In the case of urban planning though, most of the attributes refer to aspects of the physical environment. For example, spatial shopping choice behavior is influenced by attributes such as the location of the shopping center, the amount of floorspace or size of the center, its layout, the types of available shops, the presence or absence of magnet or department stores, price levels, atmosphere, and parking facilities. Likewise, residential choice behavior is typically assumed to be a function of attributes such as price/mortgage, number of rooms, tenure, size of the backyard, type of house, greenery in the neighbourhood, and facilities. Recreational choice behavior is modeled in terms of variables such as distance, type of terrain, activities that can be performed, and maintenance.

Hence, the role one assigns to the physical environment depends on the definition of this construct. In physical planning, one tends to use the concept to differentiate it from, for instance, the cognitive environment. It refers to different aspects that can be attached to objects or areas located in space. In this sense, one ensures that choice behavior bears some systematic relationship with aspects of the physical environment. Often, as, for example, in the context of spatial shopping behavior, the model is fully operationalized in terms of aspects of the physical environment. In other fields of application, such as residential choice behavior, aspects of the social environment may be incorporated into the model.

If one adopts a more restricted interpretation of the construct of the physical environment in that it refers to strictly physical features, such as light, color, wind, texture, distance, and size, it should be evident that the role of the physical environment in influencing individuals choice behavior is far less important. In the kind of studies referred to in this chapter variables such as color, light, wind, and texture are hardly ever incorporated in the choice model. Moreover, studies that attempt to elicit the factors influencing the choice of shopping centers, residential environments, and so on suggest that such variables are not important in these contexts. Thus, some compound physical features of the environment are often used as predictors in models of spatial choice, partly because the development of such models is so responsive to the practical concerns of urban planning. At the same time there is a realization that basic research is needed to reveal the nature of the decision-making processes intervening between physical features of the environment and choice behavior. What role the physical environment will play in conceptualizations of the decision-making process is a question for the future.

DISCUSSION

As is evident from the preceding review, there is considerable interest in developing models that represent actual decision-making processes. In this respect, a number of interrelated problems deserve closer critical examination. These will be considered now.

Revealed versus Expressed Preferences

Most models of spatial choice behavior, that is, the discrete choice models discussed in this chapter, are based on observed behavior. Apparently, many researchers believe that it is only in the act of choice that individuals can express their preferences. Others seem to think that one can ask subjects almost anything. Perhaps the truth is somewhere in between.

A fundamental problem with observed behavior is that it may not be the result either only or mainly of individual preferences. For example, patterns of housing market choice are likely to be influenced by constraints deriving from personal, environmental, and social factors. The effect of these factors on observed choice patterns cannot be readily determined. It is also very unlikely that these antecedent conditions will remain stable in time, implying that under such circumstances the predictive validity of models based on observed behavior is probably rather low.

Models relying on revealed preferences also have the clear disadvantage of restricting themselves to the domain of experience. Revealed preferences, by definition, concern the choice of actual alternatives. Since this set of alternatives is only one subset from among all possible sets of spatial alternatives, these models extrapolate beyond the actual types of alternatives. Even if the new alternatives lie within the range, the validity of the model may be relatively low because certain data points may exert a strong influence on the final results.

In contrast, experimental designs permit varying the attribute levels in every possible way, implying that subjects' responses to novel choice alternatives can be measured. Choice alternatives can be specified beyond the domain of experience. Therefore, in theory at least, the results of laboratory experiments can be transferred to real-world situations that previously did not exist. The problem, however, is that one has to demonstrate that subjects view hypothetical choice alternatives in a manner similar to how they consider real-world choice alternatives. Thus, one needs to demonstrate that the experimental measurements bear some systematic relationship with overt choice behavior. Over the years, a large amount of empirical evidence supporting this assertion has been accumulated in a variety of spatial choice contexts (see Timmermans, 1984, for a review). However, most of these studies have used alternatives with which subjects were familiar. If individual responses in experiments are based on the experiences individuals have had in the real world, as is commonly believed, there is also a limit to the validity. For example, individual choice behavior related to teleshopping cannot be predicted with discrete choice models, simply because data on observed choice behavior are not yet available. A decompositional preference model could be used, but since respondents have never had any experience with this kind of shopping, the validity of their responses could be seriously questioned.

Some respondents have great difficulty in understanding the experimental task that follows from the use of decompositional preference models. Others may adopt patterned responses to simplify the task. These problems already occur with simple designs. Many recent developments involve more sophisticated and hence more difficult experimental tasks, implying that the reliability and validity of such measurements may be in doubt for an even larger number of sample respondents. However, one should not conclude from these statements that the reliability and validity of measurements necessarily deteriorate (e.g., Akaah & Korgaonkar, 1983; Timmermans, 1987). Apparently, it is not only the difficulty of the measurement task that counts, but also whether the cognitive processes that are tapped by measurements show some similarity with those used in actual real-world decision-making processes.

The Theoretical Underpinnings of the Approaches

Discrete choice models can be derived from a number of theories. Basically, these models relate observed choice patterns directly to sets of influential variables. In contrast, decompositional multiattribute preference models represent more closely the actual decision-making process underlying spatial choice behavior. In a separate modeling step, the factors influencing the choice process of interest are elicited by methods such as factor listing and repertory grids. In addition, the cognitive representations of reality are gauged. Moreover, the way in which individuals combine their separate evaluations of environmental attributes into some overall preference is investigated. Finally, the correspondence between preference and choice is subject to explicit modeling.

The question is how much theory and what kind of theory is required to improve the usefulness of models to environmental design. It is well known that simple extrapolation procedures sometimes provide as good a prediction as very complicated models. Also, many practitioners advocate the development of simple models to maximize the chances that policymakers understand the theory underlying the models and therefore will actually use them. On the other hand, models may become too simple to be of any use, or mask some of the essential characteristics of the phenomenon under investigation. Hence, simple models should be advocated only if they produce the same kind of information and if their predictive success is not substantially less than that associated with a more complex model, given the role of the model in the design process.

It is evident that decompositional models produce more information than discrete-choice models. In addition to predictions of spatial choice patterns, they also yield information regarding the attributes considered important by the respondents, their cognitive representations of reality, and their perceptions. If this information is also important in the design or planning process, the decompositional models should clearly be preferred. However, the decompositional models arrive at this information by concentrating on the outcome of the psychological process. The process itself, not psychological dispositions, states of mind, or human needs, are explicitly considered. The question is whether a more detailed modeling of psychological processes would be necessary to improve its usefulness to urban planning. Again, the answer to this question depends on the kinds of information required in the urban planning process. In my own experience, policymakers are not specifically interested in such psychological phenomena. This implies that one could concentrate on the outcomes of the process as long as the predictive validity of the models is sufficient given the objectives of the planning process.

The Link between Preferences and Choice

Many researchers are against measuring preferences explicitly because they doubt individuals can validly express their preferences. Preferences are believed to be an artifact of the measurement procedure. At the very least, they are seldom related to subsequent choice behavior. Such arguments are usually substantiated by reference to studies demonstrating that factors such as social desirability strongly influence respondents' answers to preference questions. Although there may be some truth to this criticism, in the end it is an empirical question. If expressed preferences are used, it is important to show that they bear some systematic relationship to overt behavior. For many fields of application, such systematic relationships have been demonstrated (Timmermans, 1984).

Thus, empirical evidence suggests that in many spatial choice contexts, preferences are systematically related to overt behavior. This relationship is, however, not deterministic. Thus, probabilistic choice rules rather than simple deterministic ones should be used. This is an area that has received relatively minor attention so far. Explicit attention should also be given to the composition of the choice set, partly as a result of the constraints an individual faces and partly as a result of the imperfections of the perception and cognition of the environment.

Algebraic Rules versus Choice Heuristics

Discrete choice and decompositional models have in common the assumption that simple algebraic rules can be used to describe how individuals integrate their part-worth utilities to arrive at some overall preference or choice. In practice, a linear specification is typically used. Here the researcher implicitly assumes some compensatory decision-making process in which low evaluations of some attribute can be compensated for by high evaluation scores on one or more of the remaining attributes. Much research, especially in the field of process-tracing studies, has however indicated that individuals tend to use simple heuristic choice strategies. This is particularly common whenever the number of attributes or the complexity of the decision making task increases (Payne, 1982). There is a need therefore to assess more fully the potential contribution of computational process models, decision nets, and simple qualitative models, based on such choice heuristics, to the prediction of spatial-choice behavior. This constitutes an exciting new area of research. Nonetheless, the problems inherent in such an approach should not be underestimated. This is especially true if one fully acknowledges in the model-building process that the choice strategies individuals use are contingent on many factors.

A Typology of Decision-Making Processes

It is somewhat surprising to see the same theories being applied over and over again to a wide variety of spatial choice problems, such as shopping behavior, route choice behavior, housing market choice behavior, and recreational choice behavior. These various types of spatial behavior have some clearly distinctive characteristics. Spatial shopping behavior is repetitive, perhaps habitual; the choice set is relatively small and although individuals usually are not aware of all opportunities, they often have a rather good image of at least a few choice alternatives; most of the environmental attributes of the choice alternatives change only slowly, if at all, and there is relatively little risk involved in the decision that will usually also have little impact if wrong. In contrast, the housing choice decision is much more isolated; only a few of these decisions will be made during a lifetime, individuals will know only a few of the choice alternatives, and will probably have to acquire the information used in the decision-making process; the choice set may change rapidly and the impact of possible wrong decisions may be dramatic. Likewise, recreational choice behavior may be more influenced by a drive for variety rather than by habit (Timmermans, 1985).

Hence, it might be worthwhile to think in terms of a typology of decision-making processes and develop models that are tailored to some of the basic characteristics of the choice behavior of interest. Moreover, comparative analyses should be conducted to examine the superiority of some approach over the others. For example, van der Heijden and Timmermans (1987) have formulated a model of variety seeking behavior in the context of recreational choice behavior. This model captures many of the essentials of this kind of behavior better as indicated by a statistically significant improvement of the predictive success of the model compared to that of a conventional choice model.

Manipulable Variables

Spatial choice models are used to predict the likely impacts of urban planning decisions or environmental designs on choice behavior. This goal can be established only if the planning decisions or the design are defined in terms of a set of variables that is used as independent (explanatory) variables in the model. By definition, these are attributes of the environment that can be manipulated.

Many of the discrete choice models use only surrogate planning variables. This raises the problem that one does not know the form of the relationship between these surrogate variables and the variables actually influencing spatial choice behavior. If these relationships are nonlinear, as might be expected, a fundamental problem is that it is unclear how one can assume that manipulating the surrogate variables will have the desired policy effect on spatial choice behavior. In theory at least, this problem is avoided in expressed preferences because one explicitly examines the relationships between preferences and objective attribute levels. One way to proceed is to identify the variables individuals use in choosing from among spatial alternatives. These subjective variables are then compared to their objective counterparts. Alternatively, the manipulable variables are included in the experimental design, implying one can estimate individuals preferences and/or choices as a function of these planning variables.

Hence, from an applied perspective one wishes to include manipulable variables because this provides a direct prediction of the effect of planning decisions on choices. However, in terms of construct validity, one wishes to include those variables in the models that are really used in an individual's decision-making process. Often, these variables are different, implying the need for a model that links the manipulable variables to the variables individuals use in choosing among alternatives.

Situational Variables

A closely related problem concerns the inclusion of situational variables. Both discrete choice and decompositional preference models typically assume stable utility or preference functions. Discrete choice models usually do not include situational variables. Likewise, decompositional preference models attempt to uncover individual preferences or choice for a well-defined decision-making task, but again, situational factors are neither varied in the task description nor included in the definition of the experimental treatments. Yet there are many examples of the influence of situational factors: Interest levels and the overall economic prospects may influence housing market processes, income levels and last year's profits/losses may have an impact on entrepreneural decision-making processes, and weather conditions may exert an effect on recreational choice behavior. Hence, more research effort should be devoted to the analyses of situational variables on decision-making and choice processes. This might prove to be a very difficult task in the context of discrete choice models, but should be rather straightforward in the context of decompositional models. In a discrete choice framework, one needs time-series data, which are difficult to obtain. On the other hand, the situational variables can possibly be varied in experiments and individuals preferences and choices under such varying conditions observed and analyzed.

CONCLUDING REMARKS

The present chapter has sought to clarify a conceptual framework, modeling approaches, and problems that are prevalent in the study of the relationship between the physical environment, decision-making processes, and spatial choice. Available space did not allow the review at any depth of all the different approaches and issues worthy of discussion. Nevertheless, it is hoped that this chapter will contribute to a discussion of new directions in the modeling of human spatial decision-making and choice processes.

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