Chapter 16
Models of Behavioral Change and Adaptation

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Abstract This chapter explains and summarizes models of behavioral change and adaptation, which have received less application in the life choice analysis associated with urban policy. Related to various life choices, life trajectory events are major decisions with a relatively long-lasting impact, such as demographic events, job change and purchase of major resources such as a house and a car. These life trajectory events may co-vary over time and lead to dynamic changes in activity-travel repertoires. Such decision problems have hitherto been predominantly modeled in urban and transportation science using classic discrete choice models. However, because such decisions differ from daily choices, other modeling approaches may be more beneficial. The authors present discrete choice models with lifetime utility and social dynamics, attitudinal models, technology acceptance model, norm activation model, and value belief norm theory for modeling lifecycle decisions and/or lifecycle driven behavioral change.

Keywords Life trajectories · Theory of innovation diffusion · Lifetime utility · Social dynamics · Attitudinal model · Technology acceptance model · Norm activation model · Value belief norm theory

16.1 Introduction

Life trajectories describe the evolution of an individual throughout the individual's lifecycle through sequential stages of life domain careers. The identification and demarcation of careers depends on the field of study, but may include a demographic career, a housing career, a job career, an education career, a vehicle

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ownership career, etc. Generally, careers refer to personal states of an individual or of particular resources.

Recently, in parallel with the shift in interest from cross-sectional to dynamic activity-based analysis, researchers in travel behavior, geography and urban planning have evidenced increasing interest in life trajectories as important factors influencing the dynamics of travel-related decisions (e.g., Verhoeven 2005a, b, 2006, 2007; Beige and Axhausen 2008, 2012; Oakil et al. 2011a, b). The modeling of these life trajectory decisions relates to careers such as demographics, housing and job choice. Modeling these long-term decisions is critically important because they define the action spaces within which daily activity-travel behavior takes places. In addition, they concern mobility tools such as vehicle holdings and public transit passes. Thus, it is assumed that changes in these careers may prompt individuals and households to reconsider their current activity-travel behavior and adapt to the new circumstances or to the shifting needs by changing one or more facets of their current activity-travel patterns and adapt their current repertoire.

Transitions in careers reflect changes in outcomes of underlying choices. The need for change may be endogenously or exogenously triggered. Endogenous change reflects changing needs and desires or weakening constraints, allowing an individual to realize existing needs that hitherto were impossible to realize. Exogenous change induces individuals to reconsider current choices and adapt to changing circumstances. Transitions may also signify gradual moves forward to achieving particular ambitions and goals.

Most life trajectory transitions are the result of explicit choices or decisions. It is no surprise therefore that researchers, almost without exception, have rather uncritically applied their discrete choice apparatus, which they have been applying routinely to predict transport mode, destination and route choice behavior, to model housing choice, job choice, etc. These choices differ, however, in several respects from daily decisions. First, they involve a longer time perspective and create commitments. Few people will start a personal relationship with the a priori mind set or expectation to end it soon. Buying a new house is more than having shelter, but signifies building a home and often involves a considerable investment decision. Most jobs involve a contract that spans a longer period of time. Choosing an educational program is meant to develop the knowledge and skills deemed required to attain certain jobs. Because these programs demand a substantial investment in time and last over a longer time span, they require a certain commitment. Starting a personal or a business relationship is based on trust and a mutual understanding of long-term commitment. Thus, although transitions in life trajectories presume the right opportunities occurring in time (and space), which may last for just a split second, the actual decision typically involves a longer time perspective.

Second, because of this longer time perspective and the commitments involved, the consequences of decisions may have major ramifications if the wrong decision is made. Breaking up a relationship tends to be painful for at least one party; ending school or closing a business may be seen as failure and a waste of the time, money and other resources spent on the education, or the development of the business; a house is not instantaneously consumed, but the benefits and disadvantages are rather experienced over a longer period of time.

Third, although the right opportunities that lead to transitions may occur just in a split second, careers are often embedded in specific plans. These plans set targets across the life course in some chronological order. Certain states may only be accessible if certain conditions in the same or in other careers are satisfied. These conditions may not be sufficient to attain the desired states, but are necessary. For example, completion of a postdoc project may be a necessary albeit not sufficient condition to become an assistant professor; a certain job with an appropriate income may be needed to buy a house of a desired profile. Life trajectories represent different paths in the (partial) realization of these plans. If certain stages turn out to be unattainable, plans need to be adjusted.

Finally, in the context of urban and travel behavior research, lifecycle trajectories define the larger space-time context within which mid-term and short-term activity-travel decisions are or have to be made. Home and job locations define the pegs of the action space of individuals within which feasible daily activity-travel patterns may emerge. The repository of vehicles limits the available choice options, and in turn these options influence action spaces. In addition to constraints, life trajectory stages influence the needs and desires of individuals and households, influencing activity-generating processes. Lifecycle transitions may induce reconsidering current activity-travel scripts and trigger adaptations.

What is the relevance of this attempt to identify the fundamental properties of lifecycle events and transitions? We will argue, to stimulate the discussion, that dominant choice models in urban and transportation science and their underlying theories at best only partially capture these life trajectory processes or may even fail to validly formalize the quintessence of the decision problem. Consequently, we should either elaborate current choice models to better represent the very nature of these choice processes or explore the applicability of alternate models that have not yet been extensively studied in urban and travel behavior research.

In this chapter, we will endeavor both avenues. First, in the next section, we will critically reflect on dominant choice models and underlying theories in urban and travel behavior research and identify shortcomings and caveats in the ways these models are applied from a life trajectory perspective. This section is meant to stimulate discussion and identify issues for future research. Second, in Sect. 16.3, we will outline some alternate modeling approaches that have found less application in urban and travel behavior research compared to discrete choice models, but that may offer a valuable approach to model particular processes of change and adaptation. To the extent that life trajectory decisions involve behavioral change and adaptation, these theories and models may be inspirational for formulating life trajectory travel-oriented models of behavioral change. From the outset, we wish to stipulate that we do not claim to provide a comprehensive overview of the potentially relevant literature.

16.2 Life Trajectories and Choice Models

Over the years, a plethora of different models has been developed to describe and predict travel-related choice behavior. Table 16.1 gives a crude overview, differentiating between models of riskless and risky behavior as one dimension, and between utility-maximizing (rational) choice models, and models of bounded rational behavior. The cells give examples of different modeling approaches for combinations of these dimensions. The overwhelming share of studies in urban and transportation science dealing with the choice of particular facets of activity-travel behavior has conceptualized choice under certain conditions and assumed rational choice behavior. Most comprehensive activity-based models of travel demand have adopted a similar modeling approach (Rasouli and Timmermans 2014a). The most widely applied model belonging to this category is the multinomial logit model (Ben Akiva and Lerman 1985; Train 2003).

Although the mathematical specification of the MNL model can be derived from multiple, even competing theories of choice behavior, the most common foundation of the MNL model is random utility theory (McFadden 1978), assuming a stochastic utility function and the principle of utility-maximizing behavior. More advanced discrete choice models have relaxed the strict assumptions underlying the MNL model by allowing for varying variance terms and co-variances between error terms, but these advances did not affect the general modeling approach nor the principle of utility-maximizing behavior. Arguably, in applying choice models, urban and transportation researchers seem to have been more fascinated and driven by the application of a particular model rather than the desire to develop new or adjusted models that do sufficient justice to the specific characteristics of the decision problem at hand. For example, the multinomial logit model has not only been applied to model short-term decisions such as destination, route and transport mode choice, but also to long-term life trajectory decisions such as vehicle holdings and housing choice, mostly based on cross-sectional data.

While the notions of an instantaneous utility function and utility maximizing behavior may be defendable for destination and transport mode choice, this representation does not fully capture or is even too simplistic to do justice to the complexity and repercussions of life trajectory events such as buying a house, which is often the most expensive choice people make during their life. Housing choice has a number of unique features that are not incorporated in the modeling process. While destination, transport mode and route choice reflect the outcomes of a learning process in which travelers can explore different options over time, experience

Table 16.1 Classification of different types of choice models

	Rational choice models	Models of bounded rationality
Riskless choice	Utility-maximizing models	Decision heuristics
Risky choice	Expected utility Maximizing models	Prospect theoretical models Regret minimizing models

the consequences of their choice, and either reinforce or adjust their behavior, housing choice decisions are made only a few times during a lifetime.

Moreover, the set of possible choices may be huge and is not fixed. Thus, in light of the lack of experience and information and the flux in the market, the housing decision process often evolves across different stages. In the first phase, individuals will explore some available options, collect information using different media, perhaps assisted by experts, to frame their decision. Next, they often contact a real estate agent to site visit a limited set of properties. Because further search involves time, effort and money, typically the best of the limited set of inspected properties is judged against needs and desires and affordability, implications are assessed against the current and desired new lifestyle of the household and a decision is made to buy the house, extend the search process or end it to wait for new opportunities in the future.

Buying a new house does not only satisfy particular housing needs. Depending on the distance of relocation, the complete configuration of a household's job and activity locations and the social networks of its members may change, affecting commuter travel times, travel times for other activities, the feasibility of activity agendas, possible activity duration, etc. Assuming that buying a new house involves extra expenditure, expenditures on other daily activities and products may need to be reduced; opportunity costs need to be considered. Thus, the housing decision process likely has repercussions across different domains of a household lifestyle.

Because often people live in the same house for many years, the attributes of the house, its physical and social neighborhood and accessibility to a multitude of activity locations are not only judged against current needs but also against anticipated future needs that may be induced by life trajectory events. Even if decision-making would be myopic, housing generates a lifetime utility or a utility across a longer time horizon.

Random utility models constitute a meager representation of this process and largely fail to mimic its essence. The typical two-step procedure of first identifying the choice set and then predicting the choice of a particular house from the choice set is nothing but a technical way to reduce the complexity of the modeling process, but has little to do with the actual decision process. Potential housing buyers do not truly have a choice set; they may have a consideration set but only in its original process meaning. The principle of utility maximization and simultaneously choice does not seem valid for many housing choice decisions. Often the housing market clearing process is conceptualized as an auction, but in many countries in the world housing markets regulations and consumer protection in fact are antagonistic to the very notion of an auction. Moreover, the number of attributes included in housing choice models, particularly those developed in transportation research, is often very limited with a focus on transport-related attributes. Acknowledging that simple models may have an advantage, including very few attributes make these models overly simplistic to be of any use. Models developed in the housing choice literature tend to be better in this regard, but still the different lifestyle domains are rarely depicted in a balanced way.

If choice set generation would be given a behavioral interpretation, it could be viewed as evidence of bounded rationality in the sense that individual try to simplify the decision problem (Rasouli and Timmermans 2015). Other models of bounded rationality have substituted the notion of systematic, full information comparison of alternatives against a set of decision criteria for a set of simple decisions heuristics. Arguably, models of bounded rationality better mimic the actual decision making process in the sense that they represent a way of how individuals cope with the potentially large set of attributes affecting the housing choice decision. However, these models of bounded rationality share with the dominant utility-maximizing models the limitations that the larger decision process is ill-represented and that the decision problem is confined to only particular aspects of a household's lifestyle.

Another general class of choice models is based on decision-making under risk and uncertainty (see Rasouli and Timmermans 2014b for a recent overview). Risk means that the uncertain conditions are known and defined, whereas uncertainty means that the decision-maker has to attain and assess the degree of uncertainty. Some models are the equivalent of rational choice models under conditions of uncertainty. They predict that individuals will choose the alternative with the highest payoff or utility, which is defined as the expected value of the outcomes of the decisions. However, as limited empirical support has been found for this model in many fields of application, several alternate models of bounded rationality under uncertainty have been formulated. Prospect theoretic (Kahneman and Tversky 1979) and regret-based models have become most popular in travel behavior analysis (Avineri 2009; Chorus et al. 2008; Chorus 2011), although it should be noted that the number of studies involving modeling choice and decision-making under conditions of uncertainty is still surprisingly small.

Because buying a house or vehicle has a long lasting effect, one would suspect that individuals do have to consider various sources of uncertainty. The future value of the property, the ability of reselling the house if needed, the future evolution of mortgage rates, changing population distribution in the neighborhood are just of few examples of uncertain factors that may affect the utility or value of a house. Yet, we are not aware of any study in urban and transportation research where such uncertainty has been taken into account when life trajectory decisions are modeled.

Thus, in completing this section of our chapter, we argue that the travel behavior community has by and large uncritically applied modeling approaches commonly used for day-to-day activity-travel decisions to long-term life trajectory decisions. It suggests that either current modeling approaches should be elaborated to better capture the quintessence of long-term life trajectory decisions or that yet other modeling approaches should be explored and judged for their applicability in urban and transportation research.

In this chapter, without trying to be comprehensive, we discuss some alternative theories and approaches that may be useful to model certain kinds of life trajectory decisions. Some of these approaches have found limited application in urban and travel behavior research, whereas to the best of our knowledge others have not been applied in urban and transportation research yet. Where relevant, we will refer to existing applications in urban and travel behavior research.

16.3 Selected Alternate Models

Urban and transportation research has mostly relied on applied physics and economics in borrowing (choice) modeling frameworks and elaborating or applying these to choice and decision-making processes relevant for these disciplines. However, particularly social psychology has put forward many alternative theories and models of decision making, while other applied disciplines such as marketing research and environmental research also have developed models that may be relevant for urban and transportation research in general and the modeling of life trajectory decisions in particular.

Life trajectory decisions concern a transition in the status of lifecycle careers, manifested in life trajectory events that have long-lasting implications. The actual decision, representing the end of the decision process, is driven by a motivation to change the career. Motivations may also relate to the desire to change current behavior, which in some cases requires dramatic change in long-term drivers of day-to-day behavior. In this section, we will describe some modeling approaches that have been developed to model behavioral change and assess their potential for modeling life trajectory decisions that are relevant for transportation. The different approaches will be divided into aggregate and individual models.

The focus of attention of aggregate models is concerned with the aggregated outcomes of individual decisions. In contrast, individual level models aim at predicting behavioral intentions and choices of individuals. Although these outcomes are typically aggregated, the difference between the two streams of work concern the data input to the models and the definition of their explanatory variables. Aggregate models are based on aggregated data, whereas individual-level models are based on individual-level data.

16.3.1 Aggregate Modeling Approaches

16.3.1.1 Statistical Models of Temporal Interdependencies

Most research on the relationship between life trajectory events and activity-travel behavior has attempted to find evidence of significant effects of life trajectory events on behavior. It is based on the contention that life trajectory decisions trigger individuals and households to reconsider their habitual behavior that reflects s state of equilibrium (e.g., Waerden et al. 2003a, b; Klöckner 2004). Life trajectory events may involve substantial changes in available resources and choice options, and may also induce changes in activity agendas in reaction to or in anticipation of such events. Both qualitative and quantitative studies have been conducted to explore these dynamics.

Stanbridge et al. (2004—see also Stanbridge and Lyons 2006) conducted a qualitative study on the effects of residential relocation on travel behaviour. They concluded that relocation decisions are partly influenced by travel considerations. Relocation forces or prompts households to reappraise their current travel options once post-relocation travel is experienced. Similar evidence has been found in other qualitative studies (e.g., Krizek 2003; Prillwitz and Lanzendorf 2006, 2007; Rocci 2006; Hannes et al. 2007). Other lifecycle events may have a similar impact as, for example, illustrated in Lanzendorf (2010), who examined the impact of the birth of a child and found evidence of changes in transport mode.

Quantitative studies seem to have followed two modeling approaches: hazard and competing risk models, and Bayesian belief networks. Hazard and competing risk models examine the effects of a set of explanatory variables on continuous interval times between successive implementations of single activity-travel facets or on state changes. In contrast, Bayesian belief networks focus on the conditional choice probabilities of discretionized or inherently categorical variables in a network. Consequently, they require the researcher to define a time window to calculate these conditional choice probabilities. The advantage of the Bayesian approach is the richness in the specification of the relationships between the variables of interests; the disadvantage, however, is that the results are dependent on the selected time window.

Chen and Chen (2006) applied hazard models to the Puget Sound panel data and concluded that a change in residential location affected time allocation and travel patterns of individuals. Using the same data set, Rasouli et al. (2015) found that job changes (transitions between being employed and unemployed and vice versa) led to a change in shopping-travel patterns. Beige and Axhausen (2006) investigated the interrelationships between lifecycle events, such as residential choice, education, employment duration, car availability, driver's license and season's tickets using hazard/competing risk models. Their data showed that people with a driver's licence or public transport season ticket are more likely to move house.

Verhoeven et al. (2005a, b, 2006) and Xie et al. (2006) used a Bayesian network to represent the interdependencies between life trajectory events, resources and activity-travel patterns. The network included life trajectory events such as change in residential location, change in household composition, change in work location, change in study location, and other events such as change in car possession and availability, change in public transport pass and change in (household) income. The learned network, using data of 710 respondents, indicated that structural lifecycle events influence each other. Significant effects were found in within-events dependencies across time periods; between one event and another event during the same time period and across time periods, and between one event and personal characteristics. Vanhunsel et al. (2007a), elaborating Janssens (2005) and Janssens et al. (2006) applied the Q-learning algorithm for the same purpose, and showed (Vanhunsel et al. 2007b) that a regression tree used to generalize the Q-table leads to faster results.

16.3.1.2 Theory of Innovation Diffusion

Some life trajectory decisions are concerned with major expenditures such as buying a house, a boat or a car. A potentially relevant framework for investigating such decisions at the aggregate level is the theory of innovation diffusion. Various phenomena show a high degree of similarity in their particular evolution over time and sometimes space. The theory of innovation diffusion (Rogers 1962) has been formulated to describe how a new idea or product becomes popular, spreads through a population and ultimately reaches some level of saturation. The theory describes particular regularities at an aggregate level; it is not a theory of individual choice.

Underlying the typical S-shape diffusion curve that defines the theory of innovation diffusion is the idea that individuals exhibit a different attitude to innovations and change, and differ in their willingness to try different new products. The theory identifies five different adopter categories. First, innovators representing a relatively small fraction of the population are those individuals who wish to be among the very first trying the innovation. Second, a slightly larger fraction of the population shows interest in the new innovation and belongs to the category of Early Adopters. If the innovation still has more followers, the third category called Early Majority represents a larger share of the population who adopts only after they receive evidence that the innovation works or of its popularity. Next is the Late Majority – a more or less equal share of people, who are more skeptical of change, and less sensitive to innovations, and only adopt after a large share of the population has embraced the innovation before them. Finally, there is the category of Laggards, a group of conservative individuals, who are very skeptical of change and the last to adopt an innovation, if they adopt at all.

Mathematically, the well-known S-shaped logistic function is used to describe the diffusion process. That is:

$$p = \frac{S}{1 + e^{(\alpha - \beta T)}} \tag{16.1}$$

where,

p	the proportion of the population adopting an innovation,
S	the satiation level, $S \leq 1$,
T	time,
α, β	parameters to be estimated, respectively representing the proportion at $T = 0$, and the rate at which this proportion changes with increasing time

If the whole population ultimately uses an innovation, S is equal to 1. In most cases, however, the proportion of people adopting a certain new product is much smaller. For example, the market share of electric cars may only be a few per cent. If α is large, the proportion at time zero is very small. With increasing T, $(\alpha - \beta T)$ becomes increasingly smaller, implying that the proportion of the population adopting the innovation increases at an increasing rate. Once $(\alpha - \beta T)$ becomes negative, the rate of change systematically decreases until the e-term goes to zero and the diffusion and adoption process converges to the satiation level.

Some simple algebra shows that the above logistic function can be estimated using linear regression analysis:

$$S = p(1 + e^{(\alpha - \beta T)}) \tag{16.2}$$

$$S = p + pe^{(\alpha - \beta T)} \tag{16.3}$$

$$S - p = pe^{(\alpha - \beta T)} \tag{16.4}$$

$$\frac{S - p}{p} = e^{(\alpha - \beta T)} \tag{16.5}$$

$$\ln(\frac{S - p}{p}) = \alpha - \beta T \tag{16.6}$$

In case of spatial diffusion processes, in which the rate of adoption is some function of the distance from the center of origin, parameters α and β can be made a polynomial function of distance to capture spatially diverging diffusion processes. The model can be simply expanded to include different socio-demographic variables and different environmental variables assumed to influence the diffusion and adoption process. However, if we wishes to relax the symmetric nature of the diffusion process, implied by Eq. (16.6), more elaborated functions that capture non-symmetric forms are required.

Although innovation diffusion models address the issue of change, their aggregate nature makes them difficult to link to life trajectory events. Hence, in that sense their direct relevance for lifecycle studies is limited. However, these models may be useful, for instance, for modeling the adoption of electric cars. The adoption can be made a function of socio-demographic variables.

16.3.2 Individual-Level Modeling Approaches

16.3.2.1 Discrete Choice Models

The literature in travel behavior research that has explicitly taken a life trajectory perspective has tried to find relationships in the data, relying on statistical concepts. Their choice theoretical basis is weak, or has not really been articulated. In this section, we discuss two approaches that can be viewed as extensions of classic choice theory. The first approach is based on the concept of lifetime utility and thus better captures the idea that housing and job choice generate utility for a longer period of time. The second approach is based on the contention that individual choice behavior depends on social dynamics and thus offers a potentially relevant approach for those life trajectory decisions that may be influenced by social dynamics.

Lifetime Utility

Golounov et al. (2007) offer a relevant example of a model of lifetime utility. Their domain of application concerns car sharing, which may be difficult to view as a life trajectory decision, but a similar approach can be developed for the typical choices considered in this stream of literature. In line with such life trajectory decisions, the choice involves a substantial financial investment, which should be traded-off against other major investment decisions such as a house, children's education, and other expensive consumer durables. Moreover, the choice implies a loan or the spending of savings, implying that the decision-maker needs to decide whether the choice is affordable. Most importantly, consumption of the product is not immediate, but rather stretches out across a much longer period of time, implying that time-dependent utilities should be taken into account. Thus, life trajectory decisions can be seen as dynamic choice problems and these dynamics should be incorporated into the model.

The core of the model concerns the trade-off of spending money on the decision under investigation (leasing a new car), or spending the money on other goods, subject to budget constraints. The authors model change in intertemporal consumer utility as a result of possible car lease. To account for lifetime utility, the dynamic decision problem is conceptualized in terms of a vector of payments, and a vector of remaining car values. The disutility of spendings and the utility of remaining car value, and therefore the total utility change from choosing a choice option depend on the discount rate. The dynamic decision problem is solved by assuming that consumers will choose the option that maximizes total utility across time.

Let the random utility for option j of individual n be written as:

$$U_{nj} + \varepsilon_{nj} \tag{16.7}$$

where U_{nj} is the utility of alternative j for individual n, the ε_{nj}-s are independently and identically Gumbel distributed errors. Because individuals may make more than one choice, let m be an index for observation m out of M observed choices (observations) per individual (1, …, m, … M). Thus, if an individual is observed to have made M consecutive choices from a set of alternatives J_m, with $j_{nm} \in J_m$, the utility of choice option j in choice situation m, U_{njm}, is given by:

$$\begin{aligned} U_{njm}(\boldsymbol{\beta}_\mathbf{n}) &= \sum_{t=t_0}^{T} [(1+\beta_{1n})^{-t}(\beta_{2n}S_{jmt} + \beta_{3n}V_{jmt})], if \quad j \neq 0 \\ U_{n0m}(\boldsymbol{\beta}_\mathbf{n}) &= \beta_{0n} \end{aligned} \tag{16.8}$$

where each option j is represented by a vector of payments S_{jmt}, and vector of remaining car values V_{mtj}. To describe the random coefficients in the model, $\boldsymbol{\beta_n}$ defines a vector (β_{0n}, β_{1n}, β_{2n}, β_{3n}) in which the parameters are unobserved for each n. These parameters vary across individuals with vector density function $f\boldsymbol{\beta_n}|\boldsymbol{\theta}, x_n)$, where x_n is a set of observed characteristics of individual n, and $\boldsymbol{\theta}$ is a parameter vector. Assuming that the error terms are independently and identically Gumbel distributed within and across choices, and are independent of $\boldsymbol{\beta_n}$, S_{jmt} and V_{jmt}, the probability that person n chooses alternative j in choice m is equal to:

$$p_{njm} = \frac{\exp(U_{njm}(\boldsymbol{\beta_n}))}{\sum_{j'=1}^{J_m} \exp(U_{nj'm}(\boldsymbol{\beta_n}))} \tag{16.9}$$

The unconditional probability is the integral of the conditional probability over all possible values of $\boldsymbol{\beta_n}$ which depend on their density function $f\boldsymbol{\beta_n}|\boldsymbol{\theta}, x_n)$:

$$Q_{njm}(\boldsymbol{\theta}) = \int L_{njm}(\boldsymbol{\beta_n}) f(\boldsymbol{\beta_n}|\boldsymbol{\theta}, x_n) d\boldsymbol{\beta_n} \tag{16.10}$$

Denote $j(n\ ,m)$ as the alternative j that individual n chooses in choice m. Then, conditional on $\boldsymbol{\beta_n}$, the probability of the observed sequence of choices $j(n,\ 1)$, …, $j(n,\ m)$, … , $j(n,\ M)$ for individual n is a standard multinominal logit probability:

$$H_n(\boldsymbol{\beta_n}) = \prod\nolimits_m L_{nj(n,m)m}(\boldsymbol{\beta_n}) \tag{16.11}$$

The unconditional probability is the integral of the conditional probability over all possible values of $\boldsymbol{\beta_n}$, which depends on the density function $f\boldsymbol{\beta_n}|\boldsymbol{\theta}, x_n)$:

$$P_n(\boldsymbol{\theta}) = \int H_n(\boldsymbol{\beta_n}) f(\boldsymbol{\beta_n}|\boldsymbol{\theta}, x_n) d\boldsymbol{\beta_n} \tag{16.12}$$

This mixed logit approach allows $\boldsymbol{\beta_n}$ to vary randomly across individuals. We assume that the true values of $\boldsymbol{\beta_n}$ are not known, but we can estimate their distribution in the population. More advanced models can be estimated by assuming dependencies in the error terms.

Discrete Choice Model of Social Dynamics

Some life trajectory decisions such as residential choice and vehicle choice may be induced by a multitude of endogenous and exogenous drivers of change. One of these drivers is social influence. Individuals may be triggered to consider particular options because these have become more popular or mainstream in (parts of) their social network. Because in certain decision contexts, some people may exhibit a tendency to mimic or copy the behavior of others because they like to belong to the same group or gain the respect of some people, including such mechanisms into choice models would be beneficial. It should be noted that other people show exactly the opposite tendency: to differentiate oneself from a particular group exactly the opposite or at least different behavior is exhibited.

Blume and Durlauf (2003) developed a discrete choice theoretic approach to examine dynamical aspects of social interaction. Their model assumes that individual choice behavior is influenced by the accumulated choices of all other members of a social network or population. Brock and Durlauf (2001) derive results for the equilibrium state of this system. The model can be expressed as follows. They assume that individual choices are based not only the private utility derived from a particular choice, but also from the social utility associated with the choice. They consider a binary choice, where each of the binary choices is coded into y_n. The realization of the binary choice is coded as $y_n = \{-1, 1\}$. The space of all possible binary actions of the population is N-tuple $\mathbf{y} = (y_1, y_2, \ldots, y_N)$. The utility of individual n of choosing action j is assumed to consist of:

$$U_{nj} = V_{nj} + S_{nj}(\rho_n^e(\mathbf{y}_{-n})) + \varepsilon(y_n) \tag{16.13}$$

where,

U_{nj}	the utility of individual n with respect to choice j,
V_{nj}	the private utility of individual n with respect to choice j,
$S_{nj}(\rho_n^e(\mathbf{y}_{-n}))$	the social utility caused by influence of the social interactions on the utility of individual n with respect to choice j,
$\rho_n^e(\mathbf{y}_{-n})$	the conditional probability measure individual n places on the choices of others at the time of making his own decision, and
$\mathbf{y}_{-n}$	the vector of choices of all individuals other than n

Two different models were derived from this basic concept. The first model is based on the assumption of a constant degree of dependence across individuals. If it is assumed that

$$S_{nj}(\rho_n^e(\mathbf{y}_{-n})) = S_{ni}(\bar{m}_n^e) = \theta\, \mathbf{y}\, \bar{m}_n^e \tag{16.14}$$

where, $\bar{m}_n^e$ is the average of the subjective expected value from the perspective of individual n of individual n' choice ($\bar{m}_n^e = (N-1)^{-1} \sum_{n' \neq n} m_{n',n}^e$), and $\theta > 0$.

Theoretically, this specification assumes that individual choice behavior is based on an expectation of the mean choice level, which is independent of the error terms. The latter means that individuals do not communicate or coordinate their decisions. Assuming an extreme value distribution for the error terms, the probability than individual n will choose option j is then equal to:

$$p_{ni} = \frac{\exp(\beta(V_{ni} + \theta\, \mathbf{y}_\mathrm{n}\, \bar{m}_n^e))}{\sum_{y_{ni'}} \exp(\beta(V_{ni'} + \theta\, \mathbf{y}_{ni'} \bar{m}_n^e))} \tag{16.15}$$

The second specification captures conformity by assuming that

$$S_{ni}(\bar{m}_n^e) = -\theta/2(\mathbf{y}_n - \bar{m}_n^e)^2 \tag{16.16}$$

This model assumes that social utility decreases with increasing deviance from the mean. Dugundji and Walker (2005) and Dugundji (2013) expanded this model from the binary case to the trinomial case and derived the equilibrium conditions for this model.

16.3.2.2 Attitudinal Models

Choice models in urban planning and transportation research express the relationship between attributes of the choice alternatives and choice probabilities. This focus is understandable in that these disciplines, by their very nature, try to change these attributes to achieve particular goals, and therefore have a need to predict consumer response to changing attributes. However, behavioral change may also come about without changing any of the attributes of the choice alternatives but rather as a change in attitudes that people hold. For example, the policy objective to reduce environmental emission by increasing the market share of electric cars may be achieved by changing attributes of electric cars; it may also be achieved by campaigns to increase environmental awareness of particular groups to change their attitudes. It means that some life trajectory decisions such as vehicle choice may also be influenced by the attitudes that people have about particular topics, such as environmental policies, that may affect their choice and decision-making regarding these life trajectory decisions. Classic random utility models lack the variables and mechanisms to successfully predict choice behavior that is primarily driven by attitudes.

Relative to random utility theory, attitudinal theories have found less application in urban and travel behavior research. However, these theories and associated models have dominated related fields such as marketing and environmental psychology. The best-known attitudinal theories are the theory of reasoned action and its successor the theory of planned behavior. Originally, attitude theories were concerned with general behavioral dispositions of individuals with respect to organizations and institutions, social groups and societal issues. These general dispositions were, however, found to be poor predictors of behavior. One possible reason for this lack of predictive success may be that the effects of multiple other factors unique to the specific choice context are ignored. Fishbein and Azjen (1975) argued that general dispositions only indirectly influence choices in specific contexts by impacting factors that are more closely linked to the behavior of interest. They, therefore, formulated the theory of reasoned action (Fishbein and Azjen 1975; Azjen and Fishbein 1980), which was later extended to the theory of planned behavior (Azjen 1985, 1991).

Random utility theory implicitly assumes that changes in choice sets and their attributes will induce behavioral change conform the estimated parameters of the choice model that capture the marginal effects of attribute changes on choice probabilities. These models thus rely on the estimated relationships between attribute levels and choice probabilities. However, these models lack the actual mechanisms that induce such change. Where random utility models emphasize the input-output relations in choice behavior, keeping the actual process as a black box, in contrast, models based on the theory of reasoned action and planned behavior explicitly identify the concept of intention to reflect the strength of underlying motivations to engage in particular behaviors. In general, the stronger intentions, the more likely an individual will engage in the behavior of interest. However, an individual can only transform intentions into actual behavior if he/she can be engaged in that behavior at free will. The theory uses the concept of behavioral control to signify the extent that the individual has access to the required choice options and resources. Thus, the concept is quite similar to the notion of space-time and budget constraints often used in activity-based approaches to travel demand (Rasouli and Timmermans 2014a).

A commonly made assumption is that intentions and behavioral control interact in their effects on actual behavior. Intentions are assumed to positively influence performance to the extent that the individual has behavioral control, and behavioral control is assumed to be positively related to performance to the extent that the individual is motivated to become engaged in the behavior of interest. In the theory of planned action, the concept of actual behavior control was replaced with the concept of perceived behavioral control. It defines an individual's perception of the ease or difficulty of performing the behavior of interest. It is assumed that individual behavior is strongly influenced by the confidence an individual has in his/her ability to perform. Perceived behavioral control, jointly with behavioral intention, directly influence behavioral achievement. The theory of planned behavior postulates three conceptually independent determinants of intention: (i) attitude towards the behavior of interest; (ii) subjective norms, and (iii) degree of perceived behavioral control. Attitude toward the behavior of interest defines the degree to which an individual is positively or negatively disposed to the behavior in question. An example might be concerns about the environment may co-vary with a positive disposition to buy hybrid or electric cars. Subjective norms relate to the perceived social pressure to perform or not to perform the behavior of interest. One can imagine that the probability of buying a speedy car with high fuel consumption may be different if all friends of an individual own the same type of cars, or that all friends are users of public transport or all drive electric cars. The degree of perceived behavioral control refers to the perceived ease or difficulty of performing the behavior in question. Here again, the decision to buy or not to buy an electric car may depend on an individual's perception to what extent his/her routine activity travel behavior would be impacted by the more frequent charging activities and the extra time each charging episode takes. The more positive the attitude and subjective norms, and the greater the perceived behavioral control, the stronger an individual's intention to perform the behavior in question. The relative importance of these concepts in predicting behavioral intention varies across context. Figure 16.1 summarizes the theory.

As to attitudes, a cognitive approach to attitude formation is adopted, typically based on Fishbein and Ajzen's (1975) expectancy-value model of attitudes. This model assumes that attitudes develop from the beliefs people hold about the choice alternative of interest by associating an object or behavior to certain

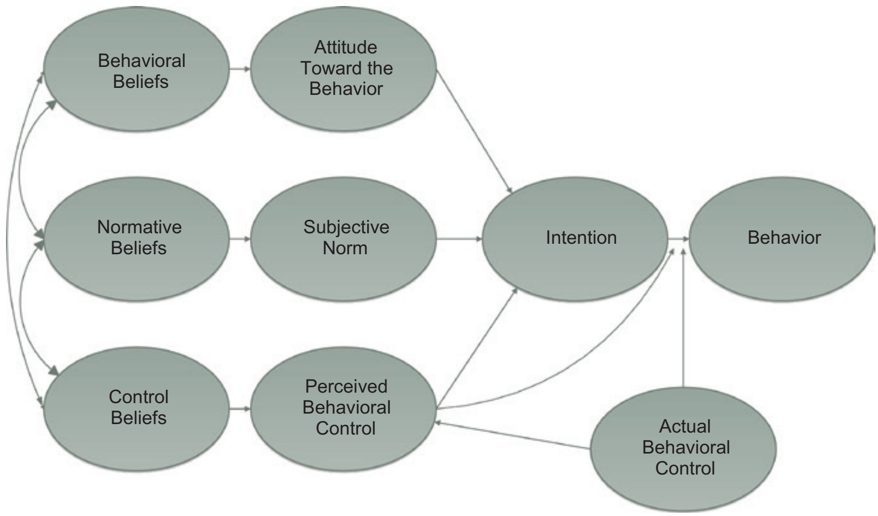

Fig. 16.1 The theory of planned action

outcomes. Mathematically, the outcome's subjective value is assumed to contribute to the attitude in direct proportion to the strength of the belief,

$$A_{nj} = \sum_{k=1}^{K} b_{nk} e_{njk} \tag{16.15}$$

where,

A_{nj} is the attitude of individual n with respect to object or behavior j;
e_{njk} is the subjective evaluation of individual n of salient belief k about choice alternative j;
b_{nk} is individual nth strength of salient belief k defined as the subjective probability that a given behavior will generate a certain outcome

Note that mathematically this function strongly resembles a linear utility function. The main difference is that in this case all terms on the right hand side of the equation are separately and explicitly measured. In most applications of the theory of planned behavior, belief strength is assessed by means of a 7-point graphic scale (e.g., likely-unlikely) and evaluation by means of a 7-point evaluative scale (e.g., good-bad). Alternatively, one can find the optimal scaling. The belief and evaluation scales can be rescaled by adding constants θandϑ respectively (Holbrook 1977). Then, the model becomes

$$A_{nj} = \sum_{k=1}^{K} (b_{nk} + \theta)(e_{njk} + \vartheta) \tag{16.16}$$

$$A_{nj} = \sum_{k=1}^{K} (b_{nk} e_{njk} + b_{nk} \vartheta + \theta e_{njk} + \theta \vartheta) \tag{16.17}$$

$$A_{nj} = \sum_{k=1}^{K} b_{nk} e_{njk} + \vartheta \sum_{k=1}^{K} b_{nk} + \theta \sum_{k=1}^{K} e_{njk} + \theta \vartheta) \tag{16.18}$$

To estimate the rescaling parameters ϑ and θ, we regress the attitude measure on $\sum_{k=1}^{K} b_{nk} e_{njk}, \sum_{k=1}^{K} b_{nk}$ and $\sum_{k=1}^{K} e_{njk}$ and divide the unstandardized regression coefficients $\sum_{k=1}^{K} b_{nk}$ and $\sum_{k=1}^{K} e_{njk}$ by the coefficient obtained for $\sum_{k=1}^{K} e_{njk}$. The resulting values provide least-squares estimates of belief strength and evaluation.

For subjective norms, a similar equation is used

$$N_{nj} = \sum_{k=1}^{K} m_{njk} s_{jk} \tag{16.19}$$

where,

N_{nj} is the subjective norm of individual n with respect to object or behavior j;
s_{jk} is the strength of social norm k about choice alternative j;
m_{njk} is individual nth motivation to comply with social norm k about choice alternative j;

Finally, perceived control is assumed to be equal to

$$C_{nj} = \sum_{k=1}^{K} p_{njk} c_{njk} \tag{16.20}$$

where,

C_{nj} is the perceived control of individual n with respect to object or behavior j;
p_{njk} is the perceived power of individual n of belief k about choice alternative j;
c_{njk} is individual nth control belief of belief k about choice alternative j;

Social norm in this context is defined as the perceived social pressure to engage in a certain type of behavior.

Over the years, the level of sophistication in measuring these concepts and estimating their relationships has dramatically increased. Nowadays, the standard is to use multiple indicators for each concept and estimate a structural equation model to identify the direct and indirect relationships identified by the model.

It should be evident that these attitudinal models are models of behavioral change and are not per se directly linked to life trajectories. However, it is possible to examine whether particular attitudes are related to different lifecycle stages and in that sense a link between life trajectories and attitudes may be established. Although the number of applications of this model in urban and travel behaviour research is still relatively limited, the potential usefulness of this approach to study behavioural change in travel behaviour has been advocated by, for example, Gärling (2005), Gärling et al. (1998, 2001, 2002), Fujii and Gärling (2003, 2005), and Gärling and Fujii (2006). Although the following examples do not concern life trajectory events, they do illustrate the contention that for some choice problems attitudes may be more important than utilities. For example, Fujii and Kitamura (2003) investigated the effects of a one-month free bus pass on travel behaviour, and found an increase in positive attitudes towards the bus, and intensified use of the bus at the expanse of decreased car travel. Similarly, Bamberg et al. (2003a, b) found that the provision of a free pass to students led to changing attitudes, subjective norms and perceptions of behavioural control. Other examples of this kind of work include Bamberg and Schmidt (2003), Chatterjee and Ma (2006), Fujii et al. (2001), Fujii and Gärling (2005, 2006), Fujii and Taniguchi (2005, 2007), and Loukopoulos et al. (2004, 2005, 2006).

Compared to random utility and discrete choice theory, the Theory of Planned Behavior has some limitations. Perhaps the most important of these is fact that it ignores economic factors influencing choices. Although, as the above examples illustrate, it is not difficult to imagine choice problems in which attitudes play a dominant role, it is difficult to imagine that these attitudes will not be traded-off against the utility derived from the choice alternatives, costs, etc. Moreover, although to some extent this also applies to stated choice models, constraints are not explicitly taken into account and the time frame between the intention and actual choice is not addressed. Another criticism raised against original attitudinal theory was the lack of rigor in measurement and parameter estimation. Developments with respect to structural equation models have, however, put that criticism to rest. In fact, structural models allow for much more complexity than commonly used random utility models. Yet, for urban transportation planners, the fact that attributes of the choice alternatives are ignored limits the applicability of these models.

In that sense, the further development of elaborated hybrid choice models may be beneficial. Hybrid models have been introduced in transportation research to include attitudinal and psychological constructs in choice models. However, this has typically been done in rather restrictive ways by assuming that both socio-economic variables and latent attitudes directly influence the utility of choice alternatives according to a linear model, and therefore choice probabilities. Forecasting with such models remains relatively difficult. Attitudes are assumed related to socio-economic variables, but often such relationships are weak and may not hold over time.

16.3.2.3 Technology Acceptance Model

Particularly, life trajectory decisions related to mobility resources such as electric cars, can be viewed in terms of consumer interest in new technology. The intention to buy new technology and the ultimate buying decision are strongly influenced by people's attitudes towards such new technology. The technology acceptance model, introduced by Davis (1985), represents an attempt to identify the motivations underlying acceptance of new technology. As will be discussed, this theory shares concepts with the theory of planned behavior, and adds components specifically related to technology.

Building on earlier work about motivations (e.g., Schultz and Slevin 1975; Bandura 1982), Davis (1985, 1989) argued that motivations underlying the acceptance of technology are influenced by (i) perceived usefulness, (ii) perceived ease of use, and (iii) attitude towards using the system. Perceived usefulness relates to the degree an individual believes that the use of a new technology would enhance particular objectives, such as for example reduction of energy. Perceived ease of use is defined as the degree to which an individual believes the use of a new technology is free of physical or mental effort. Attitudes are assumed influenced by perceived usefulness and perceived ease of use. In that sense, the technology acceptance model can be viewed as a special case of the theory of reasoned action. Figure 16.2 gives a summary of this original framework.

Later, Davis et al. (1993) hypothesized that perceived usefulness may also have a direct and not only an indirect effect on behavior. Venkatesh and Davis (1996) subsequently deleted the component of attitudes and assumed that perceived ease of use may influence perceived usefulness and that both these concepts influence behavioral intention.

In later work (Venkatesch and Davis 2000), the authors identified a set of factors influencing perceived usefulness. In particular, the mentioned image, subjective norm, job relevance, quality and result demonstrability. Experience and voluntariness were added as factors influencing behavioral intention, while experiences also moderate the relationship between subjective norm and perceived usefulness (Fig. 16.3). Venkatesh (2000) identified further factors influencing perceived ease of use. More specifically, he argued that perceived ease of use is influenced by self-efficacy, perceptions of external control, anxiety, playfulness, enjoyment and usability.

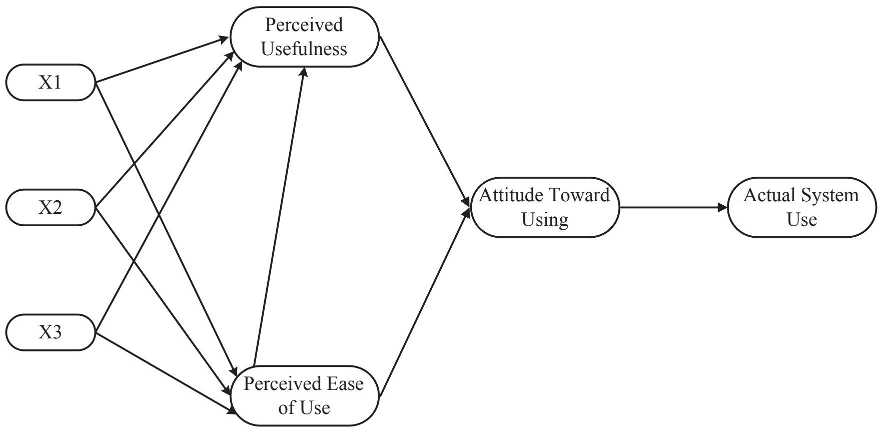

Fig. 16.2 The original technology acceptance model

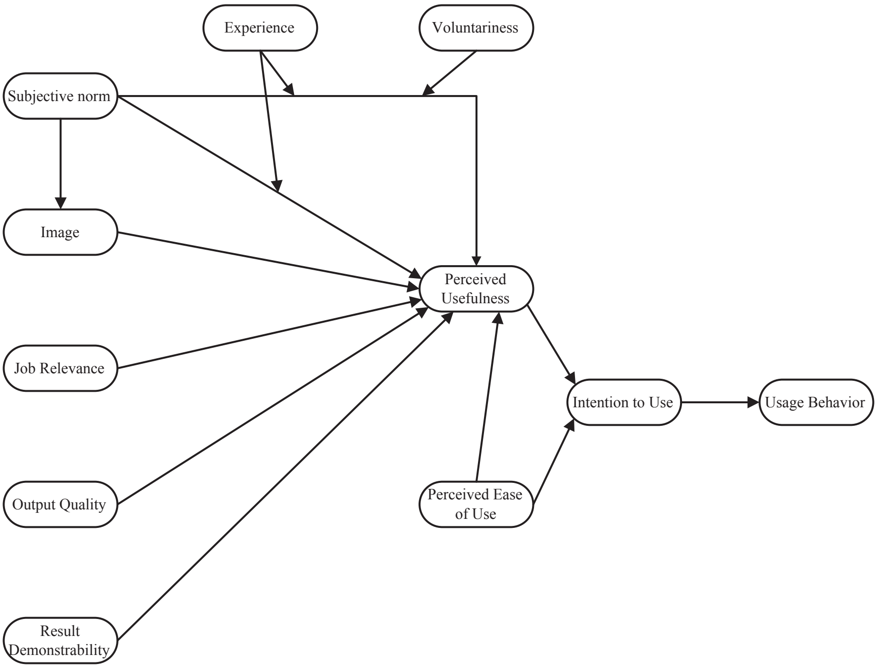

Fig. 16.3 Venkatesch (2000) technology acceptance model

It will be evident that not all these constructs are equally relevant or important for the kind of choice problems of interest to transportation researchers. Specific operationalisations will be required if one would apply this modeling approach to a problem related to life trajectory decisions.

16.3.2.4 Norm Activation Model

While the technology acceptance model focused on the acceptance of new technology as an example of behavioral change, other attitudinal models have been advocated and formulated in environmental sciences to address changing attitudes and behavior with regard to environmental issues. These models also are concerned with behavioral change, and in case with shifts in dispositions towards pro-environmental attitudes and behavior. To the extent that life trajectory decisions involve behavioral change, these theories and models may be inspirational for formulating life trajectory travel-oriented models of behavioral change.

Schwartz (1977) formulated the norm activation model to study pro-environmental behavior/intentions of individuals. The model identifies three types of antecedents to predict pro-environmental behavior: awareness of consequences, ascription of responsibility, and personal norms. Awareness of consequences addresses the question whether the individual is aware of the harmful consequences of his actions. Ascription of responsibility is concerned with the question whether the individual feels responsible for the negative consequences of not acting pro-socially or pro-environmentally. The personal norm dictates whether an individual should perform a particular action that prevents negative outcomes.

The norm activation model has been given two different interpretations, differing in terms of the relationships between the key core concepts of the model (Steg and De Groot 2010). First, it has been interpreted as a sequential model, emphasizing that problem awareness influences a personal norm that directly affects pro-environmental intention/behavior via ascription of responsibility. The second interpretation is that both problem awareness and ascription of responsibility directly influence a personal norm, which acts as an immediate predictor of pro-environmental intention/behavior (Steg and De Groot 2010).

More recently, the basic model has been expanded. It has been argued that pro-social and pro-environmental behavior reflects a combination of pro-social motives and self-interest (Bamberg and Moser 2007; Onwezen et al. 2013; Han 2015). Consequently, attitude toward the behavior and social/subjective norm have been added to the basic model, bringing this revised model closer to the original attitudinal models. Other authors (e.g., Perugini and Conner 2000; Bagozzi et al. 2003) argued that individuals assess the consequences of attaining and not attaining their goals. These assessments then result in corresponding (anticipated) favorable or unfavorable emotions from engaging in particular behavior. In particular, pride and guilt have been added to the model (e.g., Harth et al. 2013). Feelings of pride trigger compliance with the personal norm, while anticipated guilt induces violating the personal norm. Similarly, it has been argued that an individual's attitude toward engaging in ecofriendly behavior and perceived social pressure play an important role (e.g., Klockner 2013; Matthies et al. 2012). Attitudes are assumed to depend on the awareness of any negative consequences of behavior and affect behavioral intention.

16.3.2.5 Value Belief Norm Theory

The VBN theory, developed by Stern et al. (1999), can be viewed as an elaboration of norm activation theory. It adds the concepts of values and ecological worldview to the model. VBN theory assumes that an individual's eco-friendly intentions and behavior are determined by pro-environmental personal norms, which in turn are activated by the sequential process of values-ecological worldview-awareness of adverse consequences, and ascribed responsibility. Value orientations such as biospheric, altruistic, and egoistic values are directly related to the ecological worldview (Stern 2000).

Although the model may not be directly relevant for transportation and urban research, the norm activation framework, which states that individuals' awareness of conceivably harmful consequences of their behavior, together with a feeling of responsibility for these possibly detrimental consequences of not behaving pro-socially or pro-environmentally trigger personal norms that determine whether they should engage in a particular behavior that prevents damaging outcomes, may be a relevant notion to model particular life trajectory events that influence the transportation system.

16.4 Concluding Remarks

In this chapter, we have first identified some limitations of current choice models in validly representing long-term lifecycle decisions, such as housing choice and choice of transport mode. Traditional discrete choice models applied in urban and transportation research focus their attention on the attributes of choice alternatives and consider these choices as individual or household choices, assuming that attitudes and other psychological constructs and larger social contexts influence play a minor role at best and thus can be ignored. Only recently, in the context of the hybrid choice models, travel behavior researchers have added attitudes to their choice models, arguing that ultimate choices are a function of both attitudes and the utility derived from the attributes of choice alternatives (Kim et al. 2014a). Very recently, Kim et al. (2014b) elaborated the hybrid choice model to further include social influence. Their approach is based on less rigorous assumptions compared to the Brock and Durlauf social interaction model of proportionality. These types of model have to the best of our knowledge not been applied yet to life trajectory decisions, but would create more conceptually flexibility, although at the same time are still subject to the more fundamental issues that we mentioned in the introduction to this chapter.

Compared to attitudinal models developed in social psychology and several applied disciplines, the specification of the hybrid choice models is more limited. First, as any choice model, it lacks process underpinnings and therefore the issue of triggers and motivation for behavioral change is not explicitly addressed. Rather, it is implicitly assumed that regularities observed during the time of data collection are invariant across time, implying that individuals will adjust their behavior according to the relationship specified by the model. Second, hybrid choice models are based on direct relationships only, whereas attitudinal models have more flexible and complex model specifications that may involve both direct and indirect relationships. Third, while most hybrid choice models identify latent classes based on attitudinal questions (for an exception, see Kim et al. 2014a, b), attitudinal models typically identify different dimensions or different psychological constructs and explicitly model the relationships between these dimensions and their joint effects on behavioral intention and/or choice. On the other hand, most attitudinal models only identify individual's dispositions and do not include the properties of the choice options. This is not a problem if the choice behavior of interest is primarily driven by such dispositions and less by the properties of the choice alternatives. In the context of urban and transportation systems, however, most choice behavior will be influenced by both cognitive and affective factors, and hence some hybrid model may be required.

In that sense, the alternate modeling approaches, summarized in this chapter, may be worthwhile to be further explored for their suitability in modeling lifecycle decisions and/or lifecycle driven behavioral change. Perhaps the choice of electric car and other shared transport mode initiatives may be conceptualized as a choice problem that is strongly driven by attitudes or as an innovation-diffusion phenomenon with substantial social influence. Consequently, the outlined approaches might be candidate models to examine this choice problem. In any case, the models would require further elaboration because attitudes are domain-specific and hence a set of attitudinal questions needs to be designed and validated for specific constructs that the researcher will identify.

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