New Directions for Travel Behavior Modeling: Lessons from Freight Studies

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Abstract
Planners and policymakers rely on data and models to support infrastructure, operational, and other decisions. Attitudinal data, and models that use these data, provide insights into passenger travel behavior that cannot be easily explained by other types of data. However, collecting and using attitudinal data in transportation models has many challenges. Data collection typically involves surveys, which are burdensome and expensive. Attitudinal questionnaires require semantic judgments from survey designers, and they typically result in integer measurements of attitudes. Finally, when implemented in activity based models (ABMs), attitudes can exhibit inconsistent effects on traveler decision-making throughout the model system. This paper presents new ideas for passenger travel behavior modeling, focusing on emerging attitudinal data sources and methods to implement attitudes in passenger ABMs in a behaviorally consistent manner. The paper draws primarily from the freight transportation and business literature, reviewing selected recent studies in these areas and discussing their relevance to passenger travel behavior analysis. Based on this review, we argue that the freight concept of "strategic alignment" can be used to achieve behavioral consistency in passenger ABMs, although some challenges remain such as forecasting attitudes. We also argue that new, Natural Language Based methods for deriving attitudinal measurements from natural text are a promising replacement for surveys. However, while annual reports of businesses provide ample source text for these applications, more effort is needed to identify or develop similarly appropriate sources for passenger travel behavior, beyond social media posts. The significance of this work is its value as a reference and source of new ideas for planners, policymakers, and transportation modelers to consider when collecting and using attitudinal data in studies of passenger travel behavior.

Keywords: activity-based model, attitudes, machine learning, passenger, freight, strategic alignment

Introduction

Data and models provide critical information to local, state, and national authorities who make decisions that shape the transportation system. System-of-systems models, which include four-step transportation and activity-based models (ABMs), represent all travel taking place in a given region. Four-step models are widely used and have many advantages (Mohammadian et al. 2009). However, their aggregate representation of travel renders them unable to account the characteristics of individual travelers in a consistent way throughout the model stream (Travel Forecasting Resource 2024). In contrast, since ABMs account for individual travelers throughout the entire model system, ABMs can represent traveler characteristics with more detail.

This paper focuses on a particular category of traveler characteristics: attitudes. Like Bhagat-Conway et al. (2022), we define traveler attitudes broadly as perceptions, habits, values, and beliefs which are hard to measure and quantify, but which impact the traveler's decisions. Most ABMs capture details about readily observed traveler characteristics such as age and income using population data and socioeconomic projections. A few also capture traveler attitudes in mode choice (Jonnalagadda 2001) or a joint mode-scheduling model (Miller and Roorda 2002); but, to our knowledge, none capture attitudes or their impacts throughout the entire model system. The transportation modeling community widely acknowledges that attitudes are important and stable drivers of travel behavior that influence many decisions in the long, medium, and short term (Mirtich et al. 2021; Bhagat-Conway et al. 2022). For example, an individual who likes to be active may be more likely to choose a residence in a high-density neighborhood and to use walking as a mode of travel than an individual who likes the feeling of being in control while driving. Therefore, the importance of capturing attitudes in ABMs is that doing so can allow policymakers to better understand the impacts of attitudes on travel behavior.

However, there are several barriers to including attitudes in ABMs. Integrating attitudes into ABMs has numerous challenges (Mokhtarian 2024; Bhagat-Conway et al. 2022), including collecting attitudinal data in a consistent way and the daunting task of adding complexity to already complicated ABMs. Attitudes can change with new technology adoption and diffusion (Stathopoulos 2017). Earlier research makes great strides in capturing habitual choices in ABMs by modeling an entire week (e.g., Moeckel et al., 2024) and in modeling choice set parameters jointly with observed choices (Bhat 2015), which informs the current work. However, to the authors' knowledge, no existing ABMs include attitudes in such a way that the attitudes impact the traveler's behavior throughout the entire model stream.

Additionally, collecting attitudinal measurement data is challenging. The most common method for collecting these data seems to be surveys with Likert-scale questions, which ask how much the respondent agrees with various statements (e.g., see Figure 1). Unfortunately, surveys are costly and burdensome to respondents. This can lead to low sample size and self-selection issues. Question design is subjective and based on the judgment of the questionnaire authors. Responses are highly subjective, categorical, and constrained by the bounds that the survey imposes. For example, "Strongly Agree" and "Agree" could mean the same thing to some people, while another person may be "off the charts", meaning that the most extreme categories in the survey still do not adequately measure their opinions. Moreover, Bahamonde-Birke and Ortúzar (2017) demonstrated that Likert-scale responses lead to computational issues related to using integer measurements with a pre-imposed numerical range. Other challenges include inconsistencies between attitude and behavior that would affect predictability power of travel models. For example, mismatch between retrospective attitudes and behavioral choices could be observed, suggesting that relying on retrospective attitudes may not accurately reflect individual's current state of cognition (Yuan, et al., 2023). Additional analysis and simulation experiments demonstrate that simpler models may outperform models with attitudes (Vij and Walker 2016).

Figure 1. Example Likert scale question

Arriving at my destination on time is more important than comfort.
□ Disagree □ Neutral □ Agree

This paper proposes ways to improve the state of attitudinal modeling by addressing barriers related to attitudinal data collection and integrating attitudes consistently in an ABM framework. We extend findings primarily from the freight transportation and business literature, where recent research offers methods to address these challenges. The rest of this paper is organized as follows. First, the paper describes the concept of strategy from the freight domain and draws parallels between strategy and attitudes. This illustrates that some freight modeling concepts are transferable to passenger modeling. Second, a potential new way to model traveler attitudes in a consistent way in passenger ABMs is discussed. Third, the paper reviews emerging methods for collecting data on traveler attitudes, discussing the relevance of key recent examples. To conclude, implications for passenger ABMs and for transportation planners and policy analysts are discussed, along with limitations and potential extensions.

Strategy: the Freight Analogue of Passenger Attitudes

This paper uses two concepts from the business domain: strategy and strategic alignment. These concepts are important for freight transportation models, which simulate goods movement between businesses. Strategy is fundamental to business operations. The classic work of Porter (1980) defines strategy as the "...broad formula for how a business is going to compete, what its goals should be, and what policies will be needed to carry out those goals" and the "...combination of the ends (goals) for which the firm is striving and the means (policies) by which it is seeking to get there". Moreover, companies use strategic alignment to make their actions – from the long term to the short term – as consistent as possible with their overall goals (Mintzberg, 1987).

From these definitions, it follows that a company, like an individual person, can behave as a single, decision-making unit (Danneels 2008; Ben-Akiva 2010). Each company has internal, unseen preferences that inform its decisions; as such, company strategies are analogous to passenger attitudes. Strategies and attitudes guide behavior, driving companies or individuals toward their goals (e.g., Choo and Mokhtarian 2012; Ben-Akiva 2010). Previous work (e.g., Paleti et al., 2013) demonstrates that passenger attitudes, like company strategies, inform behavior from the short-term to the long-term. Moreover, strategies and attitudes are different from other behavioral determinants (like cost or travel time), as they are typically articulated verbally, and are difficult to observe and measure quantitatively.

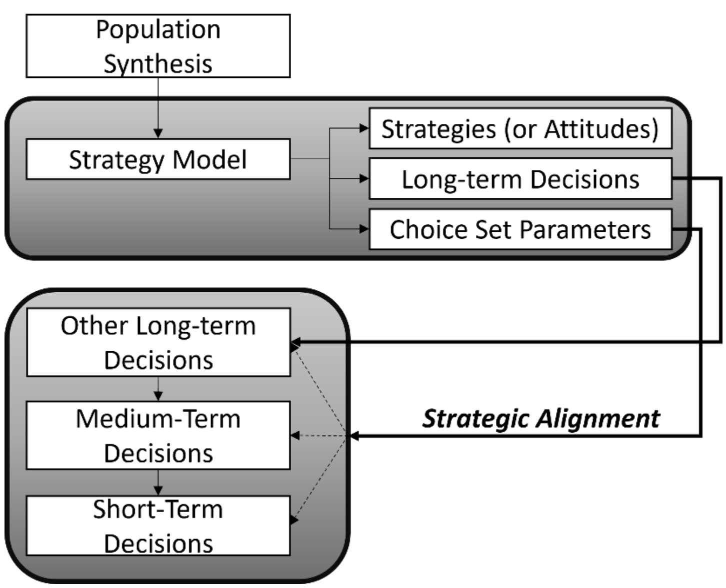
Achieving Attitudinal Consistency in an ABM Setting

As noted earlier, passenger ABMs rarely include attitudes, and none have proposed a way to capture attitudes throughout the entire ABM system. Moreover, despite the clear relevance of strategic alignment to freight, freight ABMs until recently also lacked examples that include strategy and strategic alignment concepts. The CRISTAL framework (Figure 2) proposes ways to include these concepts in a freight ABM (Stinson and Mohammadian 2022). The CRISTAL framework uses a single, joint model of strategy and strategic decisions in the long-term layer. The Seemingly Unrelated Regression with Tobits and Latent Variables (SURTLV) model operationalizes these concepts (Stinson and Mohammadian unpublished).

Several properties of the SURTLV model facilitate attitudinal consistency in an ABM. Each property is not original on its own. The novelty lies in their combined implementation, which is crucial for the attitudinal consistency that CRISTAL proposes. First, strategies (the latent variables) and strategic decisions (e.g., long-term decisions such as vehicle ownership) are modeled jointly. Second, the use of Tobit variables supports both binary and continuous outcomes. For example, decisions about whether to own a monthly transit pass and how many vehicles to own are modeled jointly. Third, the covariances of continuous decisions and binary decisions are nonzero in general. Thus, modeling continuous decisions (such as fleet size) that are related to binary decisions (e.g., whether or not to own a vehicle) is straightforward. Fourth, we exploit this feature to explicitly treat some of the model outcomes as choice set parameters. The analyst can then use these parameters to form choice sets later in the model stream – for example, in the medium or short term layers.

The freight example in Stinson and Mohammadian (unpublished) modeled location preferences in this way, focusing on distribution centers. Model outcomes include mean size (square feet), standard deviation in size, and transportation system accessibility. Other model outcomes include fleet ownership and size, distribution center ownership, and two company strategies (Customer Service & Logistical Sophistication). The location preferences are then used later in the model as choice set parameters. Since these preferences were modeled jointly with company strategies, the subsequent location decision also aligns with company strategies. We propose that passenger ABMs can adopt a similar approach to include attitudes in ABMS and achieve attitudinal consistency throughout.

Figure 1. ABM framework with strategic alignment



Source: Authors; adapted from Stinson and Mohammadian (2022)

Emerging Sources of Attitudinal Data

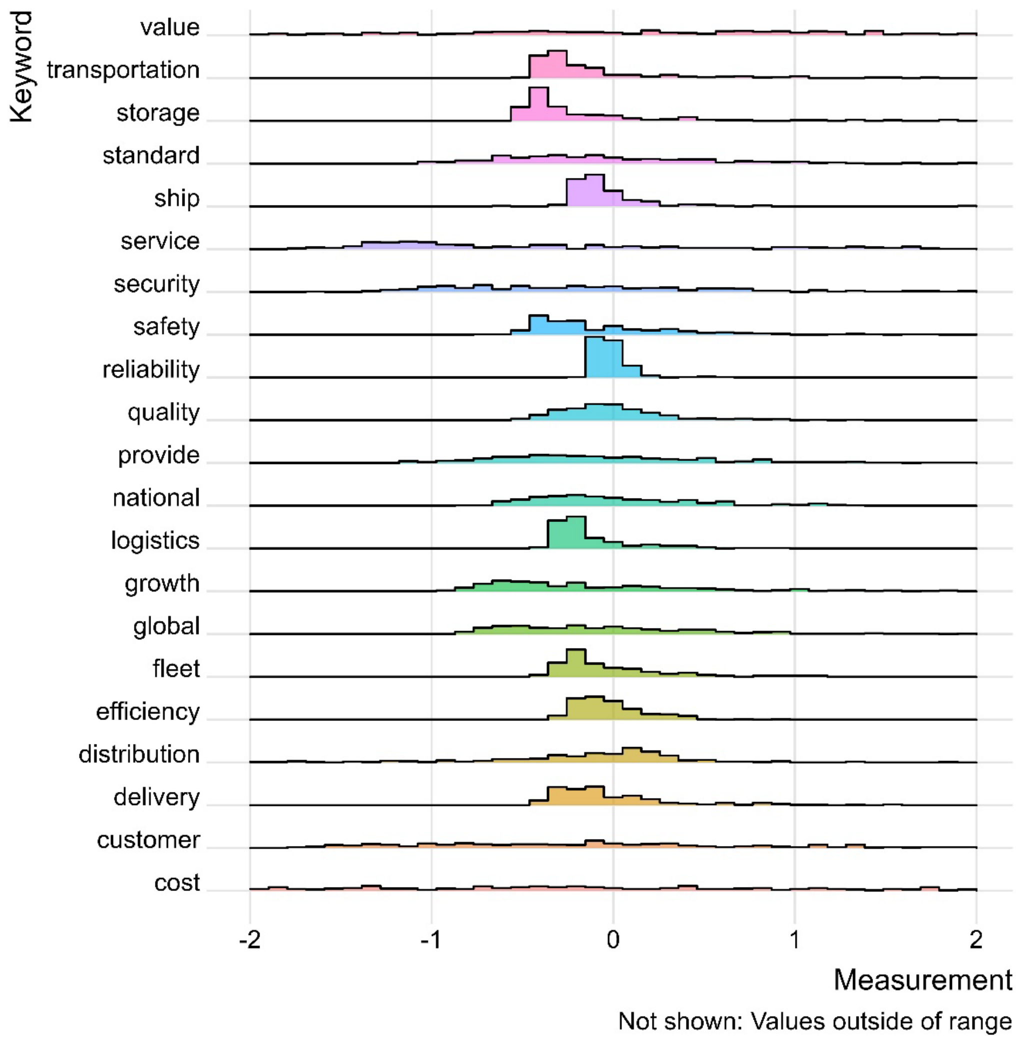
Previous works devise alternative methods to collecting attitudinal data from people and companies. These methods offer two notable advancements. First, many use pre-existing data rather than relying on new surveys. Second, these works leverage machine learning—namely text mining and natural language processing (NLP)—to analyze the data in a way that would be cumbersome with more traditional methods. Bag of words (BOW), which involves using simple frequency counts of words, has several examples in the literature. For example, Ramirez-Esparza et al. (2008) uses BOW data from online forum posts to study mood using factor analysis. However, BOW has notable drawbacks: word count does not necessarily convey importance and may be misleading since words can have different meanings in different contexts (Tausczik and J. W. Pennebaker 2010). The Computer-Aided Text Analysis (CATA) engine overcomes these limitations, but CATA tool development required intensive manual input and judgment.

The passenger behavior domain offers additional creative and useful examples. Using responses from open-ended survey questions, Baburajan et al. (2022) uses topic modeling (an NLP approach) to infer attitudes. The study finds that the resulting measurements are correlated to responses to Likert-scale questions. This result is promising because it suggests that NLP methods can replace attitudinal questionnaires. The Shaw and Mokhtarian (2021) method to transfer attitudinal data from one survey dataset to another is also promising, although such an effort is constrained by data from the donor survey.

Originally developed for freight applications, the W2VPCA method is another new option (Stinson and Mohammadian 2024). Like the BOW approaches and Shaw and Mokhtarian (2021), W2VPCA is designed to use pre-existing sources; it can also be applied to new sources. This algorithm converts select keywords that are used in “natural language”, or open-ended text, into quantitative vectors. The algorithm then uses Principal Component Analysis to generate individual-specific values for each keyword. In essence, the W2VPCA creates measurements by quantifying differences in word use, or how companies use the same words in different contexts.

Figure 3 shows the resulting W2VPCA measurements for 21 pre-selected keywords for about 250 companies in the Fortune 500. These measurements are derived from US Securities and Exchange Commission 10-K reports, which publicly owned companies are required to write and submit annually. Among the companies in this study, the average report was about 40,000 words long and contained about 5,000 unique words, which provides many options for selecting keywords for targeted attitudinal analysis.

Figure 3. Distributions of attitudinal measurements for selected keywords



Source: Authors, using data from Stinson and Mohammadian (2024)

In a proof-of-concept, Stinson and Mohammadian (2024) use these measurements in a factor analysis of company strategies. The model was compared to an alternative factor analysis model that uses measurements based on the same underlying text data and keywords, but with a BOW method instead of W2VPCA. The results led to accepting the W2VPCA-based model and rejecting the BOW-based model. This outcome, similar to the Baburajan et al. (2022) result, suggests that capturing word context is important when measuring underlying attitudes and preferences, and that NLP-based machine learning methods offer promising potential to replace or supplement traditional Likert-scale questionnaires.

As Figure 3 shows, W2VPCA generates measurements that are unbounded. The measurements are also continuous, and since they use the NLP word2vec algorithm (Mikolov et al. 2013), they account for the contexts in which each word is used. Both BOW and W2VPCA approaches are advantageous in that they are applicable to pre-existing text.

Conclusion

This work has discussed several emerging methods related to attitudinal data. We now discuss applications of these methods to passenger ABMs and travel behavior data collection.

Previous research demonstrates that including attitudes in individual models (e.g., in mode choice) feasible and generally beneficial. This paper proposes to advance the state of the art by including attitudes more thoroughly in ABMs. ABMs can achieve attitudinal consistency by modeling choice set parameters jointly with attitudes and other strategic decisions, then deploying the resulting parameters in subsequent decisions made by each agent in the ABM. Using the strategic alignment concept in passenger ABMs would be straightforward. Such an effort could use attitudinal data from traditional questionnaires or one of the newer, machine learning approaches. Challenges still remain, especially forecasting attitudes for future travel projections.

This paper also discusses alternative methods to attitudinal data collection. However, it does not offer a complete solution: while annual reports are easy to obtain for businesses due to regulation, unfortunately, the passenger realm has nothing like this. Recent efforts to identify passenger attitudes from social media postings have shown mixed results in providing ample sources for modeling (Acosta-Sequeda et al. 2024). More effort is needed to identify alternative attitudinal data sources for passengers.

Still, the results of both Baburajan et al. (2022) and Stinson and Mohammadian (2024) suggest that natural text is a promising replacement for Likert-scale questionnaires. If passenger natural text data can indeed be collected, then the resulting attitudinal measurements would be less subject to the issue (integers, bounded, subjectivity of phrasing, etc.) imposed by Likert-scale questions We therefore suggest the following extensions of this research:

- Analysis of open-ended responses from previously collected surveys
- More testing of open-ended survey responses: people may be more willing to provide an open-ended response than to fill out a series of questions. But an important question here would be “how much text is needed?” to measure attitudes, and what is the response medium (e.g., in person, phone, online)? Most people won’t type more than a few sentences; however, many may be willing to provide a 1-2 minute statement that describes their attitudes and values toward transportation and locational choices.
- Explore existing sources of natural text data for passengers: online forums such as Facebook are Reddit well known. Unfortunately, while these forums provide attitudinal data, they lack other data such as number of household vehicles. But do other sources exist that contain both, or can sources be linked to forge a more complete dataset?

This paper can help guide policy-makers and analysts in exploring new ways to collect attitudinal data and to use these data in ABMs. The idea of integrating strategic alignment into passenger ABMs can be adopted readily. Using new methods for attitudinal data collection is promising, but requires additional exploration.

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