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Innovation adoption modeling in transportation: New models and data

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1. Overview

Transportation analysts are constantly faced with the challenge of understanding new services, modes or mobility solutions, typically at early stages of conception and in the absence of market data. The IATBR workshop organized by Amanda Stathopoulos and Cinzia Cirillo aimed to discuss emerging methods to theorize, model and collect data to help our understanding of adoption paths for transportation innovations. Over sixty participants attended the workshop, emphasizing interaction and joint discussions on adoption in the context of various innovative scenarios.

2. Objectives

The workshop discussions and presentations focused on exploring two main topics.

The first part of the workshop centered on identifying theories and methodological concepts to model adoption. The focus was to summarize theory and model applications concerning penetration of new technologies among users, adaptation of choice patterns and attitude evolution over time. In connection to this, Elisabetta Cherchi presented recent research on how to measure and incorporate these effects in joint diffusion of innovation and discrete choice models.

The second section shifted the focus to behavior measurement and data-collection. Two papers were presented with novel practices to solicit responses to unfamiliar (future) transportation scenarios. The talk by Eran Ben-Elia presented research on developing serious immersive games as a method to assess dynamics in complex behavior arenas such as ride-sharing or driver cooperation. Yeun-Touh Li presented joint work with Jan-Dirk Schmöcker employing graphical representations to study passenger's future commuting adaptation pathways in response to a high-speed rail development plan.

3. Workshop structure and outline

The working method of the workshop relied heavily on audience inclusion, with the lion-part of the time dedicated to small group and joint discussions. This served the dual goal of drawing on and reinforcing evidence of the state-of-the-art on adoption models from the collective audience in addition to the organizers, thereby outlining a richer, more consolidated framework. In addition, it provided a wide array of examples and experiences from on-going, often not yet published and accessible, research.

In relation to the first objective, a brief overview of the main theories of behavioral change and their relative role in transportation and mobility analysis was given. The invited talk by Elisabetta Cherchi initiated a discussion on the need to account

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for adoption effects and on how to combine different models of adoption to obtain new insights on the individual preferences leading to acceptance (discrete choice) and the pacing of adoption in the overall market (diffusion models). The audience was then divided into groups of 7–9 people and given different future adoption scenarios.[1] Groups were asked to contemplate a number of issues, such as the current approaches used in the literature for data-collection and modeling, and were asked to propose a framework they felt would lead to insights about adoption of innovative systems. The discussion was summarized by each group and transmitted to the organizers who synthesized and presented condensed findings back to the audience on the second workshop day.

Relative to the second objective, overlooking choice data-generation and solicitation, a short introduction was presented by Stathopoulos in the second workshop day. Two presentations on emerging developments in data-collection and behavior dynamics in the presence of innovation were given by Eran Ben-Elia and Yeun-Touh Li. The presentations were followed by a plenary discussion that focused on the potential advantages, as well as, possible biases in the behavior revealed through new approaches such as immersive games.

In the following the main thrusts of theoretical frameworks, model approaches and data-collection procedures are overviewed. In connection to each section the related presentations, and group discussion outcomes are also summarized.

4. Current state of the art

The current practice in transportation demand modeling relies on static representations of travel behavior mainly based on discrete choice models. This implies that even complex model systems are based on one-point reference data, often the single year data collection available through National Household Travel surveys. This approach limits the ability to analyze system changes, to monitor individual and group adaptation and to forecast behavioral changes and new technology uptake. Stated Preference (SP) methods typically collect data on hypothetical future scenarios whereas observations are collected at a single time-point and do not monitor actual behavior over time. Furthermore, causal relations among indicators are based on simple modeling concepts and are not updated to take into account system changes and agents' adaptation. These limitations on modeling capabilities and data availability motivated the workshop and were addressed by the workshop chairs, the invited speakers and through ample discussion with the audience.

4.1. Theories and models of adoption innovation

4.1.1. Background

Numerous theories of how individuals and societies adopt innovation have been proposed to explain and aid in guiding behavioral change. The workshop set the scene by summarizing how insights from broader behavior transition models can help transportation research in understanding adoption of new practices, new technologies or shift to new uses of mobility. As a general finding, the utility-theoretic center of transportation modeling would benefit from incorporation of other perspectives and approaches (Chorus, 2012).

The trans-theoretical model (Prochaska and DiClemente, 1983) posits that change should not be viewed as an event, but rather as a process consisting in a series of stages. A decision-maker moves through consciousness, contemplation, preparation, action and maintenance stages in the case of a behavioral change. In the realm of transportation analysis, possible issues are the difficulties of identifying the various stages and understanding complex changes such as composite adaptation in mobility patterns.

Information diffusion theory (Rogers, 1962), on the other hand, focuses on market-level innovation penetration. The theory provides an account for how an innovation moves from the stage of invention to widespread use (or not). Decision-makers are postulated to gain knowledge, be persuaded, decide, implement and maintain change, with specific features identified to drive each stage. For transportation research, a crucial challenge remains in postulating diffusion patterns of mobility innovations in the absence of reference markets as diffusion parameters require referential patterns.

Acceptance of innovation has also been conceptualized as an outcome variable in several frameworks focusing on the psychological process broadly moving from intention to action. In the Theory of Reasoned Action (TRA) from social psychology, Ajzen and Fishbein (1980) define relationships between beliefs, attitudes, norms, intentions, and behavior. According to this theory, individual behavior (e.g., adoption of technology) is determined by one's intention to perform the behavior, driven by the individual attitude and subjective norms. The Theory of Planned behavior (TPB) (Ajzen, 1991) added a perceived control element, while the Technology Acceptance model (Davis et al., 1989) focused on technological uptake and antecedents of user attitudes. The social cognitive theory by Bandura (1986) highlights the concept of self-efficacy and extensive feed-back between determinants. The psychological path-approaches to understanding reasons for accepting an innovation still suffer from shortcomings related to survey wording to define the behaviors and the uncertain links between the attitude constructs. Moreover, these models allow for cognitive dynamics where, for instance, outcome beliefs impact on attitudes, while frequently not specifying the timing and rate at which such adaptation occurs.

A number of theories and approaches have examined the lack of change despite the launch of new options that are, in theory, performing better than existing ones on central features. Stability between past and future conduct would explain lack of adoption. A central question then concerns the shift between different decision-processes. A main objective has been to identify the factors that

[1] The adoption scenarios were; a) advanced vehicle technology, b) car-sharing, c) bike-sharing, d) on-demand transportation, e) high-speed rail lines f) crowd-sourced goods delivery.

cause a shift from near automatic repetition of past behavior (where past frequency is a central predictor of the future behavior (e.g Triandis, 1977)), to a conscious deliberation (Verplanken, 1997).

An examination of published transportation and mobility papers revealed a highly variable application of different model paradigms. There is a clear dominance of TPB that dwarves the examination of all other adoption of change frameworks (in particular trans-theoretical and diffusion models). In addition, there is different emphasis for different transportation behavior change problems, with issues like active transportation, driving/car-use studied more extensively than freight behavior, or rail/airline innovation acceptance.

4.1.2. Invited talk

Elisabetta Cherchi's talk on "Experience, adaptation and diffusion modeling for electric vehicle choice" underscored how electric vehicles are a prominent example of an "innovative" transport system. At the same time, it exemplifies an adoption challenge, given that despite being available in the market for quite some time, they face extreme difficulties in developing into a mass marketed product. More importantly, predictions of future demand have been misleading, as they forecast a much more accelerated market penetration than observed in reality.

Cherchi called attention to the fact that traditional disaggregate demand models are suitable to forecast demand in relatively stable markets, but show limitations in the case of innovations. When predicting the market for new products it is crucial to account for the role played by innovation and how market penetration occurs over time akin to a diffusion process. Innovative products often diffuse slowly and need time to obtain a significant market share. Typical diffusion models in marketing research account for the dynamic evolution of demand over time, but use fairly simple substitution models and do not explicitly estimate the impact of experience and information with the new product on individual preferences, attitudes, and goals.

The talk continued to overview previous work proposing a new method to combine advanced choice models with a diffusion model (Jensen et al., 2017). The main idea consisted in replacing the probabilities of choosing an innovative technology (typically used in the joint diffusion/substitution models) with the models estimated at a disaggregate level. This approach assumed the trade-offs to be stable over time and the dynamics in the model to be related to the re-estimation of the scale and alternative specific constants (ASCs) to adjust to observed market shares in the joint model. Further work relied on a unique database where individuals were interviewed *before* and *after* a 3-month real life experience with an electric vehicle.[2] Findings from the discrete choice models show that individual preferences for half of the attributes were significantly different before and after the direct EV experience. Notably, individuals' concern about driving range doubled after the experience. At the same time, after respondents gained experience, they expressed more skepticism about being able to maintain current mobility (they had to cancel some activities).

The marked impact of different model approaches on prediction results is reported in Fig. 1. The figure contains the substitution model without (Uncalibrated) and with re-calibration (Calibrated) of the ASC to match the base year market shares; and using the joint substitution/diffusion model (Joint). Results indicate that typical choice models (with constants adjustments) forecast a demand that may be too restrictive in the long run. Accounting for the diffusion effect, instead, allows approximating the slow penetration of the initial years and a faster market share increase after diffusion takes place. Results show that a model estimated after individuals obtain real-life experience with electric vehicles produces what appears to be more reasonable aggregate market shares, especially for the base year.

Notably, adoption of innovation is also affected by indirect experience (i.e. information on experience acquired by others and by observing the diffusion of the EV market). In the joint diffusion/substitution model this is accounted for by the coefficients of innovation and imitation of the diffusion model.

Cherchi's talk then elaborated on methods to account for the effect of indirect experience within stated choice experiments between electric and conventional vehicles (Cherchi, 2015). In the experimental setup the same individual responded to the choice tasks before and after receiving information from a friend about her/his EV experience. Information was not generic but instead referred to the following three specific aspects: driving range, parking policies and modifying current activity patterns. In this way, the effect of indirect experience can be estimated directly in the substitution model and the coefficients entered in the joint diffusion/substitution model. Findings indicate that negative referred information has a more marked effect on individual's preferences than positive information, and the effect amplifies with the number of negative messages received.

An overarching finding from Cherchi's talk is that experience and (in)direct information has important impact on adoption. The findings highlight the need for models that are able to pick up dynamic changes in preferences and choices from multiple channels of influence at different stages of EV familiarity.

4.2. Collecting data on adoption innovation

4.2.1. Background

Different methods have been proposed to obtain observations and insights about innovation adoption before its launch. Since the early 90's, data based on behavioral intentions and responses to hypothetical choice situations have been used to study future market conditions (Ben-Akiva et al. (1994)). SP data collection has evolved tremendously and consolidated techniques exist to determine all aspects of the survey design: alternatives and their types, number of variables and their levels of variation, selection of scenarios according to orthogonal or optimal design. However, the validity of SP data has remained an issue and joint modeling techniques

[2] More details can be found on the survey development (Jensen et al., 2014) and the modeling results (Jensen et al., 2013).

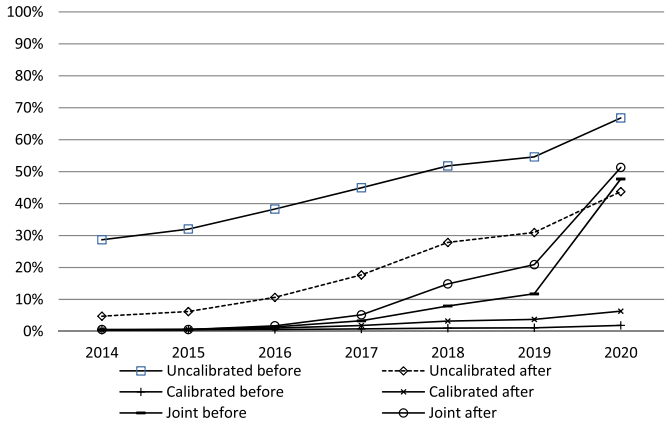

Fig. 1. Predicted EV market shares (with constants correction, before/after EV experience, joint diffusion models, from Jensen et al. (2017)).

with Revealed Preference (RP) data have been proposed in order to better represent actual market conditions. Models based on SP data or joint RP/SP models are largely used in transportation research and practice (Morikawa et al., 2002).

Researchers in marketing have suggested that multimedia representations of potential new products can be better suited to understand and forecast consumer responses. In particular information acceleration (IA), has been used to test new consumer durables and business-to-business products. Urban et al. (1996) described how IA was used to create a virtual showroom for an electric vehicle in which the potential consumer could "walk" around the car, "climb in", and discuss the purchase with a salesperson. The customer could access television advertising and consumer magazine articles, study prices in a virtual newspaper, and even get advice from fellow consumers—all simulated on a multimedia computer.

Typically, SP surveys have placed the respondents in future situations without clearly specifying when these conditions will be available or have looked at a generic 'next purchase'. Those approaches artificially isolate the decision timing from the actual environment. In a recent study, Maness and Cirillo (2012) proposed a survey design that allowed the respondent to see the state of the hypothetical environment which allowed for modification of purchasing behavior according to those conditions. Dynamically changing attributes were used in the survey design to help mimic a real marketplace.

Some academic groups have developed tracking and feed-back systems delivered via devices to study adaptation of travel patterns, in particular mode choice (Jariyasunant, 2013, Fan, 2012, Castellanos, 2016). Devices allow timeliness, personalization and adaptiveness in both monitoring and testing incentive schemes, such as self-monitoring and gamification. However, limited sample sizes and trial periods limit generalizations concerning the motivations for, and stability of, observed mobility changes.

4.2.2. Invited talks

Eran Ben-Elia's presentation entitled "Behavior inference and modeling with serious immersive games related to traveller cooperation" began by pointing out how ubiquitous computing and pervasive information communication technologies (ICT) are transforming the way we travel (Miller, 2013). New spatiotemporally flexible forms of mobility such as ridesharing, holds promise for wide-ranging congestion prevention in a future expected to be dominated by autonomous connected vehicles. Nonetheless, these new mobility forms pose serious challenges for travel behavior modeling. A main challenge is that ridesharing is a form of cooperation that is difficult to conceptualize and model using standard travel behavior theories and methodologies. The rational choice underpinning, along with the view of travelers as competitive selfish maximizers, has given scant attention to phenomena such as cooperation in theory and research. Studies in social psychology and social physics show that it can emerge from the social dynamics of complex systems under quite general conditions, particularly in small groups (Helbing et al., 2005). However, data on cooperation within large groups remains a major knowledge gap.

An important contribution of the talk was to point out that, on the methodological side, using traditional approaches for estimating static discrete choice models based on RP and SP sources is problematic. Ridesharing has too few RP mobility observations, while SP choice experiments suffer from hypothetical bias (Fifer et al., 2014), especially with unfamiliar alternatives like ridesharing or autonomous vehicles. The state-of-the-art approach, based on plugging these static choice models to program agents' decision rules to simulate system dynamics in agent-based models (ABM), is thus conceptually unreliable for predicting the future evolution of ridesharing (Jager and Janssen, 2003).

Ben-Elia therefore suggested that game-based models, which merge ABM and serious immersive games (SIG) appear to be a promising avenue for travel behavior modeling. SIG is a virtual ecosystem where human players engage in a well defined, quantifiable artificial, albeit realistic, conflict (Salen and Zimmerman, 2004). Incorporation of reinforced learning in reaction to other players' behavior and to emergent system dynamics makes SIG a natural tool for investigating cooperation and ridesharing, while immersion within a virtual reality environment will likely contribute to reducing hypothetical bias (Zyda, 2005). In game-based models this is extended so that both artificial agents and human players interact, learn and evolve (Riensche et al., 2012).

The talk described a recently developed game-based analysis of dynamic parking behavior developed by Ben-Elia and colleagues (Ben-Elia et al., 2015). The ParkGame (2014) is a GIS-based computer game where users are exposed to different levels of

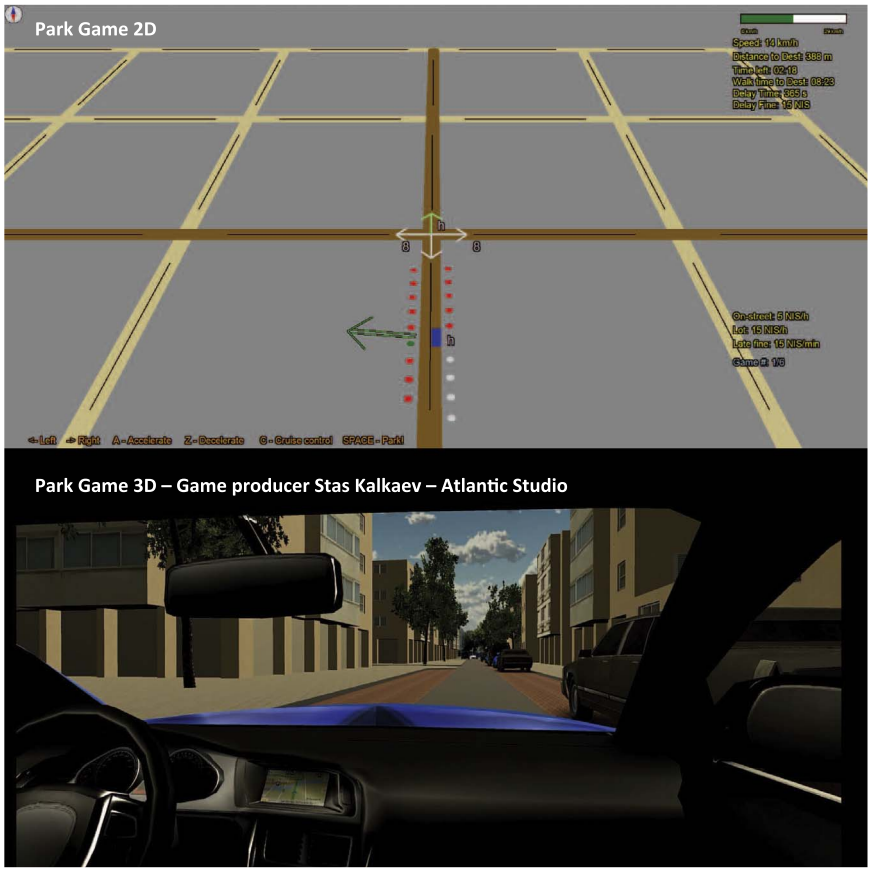

Fig. 2. ParkGame 2D and 3D versions.

occupancy, turnover and parking prices and seek for a parking solution (Fig. 2). The game allows elevated control in varying parking conditions, and to observe how drivers cruise for urban parking and learn and develop strategies over time to park in the city.

Ben-Elia recapitulated the advantages of game-based models as twofold: (a) consistent agent decision rules are derived in conjunction with human behavior and the global dynamics of the entire system; (b) if the immersive game makes humans and agents indistinguishable to an external "observer" it becomes a behavioral metaphor of "Turing's Interrogation Test" of artificial intelligence (Turing, 1950). Reaching a level of realism to pass the Turing test would imply that the game-based models could reliably stand in for real world observation. The game-derived rules of interaction then are valuable in defining support policies promoting sustainable traveller - transportation co-evolution.

The talk by Yeun-Touh Li entitled "Adaptation towards high-speed rail: Analysis with 'long term graphical usage patterns" proposed a different data-collection idea to grasp progressive changes in mobility systems. Li argued that understanding the gradual changes in travel behavior over time is essential to comprehending the association between travelers' adaptation process and travel demand. However, capturing cause and effect relationships in long-term travel behavior patterns is generally difficult, even with panel data. The talk presented a novel data collection methodology, aiming at specifically analyzing the gradual changes of travel behavior (Li & Schmöcker, 2016). The approach hinges on asking users for their long-term travel behavior with graphical patterns including questions on the reasons that lead to significant changes in usage. Li presented results from a case study analyzing the usage of high-speed rail (HSR) in Taiwan and China over the last 8 years. Ten graphical long-term usage patterns were developed with detailed usage descriptions (see Fig. 3). The behavioral dynamics of the sample could be captured and to some degree explained. Allocation to overall usage patterns provides a view of expected use, shedding light on the perceived future pattern. Further analysis of the pattern choice was carried out by applying regression analysis explaining the choice across all respondents. The findings shed further doubt on the assumption of utility maximization for models analyzing long-term patterns, in which decisions are likely to be conditional on previous decisions and other external factors. In other words: there is no strict evidence as to whether travelers choose patterns or if patterns emerge from outside factors. An important discussion that emerged concerned the appropriateness of both Multinominal Logit model (MNL) and discriminant analysis in detecting how attitudes and perceptions among travellers can explain choice patterns.

Li concluded by remarking how the analysis of causes of long-term pattern changes revealed important differences between motivations according to the stage of usage. While initial uptake was driven more by personality related factors, later gradual usage increases were more related to service quality, while finally, usage reductions were mainly linked to life events.

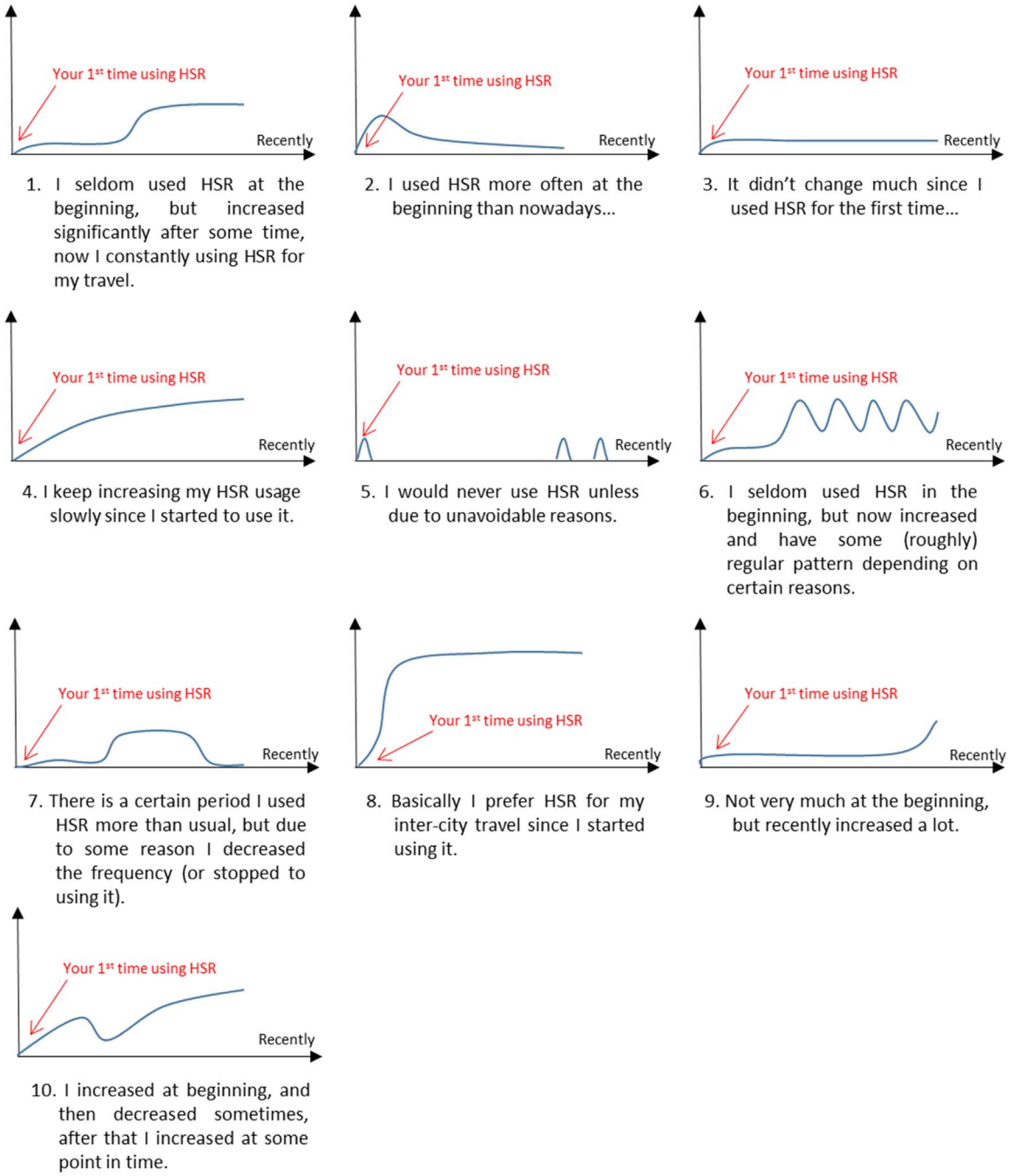

Fig. 3. Hypothetical high-speed rail graphical usage patterns from Li & Schmöcker (2016).

5. Summary of discussion findings

Discussion from the roundtables provided a number of interesting insights on the methods currently in use for the analysis of innovation and technology diffusion in transportation, on the limitations of both data and models, on the emerging needs and on methods recently proposed to overcome these limitations.

5.1. Existing methods and their limitations

A number of points coming forth from the discussions of existing approaches for grasping innovation uptake are summarized in the following.

1. Participants to the roundtables concurred that the majority of current studies on transportation innovation adoption are based on static discrete choice models estimated on SP data. Typical outputs include market shares and changes in demand, willingness to pay, identification of the factors that affect individual choices and trade offs (including latent variables), taste heterogeneity, and elasticities.
2. Concerns were expressed about the optimism bias in SP data, and the limited availability (or lack) of data for the case studies proposed. Often, data contain a limited number of variables and cover specific adoption aspects only. This leads to a partial description of comprehensive mobility changes. Having data on one 'element' does not lead to an understanding of new transportation modes/services and on their integration in complex social systems.
3. Models currently in use suffer from several limitations. When dealing with technological evolution in the market of interest, it is unclear how to model changes in attitudes, and preferences, and which factors motivate rejections or adoptions. Even if an assimilated 'anchor' market is found, it is necessary to update alternative specific constants to account for temporal dynamics. In the absence of evident external references there is little guidance on how to target constant adjustments and updates to approximate future market diffusion. Similarly, tracking evolution in goals, motivations and preferences is difficult in the currently dominant framework.
4. Alternative modeling frameworks to utility maximization have been proposed. Among these, some are based on techniques already in use in other disciplines and their integration in classical transportation modeling framework has been attempted. Those theories include alternative decision processes (e.g. Chorus et al., 2006; Abou-Zeid and Ben-Akiva, 2011; Hess et al., 2012), dynamic discrete choice models (Cirillo and Xu, 2011); or theories highlighting social mass effects (Abou-Zeid et al., 2013). The model integration is still partial and applications are limited to a few case studies and relative to specific problems. Similarly, the matching of theoretical frameworks to adoption problems and contexts is unclear and applications seem to be done based on intuition of what might matter in a given context.
5. There was a converging acknowledgment that certain effects are inherently difficult to formulate and study. One highlighted effect is the issue of trust in crowd-based delivery systems.

5.2. Emerging techniques and their potential

Group discussions identified several promising notions and approaches from transportation and other sectors to improve the way that innovation is modeled.

1. Expert knowledge is used in energy/environmental analysis to help decision-making in complex systems when empirical data is scarce or unavailable. Experts may be called to define the problem and the model structures, to inform the selection of data or variables, to help define future growth potential in future market scenarios. It remains to be defined who are the transportation experts related to various areas of analysis. Uncertainty as to the availability to participate in academic studies and issues related to representing uncertainty were also raised. This was formulated by one participant as "The idea is to move from speculation to scenario building, incorporating some realistic boundaries and thresholds"
2. A number of innovative data collection methods were mentioned. Inter-temporal SP surveys have been adapted to track adoption of new technology vehicles (electric and hybrid vehicles) (Maness and Cirillo, 2012). Inter-temporality has also been studied by projecting future evolution of costs and benefits to inform current freight operator choices (Ellison, 2014). Repeated SP surveys, pre/post experiencing new vehicle technology have been used to estimate changes in preferences and attitudes (Jensen, 2014).
3. Virtual reality and serious game approaches were proposed to overcome limitations of SP data collection and to have more realistic representation of travel behavior in future conditions. A new research line concerned developing app-based data-collection tools, possibly designed as travel recommendation systems to allow user profiling, testing incentives and novel approaches like social comparison and reward systems, and to more consistently track evolution of behavior changes.
4. The group examinations called for more thorough and transparent examination of attempted and failed cases of innovation adoption prediction (the provocative working title for this was "hall of shame" which should serve to reflect a desire to counter the bias towards diffusion of solely positive findings).

5.3. Open issues

1. In line with SP hypothetical bias, a new line of concern emerges when evaluating gaming, simulations and virtual reality approaches. The game-like nature of these data-collection tools may trigger (novel) un-realistic behaviors. There is some evidence of gamification leading to more extensive travel to collect more 'points' in a gamified mode-choice environment. Likewise, anecdotal evidence of driving behavior triggered to be reckless and game-driven, at least in the first stages of a realistic driving simulator, was discussed. This suggests the possibility that unexamined behavioral artifacts need to be accounted for in new generation data-collection tools.
2. There is a tension between conscious and unconscious aspects of the adoption process. Most current approaches rely on some form of verbalization and awareness when revealing travelers motivations. This implies they are not suited to examine acceptance and choice driven by unintentional cues.
3. Initial literature analysis and discussions indicated that some adoption theories have seen extensive application in transportation (e.g. TPB) while others were nearly absent (Trans-Theoretical model). Moreover, the applications appear to be clustered in specific areas (e.g. safe driving, transit use) more than others (air or rail choice, freight). There is little understanding and guidance on

what model frameworks to apply for which problem areas.

4. Several observations throughout the workshop pointed out that transportation analysts trying to model adoption of radically new systems need to consider the many associated decision-bodies and markets. Depending on the adoption scenario there is a need to consider insights and developing models relating to; automaker/producer strategies, evolving social habits, federal and state policy making, impact of competition and complementary technology launches.

6. Conclusion

An important outcome of the workshop was to begin defining both the current state of the art in formulating models of innovation adoption, and a mapping of the parts that are poorly understood. A first step towards thinking of good practice in data collection and modeling in connection to situations that involve innovation and novelty was taken.

Richer models of uptake, adaptation and diffusion and how this should be monitored and modeled will greatly aid in forecasting transportation choices in new decision environments or adoption of innovative policies.

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