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Advancing the Science of Travel Demand Forecasting

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Table of Contents

Executive Summary

Introduction

Travel demand forecasting models play an important role in guiding policy, planning, and design of transportation systems. There is no shortage of literature critiquing the accuracy of model forecasts (see, for example, Pickrell, 1989; Wachs, 1990; Pickrell, 1992; Flyvbjerg, Skamris Holm, and Buhl 2005; Richmond, 2005; Flyvbjerg, 2007; Bain, 2009; Parthasarathi and Levinson, 2010; Welde and Odeck, 2011; Hartgen, 2013; Nicolaisen and Driscoll, 2014; Schmitt, 2016; Odeck and Welde, 2017, and Voulgaris, 2019), not to mention several high-profile lawsuits (Saulwick 2014, Stacey 2015, Rubin 2018). Many researchers and practitioners feel more can be done to advance rigorous travel analysis methods for the public good (see, e.g., zephyrtransport.org). Motivated by these critiques, a two-day, NSF-funded workshop was held at UC Berkeley in the Spring of 2017 to engage in a fundamental review of the state of the art in travel demand modeling, to discuss the future of the field, and to propose new directions and processes for advancing the science.

Travel demand forecasting is an inherently practical enterprise. While academics drive the fundamental research, the users of travel demand models and forecasts are typically government agencies and transport operators that use the models to inform long-range investment, funding, and planning decisions. Private firms play a key role in assisting the agencies in both development and application of the models, and, more recently, high-tech firms have entered the development fray. While all of these actors have important roles in advancing the science of the field, in this report we focus our attention primarily on the academic side of the enterprise, consistent with the orientation of the funding agency (NSF), and in order to make the task manageable. That said, other sectors are represented in various parts of this report as they interface with academics or play particularly central roles in our proposals for advancing the science.

The travel demand modeling field is ripe for re-invention as we are on the cusp of the next generation of models. We find ourselves in arguably the most dynamic transport environment in the history of the field. Massive data are becoming available and new developments in data analysis methods are being developed. Researchers from disciplines such as computer science and physics are entering the domain, along with high-tech, entrepreneurial firms. There is also a change in the nature of data. Whereas historically the most important data sets in transportation—Census data, household travel surveys, origin-destination surveys—were collected by public agencies, the new generation of "big data" is most often held by private entities (Shuldiner and Shuldiner 2013). There are important questions around the continued availability of such data to modelers, as well as what model developments need to take place to fully exploit the potential of such data. Finally, not only are new data and methods changing the modeling, but transport technology and patterns are themselves rapidly changing as new modes such as app-based ride sharing of cars, bikes, and scooters are making their presence felt in large US cities. Looking to the future, partly or fully autonomous passenger, freight, and aerial vehicles are rapidly advancing.

With this background in mind, invitations were made, and the workshop was attended by 37 researchers and practitioners from both traditional and new domains, ranging from an undergraduate student to a Nobel Laureate. See page 3 for the full list of workshop participants and see the Appendix for the workshop program. The task assigned to the attendees was to help define and describe the next generation of travel demand models to address needs for rigorous, scientific testing; effective integration of researchers and ideas from different disciplines; and relevance to the ongoing revolution in transport technology.

The roadmap that was produced from the workshop for advancing the science of the field is organized around the six critical themes that emerged from the discussion:

1. Apply the scientific method
2. Build a collaborative ecosystem
3. Integrate researchers and ideas from related fields
4. Strengthen links with policy and planning
5. Develop the workforce
6. Continue conducting foundational research

After the workshop, the attendees collaborated to build out these themes. Initial thoughts were presented at TRB podium session 669 in January of 2018 in Washington DC and ideas were then further refined for this report. For each theme, we present a problem statement, aspirational goals, positive examples from within and outside the field, and a call to action. In the remainder of this executive summary we discuss our inspirations for this project, identify issues that challenge the field, and finally list a selected set of needs and related action recommendations that are extracted from the larger report that follows.

Inspirations

A number of examples outside the field of travel demand modeling motivated this effort and we refer to these throughout the report. A prominent model is the Hurricane Forecast Improvement Program's collaborative and continuously evaluated model building program. We are also inspired by the open-science culture of machine learning that has fueled that field's rise, including open access to data and programming code, as well as open source publication of scholarly papers. There are also cases of open science within our own field, but this is more the exception than the norm. We note that prominent scientific journals such as *Nature* and *Science* have recently focused on improving research reproducibility by placing requirements for data and code sharing on published articles, and journals such as the *Journal of Machine Learning Research* with all published papers freely available online.

A number of us have participated in or observed high-profile scientific competitions, such as ImageNet and the Kaggle platform, that have brought new minds, data, solutions, and excitement to research problems. We see such competitions as having the potential to help advance improvements in model development while opening up their workings to a larger set of interdisciplinary scholars.

One challenge in our field has been to validate demand forecasts produced by models since they are years in the future. Research on chlorofluorocarbons (CFCs) provides a good model; CFC researchers have carried out an exemplary approach to validating and building confidence in very long-term forecasts by testing and validating short-term predictions.

Another challenge in our field is workforce education. There are a number of exemplary educational initiatives, including the interdisciplinary summer school of the European Association of Environmental and Resource Economics, the fellowship models of the Data Science for Social Good program (at the University of Washington and University of Chicago), and curriculum development initiatives such as Software Carpentry by NumFocus Foundation and Google's Tech Dev Guide.

An important aspect of travel demand modeling is making connections to the use of forecasts by practitioners in order to more directly advance the usefulness of the science. There are some good examples of long-term, transformative collaborations between transport planning agencies and travel demand modeling academics, such as Oregon DOT's TLUMIP and the Toronto Regional Travel Modeling Group.

Issues

There was a general sense among workshop participants that there is a lack of unity in the travel demand modeling field around a clearly defined mission. Most academics are focused on making particular scientific advancements to aspects of models that are internally validated but not often subject to external testing, while practitioners are often focused on managing complex planning processes and justifying specific policy solutions.

While the body of knowledge derived from travel surveys and travel modeling exercises has continued to grow over the years, the travel demand modeling domain has lacked a strong backbone of core knowledge in travel and activity behavior. Without a broadly accepted and rigorous framework the core knowledge tends to dissipate and the continuing stream of new discoveries is disconnected.

Because limited resources are available for data and modeling, public funds are spent almost entirely on development and application of models to produce policy-relevant outputs, rather than on rigorous post-facto evaluation of their accuracy. Firms write proposals and compete for public agency contracts; once the single model development team is selected, conceptual development is complete. Models are rarely tested in the way they are applied. At best, the testing of models is on conditions close to what is observed in the estimation data, that is, either a hold-back sample or backcast, whereas in application the models are usually used to make predictions 20 years into the future, for conditions that may be far out of sample. Thus the field’s knowledge of model performance is quite limited.

The travel demand modeling community lacks a strong collaborative ethos. Academics are promoted on individual accomplishments, often in niche areas. Academic journals often reward scholars with restricted access to novel datasets. There are currently no requirements and little expectation in the field that published work must be reproducible. Both data collection and model development are typically carried out independently from project to project, and so the field abounds with individually held customized models estimated from different, mutually inaccessible datasets.

There was also a strong concern that our current travel demand modeling tools are generally not flexible or dynamic enough to account for a rapidly changing transportation environment, and they are not leveraging the new big data environment. And although the travel demand modeling community has been doing fairly well in drawing from multiple disciplines, the latest methodological developments and insights from fields such as cognitive science, computer science, statistics, and econometrics are not yet integrated into travel analysis. The field would benefit from more direct engagement from people in these other fields and more interdisciplinary academic programs and research labs.

Most academics do not feel they have a strong understanding of, or personal connection to, practical uses of the models their work is meant to inform. Meanwhile policy makers and planners perceive that their needs are often not met by academic advancements in modeling methods. Model processes and outputs are often difficult for practitioners and academics alike to understand, and they typically do not reflect forecast uncertainty, which makes them often not well suited to being productively used by practitioners or in plans.

There are concerns about how prepared the workforce is to implement and participate in the development of travel demand models. Once trained, many qualified individuals are recruited away to more lucrative careers, leaving key positions under-filled; professionals often lack the time and resources to advance their knowledge and skills at the pace of technological innovation; the field is not regarded with respect commensurate with its qualifications and educational attainment; and there is a severe lack of diversity in that the demographics within the field do not come close to reflecting the demographics of the populations served by the tools and models.

Needs and actions

Given these needs, and the inspiring examples from outside the travel demand modeling field, our group identified particular actions that could be taken in order to advance the science. Some of these actions are aspirational because they require significant changes in culture or institutions. Others are more readily achievable. Below we list overarching actions first, and then we group selected action items by theme.

Overarching actions

- **Establish an interdisciplinary committee of scientists** who are responsible for promoting and monitoring the recommendations of this report.

- **Unite around a singular mission**, such as to make demonstrable, continuous progress towards accurately representing human travel behavior and improving the predictive accuracy of practical travel models.

- **Reorient the mission of the relevant professional organizations** (TRB ADB40 and Innovations Conference, IATBR, the Zephyr Foundation, etc.) to tackle this mission.

1. Apply the scientific method

- **Adhere to principles of travel modeling as a science**:
  - Grow our use of verification and validation.
  - Evaluate models on their ability to predict the change that we build them for.
  - Make testable predictions of important outcomes.
  - Enable models to be compared directly via competing predictions.
  - Apply models to multiple points in time and space.
  - Hold ourselves and our colleagues to the ethical standards of our professions that put the public interest first.

- **Fully embrace the principles of open science**.
  - Re-align incentives (via grants, publishing, and promotions) to make open science the expectation and the norm, not the exception.
  - Require funded research and published papers to meet open science thresholds. Implement strong reproducibility standards for our journals such as those in *Nature* and *Science*. Any published research should provide the information necessary--data, code, specification--for a knowledgeable reviewer to be able to reproduce it.
  - Explicitly penalize, rather than reward, papers that work with unique datasets not available to other researchers. Little is lost in the realm of data privacy or data risk in sharing unique datasets with at least two other research groups, if not more widely. Researchers who invest considerable intellect, time and money collecting a unique dataset should have sole access to their data for some period of time. However, the expectation is that these data will eventually (and in this lifetime) be made available for independent and additional analysis by other researchers. It then becomes the track record of doing so that will be considered by the journal editors.
  - Maintain high expectations and thresholds for open science, taking care to do so with a healthy respect for intellectual property.

2. Build a collaborative ecosystem

- Incentivize via funding sources and recognition the creation of and contributions to shared data resources.
- Create benchmark problems and datasets.
- Develop and implement standards for networks, matrices, and other travel model artifacts.
- Expand the National Household Travel Survey to be on-going, with a panel of experts guiding improvements and analysis.

3. Integrate researchers and ideas from related fields

- Expand interdisciplinary knowledge of those core to the field: generate and maintain an updatable list of interdisciplinary resources and events; develop an expectation that those in the field will engage.
- Excite researchers from non-core disciplines and incentivize multidisciplinary collaborations: take better advantage of existing conference and funding infrastructure; generate dedicated funds (seed level and more significant) to support efforts (travel, conference participation, fellowships, augments to major funds).
- Foster multidisciplinary student profiles: organize interdisciplinary summer schools, create fellowship funds à la the Data Science for Social Good program, make degree programs and research labs more interdisciplinary.
- Survey the state of the disciplinarity of the field, and develop a marketing plan oriented towards those outside the field.
- Adopt approaches from other fields on model development and validation.
- Create and host model competitions to attract teams from multiple fields using shared datasets that target the development of useful and accurate predictive frameworks.

4. Strengthen links with policy and planning

- Make the tools and methods more transparent and more relevant to today's (and tomorrow's) problems faced by practitioners.
- Increase interaction between faculty, students, metropolitan planning organizations and other agencies that use travel demand models. Faculty and students should meet with their local transport planning agency staff to present and discuss their research, to dialogue about how and whether it could be made more relevant to planning, and discuss critical issues the planning staff is facing. And, conversely, coursework should

include a variety of first-hand practitioner perspectives and encourage internships and projects that collaborate with industry. Such participation by practitioners should be compensated and encouraged by employers and organizations.

- Take "tech transfer" more seriously by creating an expectation that faculty and students will participate in direct efforts to translate research results for planning agencies (e.g., a requirement by funding agencies for policy briefs).

- Develop a track record of model successes and failures, as evaluated in terms of accuracy of forecast as well as effectiveness in informing policy decision making. Develop case books of modeling applications, with a focus on real world complications and frank assessment of performance.

- Address issues of importance to practitioners: demonstrations and descriptions of innovative models in specific practice contexts; post-facto evaluation of model accuracy and relevance; direct comparisons of different modeling approaches; and research about how and whether innovative models are used in practice.

5. Develop the workforce

- **Scale and inform salaries and benefits by the labor and jobs markets** by conducting and publishing a regular state of the workforce survey. Develop job titles and salary ranges that consider the market for similar skill sets, and make up for monetary shortfalls via less tangible benefits (important and exciting work, a jovial workplace and professional community, opportunities to broaden skill sets, and public recognition for excellence).

- **Cultivate a front door to the community and a brand for the field** – welcoming would-be travel modelers and concerned stakeholders alike, with a focus on engaging people who are typically underrepresented in the travel demand modeling field. Develop a speaker corps of trained speakers, be a presence at *adjacent* industry events, and package and broadcast important information between sectors and industries via newsletters as well as synthesis of ripe topics.

- **Actively promote and further this agenda** via calls for papers, workshops, and sessions at TRB, Innovations, Planning Applications, and adjacent conferences; via special issues of journals; and via grants made by metropolitan, state, federal and private agencies.

6. Continue conducting foundational research

- **Undertake a fundamental and comprehensive effort to define core knowledge**

  - Provide a framework for advancing and updating that knowledge, reflecting common themes and differences across various studies, lessons learned and best-practices as well as identifying gaps that would serve to motivate further work aimed at filling those.

    - Identify one aspect of travel behavior in which we seek to develop a theory, test the theory empirically, verify the theory empirically, and translate the theory into mathematical expressions that can be incorporated into practical, predictive models of travel behavior and that can be updated over time.

    - Develop an epistemology of travel demand modeling: to define what makes a "good" model, what criteria we use to reject a model, and what we aim to learn from models.

- **Advance fundamental research in**:

    - Measurement: characterize and fully leverage and merge new and old sources of data.

    - Travel and activity choice processes: capture richer behavioral features and phenomena.

    - Formal representations of choice processes: integrate streams from psychology, econometrics, and artificial intelligence.

    - Modeling frameworks: more agile, adaptive, and transferable.

    - Forecasting in response to policies: evaluating, testing, updating models and forecasts to connect with decision-making.

Conclusion, and a note on the larger report

Following the dynamic, diverse workshop with many great minds and creative ideas, it was a challenge to generate this report. While there was reasonable agreement on the state of the field and the desired outcomes and future state, there was also a wealth of ideas whose translation into concrete actions was not always straightforward. And the obstacles to rapidly advancing the science are daunting, given the long history, entrenched norms, politics, and incentive structure of the academic travel demand modeling field. Our recommendations range from relatively small things that individuals can do, to changes in professional norms, to items that require significant investments. With that said, we forge ahead and present our road map for change.

Our mission is to make demonstrable, continuous progress towards accurately representing human travel behavior and improving the predictive accuracy of practical travel models. There is no silver bullet. A host of changes, big and small, from both individual actors and organizations are necessary to advance the science of travel demand modeling. What will *you* contribute to advance this agenda?

Workshop participants

(Affiliations listed are those at the time of the workshop)

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Theme 1: Apply the scientific method

Science is a process for advancing knowledge through inductive reasoning. It involves making observations about natural phenomena, proposing possible explanations for those phenomena, and testing those explanations against reality (Sant n.d.). Science is powerful because it provides a mechanism to advance knowledge *systematically*—while individual explanations may be incorrect, testing provides a means for the best ideas to rise to prominence while others are rejected. This is analogous to pruning a tree—it is necessary to grow new shoots to advance, but it is also important to trim those branches that are less promising so the overall effort can be steered accordingly.

In travel demand modeling, we are interested in systematically advancing knowledge about our domain, and science may provide a means for doing so. Consider the comparison of the scientific method to travel modeling research and travel forecasting practice shown in Table 1. Collecting and analyzing travel data, whether it is in the form of household travel surveys or big data, is a form of observation. A travel demand model can be considered a hypothesis of travel behavior, such as the hypothesis that travelers maximize their utility in a choice framework, or that drivers follow the shortest path through a congested network. Travel models are commonly used to make predictions, although the nature of the prediction can vary. Although travel modeling research is diverse, one common approach involves making predictions in the existing data set. Sometimes a hold-back sample is used for validation, but even this only tests the model performance for conditions close to what is observed in the estimation data. In contrast, when travel demand models are applied in practice, they are often used to make predictions 20 years into the future, for conditions that may be far out of sample. Due either to the long time horizon, the lack of data or funds or interest, such models are rarely tested in the way they are applied, with model validation dominated by comparisons against cross-sectional data (Cambridge Systematics, Inc. 2010; Hartgen 2013; Nicolaisen and Driscoll 2014). This leaves a gap in our analogy to the scientific method, with the experiment stage missing.

Table 1 Comparison of scientific method *(Sant n.d.)*
to travel modeling research and travel forecasting practice

Scientific Method	Travel Modeling Research	Travel Forecasting Practice
1. **Observation** and description of natural phenomenon.	1. Collect and analyze travel data for a city.	1. Collect and analyze travel data for a city.
2. Formulation of a **hypothesis** to explain the phenomenon.	2. Develop a more sophisticated model component based on a hypothesis of that aspect of travel behavior.	2. Develop a system of models based on hypotheses of travel behavior.
3. Use the hypothesis to **predict** other phenomenon or results.	3. Apply that model to predict observed outcomes in existing travel data.	3. Use that model system to make predictions with a 20-year horizon.
4. Perform an **experiment** or experiments to ensure that results predicted based on hypothesis are achieved in the experiments.	4. Test that the goodness-of-fit measures for the new model are better than the old.	4. Wait.

This issue is not limited to travel demand modeling, but true of modeling and simulation more broadly, as articulated by Tolk et al. (2013):

> "While the complexity of simulations allows for them to extend our cognitive capabilities it also makes it extremely challenging and time consuming to independently verify and validate the simulation and its results. Accordingly this independent testing is rarely practiced, but it is absolutely vital in the scientific method because without it the whole philosophy pragmatically falls apart and no significant progress can be made beyond individual self-interests."

Aspirations

Lest we think that modeling is different, and the rules of science need not apply, it is worth noting that modeling has been called "the essence of science" (Rosen 1999), and that the history of science can be viewed as "a series of models continuing to replace each other" (Tolk 2015). For example, Newton proposed a mathematical model of gravity, and Einstein proposed a replacement. Einstein's model predicted that the gravity of the sun would bend the light of stars passing by it, and his model was accepted more broadly after experimental evidence collected during the solar eclipse of 1919 confirmed this prediction. We can draw two lessons of relevance to travel modeling from this story:

1. It is the interplay between theoretical and experimental science that allows knowledge to advance. Much as there are both theoretical and experimental physicists, we may consider how theoretical and experimental travel modelers can best complement each other.
2. Even though Einstein's model of gravity replaced Newton's, Newton's much simpler model remains useful in a great many circumstances. The same may be true in travel modeling.

Our aspiration for travel modeling is to provide a mechanism for evaluating whether our models (hypotheses) are correct. We propose to do so using a scientific process. Further, this process should recognize the many uses of models (Epstein 2008), including the power of models that comes precisely from their ability to make out-of-sample predictions and run virtual experiments (Axelrod 2006).

Falsifiability

As we consider this strategy, we must be clear about what makes something scientific. Popper (1935) argues for falsifiability as the demarcation of science, either through experiment or through logic. *In travel modeling, this implies that we should use our models to make testable predictions, and that we must actually test them.*

Generalization

Building upon falsifiability are questions of generalizability or external validity. External validity is the degree to which conclusions in a study would hold for other persons in other places at other times (Campbell and Stanley 1966). Often, the travel models for each city are so customized that it is difficult to apply them elsewhere. Even more limiting is a situation where a model is customized to the point that there is no way of knowing whether the model results are valid for more than one point in time. If we wish to generalize our findings, we should aspire to testing them in multiple locations, and across multiple years.

Data recording and sharing, reproducibility, and external review

Even with a strong scientific process, Galilei (1638) argued that additional community-level components are required to ensure the validity and credibility of science, including data recording and sharing, reproducibility, and external review. Academic journals have long provided a mechanism for all three. A conclusion can only be considered scientific if the data, methods and logic that lead to a conclusion are available for scrutiny, and we should continue to view work that is subject to this scrutiny as more credible than work that obfuscates details to avoid criticism. Travel demand models pose a challenge in this respect because as our data sets become larger and our models more complex, it may be impractical to fully document them within the space constraints of a journal article. A model that is well formulated and clearly expressed mathematically is a good start, but often we are also interested in the implementation of a model. We can consider the implementation of a model to consist of code, data, parameters and assumptions. Code that is either not shared or not readable, data with privacy restrictions, buried parameters or assumptions are all barriers to reproducibility. We should aspire that for any research we publish, a knowledgeable reviewer, such as a PhD student in transportation modeling at a different university, should be able to reproduce our results. This enables them both to test our model's predictions, and to build upon it in their own research. This contributes to the collaborative ecosystem emphasized next in Theme 2.

Considered together, these three aspects of the scientific process—falsifiability, external validity and community-level components—provide a mechanism for choosing among competing models. If two models both make testable predictions and can be reproduced such that they apply in multiple locations and years, then it is possible to make competing predictions of the same outcomes, which controls for differences across cities or projects. As we do this, we may find the answer is situational, much like we can identify the conditions where the differences between Einstein's model of gravity and Newton's model of gravity are important, and those conditions where the models agree and reinforce each other. We also must apply these aspects both to the large-scale urban models used in practice as well as the development of component models and methods that are the building blocks of these large-scale models.

Positive cases

As we aspire towards these goals, we might take inspiration from positive examples both within the travel modeling community and more broadly. The focus is first on examples from other modeling domains as the issues may be related.

Falsifiability and Generalization

The inspiration for this effort at advancing the science of travel demand modeling comes from the Hurricane Forecast Improvement Program (HFIP) (National Oceanic and Atmospheric Administration, 2010). HFIP involved a concerted effort across government and researchers to improve hurricane forecasts. It used an ensemble modeling approach that explicitly considered the uncertainty implied by differences in forecasts made across models, and included a model evaluation and improvement process at the end of each hurricane season when each model could be evaluated against observed outcomes. This combination of ensemble forecasting and evaluation led to substantial improvements in the accuracy of hurricane forecasts during the program.

Hurricane forecasting has the advantage that the forecasts can be evaluated against actual outcomes immediately after the storm. In transportation, our forecasts are often longer term, and waiting for projects to be built slows progress. A similar dilemma occurred when modeling the effect of chlorofluorocarbons (CFCs) on ozone depletion (Gilet, n.d.). In the 1970s, scientists used complex atmospheric models to hypothesize that CFCs from aerosol sprays would cause significant depletion of the Earth's ozone layer. Unfortunately, the prediction was difficult to test against observations, because the predicted effects were long-term. Instead, scientists turned to a different prediction made by those same models—that CFC concentrations would be different at different altitudes—and collected data to confirm or refute that hypothesis. The data confirmed their short-term predictions, which helped build enough confidence in the models to spur a CFC ban.

The CFC case provides an example of how modeling and hypothesis testing can be used effectively in a policy context. One important point is that there are a number of strategies that can be used for the verification and validation (V&V) of simulation models, including predictive validation, historical data validation, internal validity, comparisons to reference models, and other strategies (Sargent 2011; Tolk, Diallo, et al. 2013; Lanza 1990) that extend beyond the cross-sectional validation that dominates in travel demand modeling practice. Similarly, researchers in computational biology have developed a framework for establishing model credibility that ranges from testable to untestable and known to unknown conditions (Patterson and Whelan 2017). Often the purpose of a model is to provide insight into the untestable or unknown, so we cannot dismiss that insight, but must be more cautious when working in those ends of the spectrum. Others in biology (Casadevall and Fang 2016) have proposed a simple how-to guide for rigorous science, focusing on five dimensions:

- Redundancy in experimental design,
- Sound statistical analysis,
- Recognition of error,
- Avoidance of logical traps, and
- Intellectual honesty.

Redundancy in the guide can include elements such as validation, generalization and replication. Note that replication and reproducibility are different. Replicability is the ability to create a new implementation of a conceptual model that differs in some way from the original model, while reproducibility is the ability to independently recreate computational artifacts associated with published works (Tolk, Heath, et al. 2013). For example, a trip-based and an activity-based travel model that each produce similar forecasts would be considered replicates, while a second researcher repeating the calculations with one model is reproducibility. Replications are one way of attempting to falsify a result when it cannot be done experimentally. Generalization is another way of attempting to falsify a model, with one that applies in a broader range of circumstances more likely to be correct in its core hypotheses.

Broadly, these efforts fall within the category of epistemology, which is the field of philosophy associated with how we advance knowledge (Tolk, Diallo, et al. 2013). As a travel modeling community, we may do well to take a philosophical view about issues such as what makes a credible model, and what we can or cannot learn from models. Such guidance may be greatly appreciated by young researchers as they find their way in the field.

Within travel demand modeling, there has been progress in testing model predictions against actual outcomes in the form of temporal validation (Rossi 2016) and testing against specific events (Dixit, Montz, and Wolshon 2011). There is a body of literature examining travel forecast accuracy, including possible reasons for inaccuracy (Flyvbjerg 2007; Bain 2009; Miller et al. 2016; Andersson, Brundell-Freij, and Eliasson 2017), but even in the best studies, the reasons for inaccuracy are difficult to discern (Nicolaisen and Driscoll 2014). This was the experience of recent research on project-level traffic forecast accuracy (Erhardt et al. 2019) where it was possible to identify some sources of forecast error, but difficult to identify whether some types of models produced better predictions than others. There were two reasons for this. First, the type of model used is correlated with other factors, such as the type of project and the agency conducting the forecast. A cleaner research design would allow for competing forecasts of the same outcome, allowing for a more direct comparison. Second, the most informative analyses were possible when the original travel model runs were available and reproducible, rather than just the resulting reports. Access to original code and data remains rare, but the importance of this availability is discussed below.

Data recording and sharing, reproducibility, and external review

While not an absolute requirement for drawing valid conclusions, *data recording and sharing, reproducibility and external review greatly facilitate the independent testing of models.* Ensuring the practical reproducibility of research has been a point of focus by a number of journals in recent years. For example:

- *Nature* started an initiative focused on improving research reproducibility in part by requiring authors to complete a “score card” tracking their efforts at promoting reproducibility (“Announcement: Reducing Our Irreproducibility” 2013).

- *Science* has very strict editorial standards, with variance due to "truly exceptional circumstances" requiring discussion with the editor ("Science Journals: Editorial Policies" 2018). The standards include:
    - "All data used in the analysis must be available to any researcher for purposes of reproducing or extending the analysis."
    - "We require that all computer code used for modeling and/or data analysis that is not commercially available be deposited in a publicly accessible repository upon publication."
    - "Large data sets…must be deposited in an approved database and an accession number or a specific access address must be included in the published paper."
    - "After publication, all data and materials necessary to understand, assess, and extend the conclusions of the manuscript must be available to any reader of a Science Journal…. Problems in obtaining access to published data are taken seriously by the Science Journals and can be reported at science_data@aaas.org."
- The American Society of Civil Engineers (ASCE) has issued a new data availability policy for journals it publishes (Govindaraju, Hantush, and Chu 2019; Rosenberg David E. and Watkins David W. 2018), including the *Journal of Urban Planning and Development* and *Journal of Transportation Engineering, Part A*. The policy requests authors to comply with the FAIR data principles: Findable, Accessible, Interoperable, and Reusable.

In this realm, it appears there is already a set of principles available to promote reproducibility in modeling, as well as a separate effort aimed at identifying how to engineer reproducibility into computational models (Taylor et al. 2013). There has also been progress within travel demand modeling in terms of sharing code and data that corresponds to papers. What remains is to fully embrace these principles, ensuring that they become the norm and not the exception. This includes doing so both as authors ourselves and as reviewers. Because there is effort involved in doing so, it may involve accepting a lower publication count in exchange for higher quality, more reproducible research. It may also involve making difficult trade-offs between the desire to do research with unique, but restricted data sets, and the desire to make the resulting research reproducible.

Call to Action

Given these aspirations and examples, *we propose four principles of travel modeling as a science*:

1. **We build travel models to predict change. We should evaluate them on their ability to do so.**
   The power of a travel demand model is to go beyond existing conditions. This implies that our validation should focus on validating the predicted change, and not be dominated by matching present-day conditions.
2. **Our models should make testable predictions of important outcomes.**
   Testable implies that there is some mechanism by which to reject a model, with possible tests identified early in the development process. Important outcomes imply some alignment of the validation tests and what we actually want to learn from a model. This principle can be met through a combination of present-day testing and long-term archival of our forecasts.

Backcasting is another important avenue for testing, i.e. predicting the past, as is using models calibrated on past data to predict the present.

3. **To compare models, we need competing predictions.**
   Competing predictions allow the methods to be compared more directly. We must overcome barriers to comparison caused by the development of customized models that are difficult to replicate.
4. **To generalize our models, they should apply for multiple points in time and space.**
   This suggests that a strong model should apply for more than one city, in more than one year. Otherwise, there is a risk of over-calibrating to fit very specific base-year conditions.

As we implement these principles, we should identify and articulate what we aim to learn from a model, as that may affect what we predict. This goes beyond generic statements like, "the model informs policy" into descriptions of what specific questions policy-makers may seek to answer.

There are several specific actions that we, as a travel modeling community, can take to implement these principles:

- Validate our models across time and space. This means committing to testing our models for specific changes that have occurred within cities and for specific differences between cities. A specific short-term goal is for multiple MPOs, with aid from the academic community, to publish either backcast evaluations or project-level before-and-after evaluations of their model's performance. Further, testing not only the models themselves but also the underlying assumptions, such as demographic land use forecasts.
- Value hypothesis testing as a complement to method development. Too often, model applications are dismissed as the realm of practitioners, and not a serious academic pursuit. Both are important if done well. A specific short-term goal is for methods researchers to publish articles suggesting a set of criteria that would either demonstrate that their methods are useful and should be explored further, or are not useful and should no longer be explored, and for separate researchers to test the models against those criteria.
- Create incentives for model reproducibility. A simple approach is for more transportation journals to adopt the ASCE data availability standards. In practical terms, this means that articles should be published with data sets and scripts documented sufficiently to allow a PhD student to recreate the findings. This would be the estimation file and scripts in a model estimation paper. In a model application paper, it would include the travel model runs themselves in a form that they can be downloaded and run with the applicable software licenses. This standard should also apply to official forecasts produced in practice, such as for an Environmental Impact Statement or for a long-range transportation plan.
- With the push for open science, to recognize the importance of attribution and protecting intellectual property in the course of sharing methods, programs, and scripts.
- Create incentives for model replication studies, generalization studies and other forms of redundancy. This may take the form of a special journal issue dedicated to the replication or testing of previous seminal findings in transportation.

- Question our practice that when major resources are obtained for data collection and/or model development, there is a major competition among bidders to obtain the project, and the competition ends once the work commences resulting in one solution without comparison. The practical realities of halving the money available for development need to be overcome by leveraging or pooling funds with the eye on producing more useful models for everyone in the long run.
- Develop an epistemology of travel modeling. There is a need to define what makes a "good" model, what criteria we use to reject a model, and what we aim to learn from models.

As we consider these strategies, we should recognize that they are no substitute for intellectual honesty. The technical complexity and need for subjective assumptions in travel models makes it easy to use models as a means of masking pre-determined conclusions (Wachs 1990). As we aim to include ideas and people from a range of fields in travel modeling, there remains a need to hold ourselves and our colleagues to the ethical standards of our professions that put the public interest first (American Institute of Certified Planners 2016; National Society of Professional Engineers 2018). However, just because there are examples that violate these standards, it does not mean that is the norm. In fact, there is a risk that the standards of rigorous science will be used to discredit good, but imperfect, science (Aschwanden 2017). For example, to discredit honest practice that necessarily must rely on judgment and assumptions to bridge the gap between what we know and what is needed to advance decisions in a timely fashion and with available resources. Therefore, even as we hold ourselves to high standards, we should take credit for what we get right, and speak clearly about the implications of our findings. This includes the freedom to use the results of our research to advocate for policy changes, as articulated by the Chief Executive Officer of the American Association for the Advancement of Science (AAAS) (Holt 2017):

> "A scientist must take great pains to prevent ideology, bias, or wishful thinking from contaminating the collecting or analyzing of evidence—that is, one must avoid politicizing the science. But it is a fallacy to say the converse is true. One need not avoid—indeed, should not avoid—applying relevant science in political or societal situations where it can help address problems. The need to maintain the purity of the majestic scientific enterprise should not be used as an excuse for inaction."

Theme 2: Develop a collaborative ecosystem

Barriers to collaboration abound in the travel modeling space. In the academy, where publishing is king, journals bestow outsized rewards to those with restricted access to novel datasets and generally do not reward those conducting open and reproducible results. Lack of comparability among models and across model results stymy progress in the field. Practitioners must navigate scarce resources and strict procurement rules in order to collaborate with their colleagues, and collaboration is discouraged because it dilutes competitive advantage.

Beyond these institutional issues, the travel space generally lacks a collaborative ethos. Academics can achieve tenure by extending explorations into a niche area, avoiding the challenge and potential failure inherent in pursuing seminal findings. Practitioners often form strong, unique ideas of how things should be done while climbing the career ladder and once they achieve a position to implement their ideas as a modeling lead or other decision maker, they often want to see their vision through. Further, they often do not have the luxury to explore alternatives and hence they perpetuate approaches that have been accepted to preserve competitive advantage.

In sum, the above infrastructure and collective ethos stymies fundamental progress in our field. Consider, for example, the Hurricane Forecast Improvement Program, in which federal research funds are directed towards a collaborative model building program that is assessed each season as new hurricanes are observed. The hurricane forecasting community is united by a compelling and common goal: improve forecasts to provide accurate and reliable evacuation orders, saving lives and time/money. The travel modeling community is not united around a singular mission.

A singular mission for our community could be to make demonstrable progress towards accurately representing human travel behavior with mathematical representations, and therefore, over time, improving the predictive accuracy of practical travel models. Practical travel models should be repositories for what we know to be true about traveler behavior. And what we know to be true about traveler behavior should be discovered and confirmed by academic research.

Consider, for example, the relationship between the relative onerousness of spending time waiting for, versus riding on, a public transit vehicle. Nearly every practical travel model (thousands of them) assume that this ratio is between two and three, i.e., every minute spent waiting for the vehicle to arrive is as onerous as two or three minutes spent riding on a transit vehicle. The inclusion of these ratios in practical travel models influences billions of dollars of investments every year as predicted ridership is maximized by modifying frequencies. However, there is a disconnect between the quite vast academic literature that attempts to estimate and validate these ratios (e.g., classic meta reviews such Wardman, 2004; or major, more recent studies such as Batley et al., 2019) and the practitioners who are tasked with incorporating them in practical models.

Aspirations

Incentives that encourage our community to make measurable, continuous improvements in accurately describing and then predicting travel behavior are needed. Broad ideas for such incentives include the following.

- **Rewards for seeking seminal contributions.**
  The academy does not currently reward or support those seeking to make seminal, rather than incremental, progress in our field. Academics in positions to influence change should nudge the tenure review process towards paper quality, not quantity. Doing so may spark our academic community to think more broadly and take more risks.

- **Shared data resources.**
  The creation of customized models from customized data sources is antithetical to collaboration. Funding bodies should first incentivize the creation of and then make contributions to shared data resources. Complementing such an effort, data standards need to be developed and enforcement.

- **Benchmark problems and datasets**.
  There are common problems in travel behavior that we can more efficiently solve collectively than individually. Consider the example of predicting the mode choice decision. This problem could certainly be addressed more efficiently if there was a common set of observed data upon which models could be benchmarked and tested.

- **Competitions.**
  Consider a competition in which academics build travel models against multiple, shared datasets and are then asked to make predictions against a separate set of inputs in which the outcomes are known. The model that makes the most accurate predictions against a predefined set of criteria is acknowledged and rewarded. Such an approach is likely to achieve forward progress in predictive accuracy for the simple reason that it is designed to do so. It also has the potential to attract talented newcomers to the transportation space as well as fresh and innovative ideas. Further, when major resources are obtained for model development, push the competition beyond the bidding phase and into the development phase so that multiple solutions are produced that can be compared.

Positive cases

Within our field, there are individuals and agencies contributing to collaborative ecosystems. Examples (and by no means a complete list) include: econometric estimation software (Biogeme[1],

[1] http://transp-or.epfl.ch/pythonbiogeme/

Apollo[2], PyLogit[3]), open source development platforms (CycleTracks[4], MATSIM[5]), posting of estimation code used in academic publications (Bhat[6]), and low bars of entry to rich datasets (ETH Travel Data Archive[7], NHTS[8], MTC[9]). However, collaborative cases in our field are more the exception than the rule and represent only a small fraction of the expended effort.

There are myriad examples outside of our field in which a collaborative ecosystem has led to transformative progress towards a specific goal. Particularly impressive are the following examples:

- The Hurricane Forecast Improvement Program cited above. In 2018, NOAA reported that the program "successfully attained its initial goal of reducing the error in track and intensity forecast guidance by 20% within the program's first five years, on its way toward meeting its even more challenging goal of a 50% reduction of error within 10 years." (Toepfer et al., 2018)
- The rise in machine learning has been fueled by an open-source culture for data, code, and scientific publishing:
    - **Data:** Easily available and widely used databases are used as benchmarks and in competitions. For example, the Modified National Institute of Standards and Technology (MNIST) Database of Handwritten Digits, which is commonly used to test image processing procedures. The predictive accuracy of machine learning algorithms to classify these images has demonstrably improved. Similarly, the Canadian Institute for Advanced Research (CIFAR) Databases of Tiny Images, which contains over 80 million databases of labeled images, have reduced the error rate for classifying images using machine learning and computer vision by an order of magnitude in the last decade. Other widely used data repositories are the UCI Machine Learning Repository[10] and the competition datasets produced by Kaggle[11] and ImageNet[12].
    - **Code:** Free data analysis tools to access the latest machine learning advancements such as Tensorflow (Abadi et al., 2016) and Scikit-learn (Pedregosa et al., 2011). These papers each have over a dozen authors and have been cited many thousands of times.
    - **Scientific Publishing:** It is the norm that academic articles are quickly and freely made available through ArXiv. This is an early entry in the open access movement (started in 1991), and grew out of physics to now host a number of fields (including computer science, statistics, and economics). Scholars can self-archive e-prints on ArXiv, which are posted with moderator approval but without requiring a full paper review. While most of these articles eventually are published in peer-reviewed journals, many are not, including

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[2] https://cran.r-project.org/web/packages/apollo/apollo.pdf and www.apollochoicemodelling.com
[3] https://github.com/timothyb0912/pylogit
[4] https://github.com/sfcta/CycleTracks
[5] https://www.matsim.org
[6] http://www.caee.utexas.edu/prof/bhat/FULL_CODES.htm
[7] http://archiv.ivt.ethz.ch/vpl/publications/ethtda/index_EN.html
[8] https://nhts.ornl.gov
[9] http://opendata.mtc.ca.gov
[10] http://archive.ics.uci.edu/ml/index.php
[11] https://www.kaggle.com/datasets
[12] http://www.image-net.org/

some highly influential work. Within the peer-reviewed publishing space, leading scholars in machine learning resigned from the editorial board of the restricted-access Machine Learning Journal[13] to support the open source Journal of Machine Learning Research[14].

Is it possible for the travel demand field to learn from these fields?

Call to Action

We call the travel behavior community to action. Specifically, we recommend the following:

- The academic community should formalize a problem statement articulating the role they should play in improving the predictive accuracy of practical travel models.
- The academic community should identify at least one aspect of travel behavior in which they seek to develop a theory, test the theory empirically, verify the theory empirically, and translate the theory into mathematical expressions that can be incorporated into practical, predictive models of travel behavior and that can be updated over time.
- The department of transportation to continue the expansion of the National Household Travel Survey to ensure that it is on-going, with a panel of experts guiding improvements to the questionnaire over time as well as conducting useful experiments on sub-samples. Funding agencies can then incentivize model building exercises that use these shared data resources.
- Journal editors should explicitly penalize, rather than reward, papers that work with unique datasets not available, and will not be made available, to any other researchers. Little is lost in the realm of data privacy or data risk by sharing unique datasets with at least two other research groups. Researchers who invest considerable intellect, time and money collecting a unique dataset should have sole access to their data for some period of time. However, the expectation is that these data will eventually (and in this lifetime) be made available for independent and additional analysis by other researchers. It then becomes the track record of doing so that will be considered by the journal editors.
- Journal editors should implement reproducibility standards such as those in Nature and Science described above, again having high expectations and at the same time taking care to respect intellectual property.
- Submitting papers to Arxiv should become a standard, and platforms that encourage open access and open peer review should be championed by all.
- Travel modelers should develop and implement standards for networks, matrices, and other travel model artifacts such that everyone can more readily engage in collaborative research.
- Travel model practitioners and academics should establish and implement competitions to engage everyone in developing useful and accurate predictive frameworks, learning from the experience of crowdsourcing success and failures (Van Alstyne et al., 2017).

The ultimate objectives are to work towards a collective and clear mission, to set professional norms/expectations of collaboration, and to create an infrastructure that supports collaboration.

[13] https://www.springer.com/computer/ai/journal/10994
[14] http://www.jmlr.org/ ; http://www.jmlr.org/statement.html

Theme 3: Integrate researchers and ideas from related fields

Travel demand forecasting has drawn and continues to draw from multiple disciplines. For obvious reasons, it has always had a symbiotic relationship with urban planning, itself an interdisciplinary field that draws on geography, architecture/urban design, landscape architecture, sociology, and public policy, among others. The random utility model (RUM) that has been widely adopted for the discrete choice models that lie at the heart of travel demand forecasting has its root in econometrics, and one of Daniel McFadden's early applications of the RUM was Bay Area Rapid Transit (BART) ridership prediction. The influences are bi-directional: travel demand researchers have made contributions to econometrics as they apply RUM to complicated, large-scale problems aimed at generating insights or parameters suitable for real-world policy or management decision making (e.g., nested logit by Moshe Ben-Akiva, continuous-discrete models by Chandra Bhat, and many more). As economists continue drawing from behavioral science to represent richer and more heterogeneous behaviors (e.g., Bounded Rationality by Simon, Prospect Theory by Kahneman and Tversky), such influences are channeled to the travel demand forecasting community thanks to the tradition among travel demand modelers of seeking insights from economics. Sometimes the inspiration comes directly from behavioral science to travel demand forecasting, e.g., wayfinding behaviors as studied by Tommy Garling in Environmental Psychology. More recently with the availability of large data sets and advance of computer science, big data analytics and machine learning have become a magnet for the travel demand modeling community (e.g., work by Bilal Farooq, Marta Gonzalez, Francisco Pereira, and Alexey Pozdnukhov). These relationships are reciprocal, in that the applications to transport problems and the involvement of the travel demand modeling community lead to advancements in the contributing fields.

Although the travel demand modeling community has been doing fairly well in drawing from multiple disciplines, there are still gaps that need to be closed, and the latest methodological developments and insights from fields such as cognitive science, computer science, statistics, and econometrics are not yet integrated into travel analysis. Further, the field would benefit from more direct engagement from people in these other fields. Examples of advances in other disciplines that would be beneficial for travel demand modeling include:

- Cognitive science (dynamic and volatile utility due to reference-points, inertia, salience, prominence);
- Causal inference, and machine and statistical learning;
  - The role that causal inference plays in computer science-focused emerging tools;
  - Taking advantage of natural experiments;
  - Forecasting conditions far away from current situations;
- Behavioral experiments (embrace culture of experimentation enabled by technologies and translate findings to models);
- Deep uncertainty and robust decision-making (e.g., Marchau et al., 2019).

Aspirations

To better integrate interdisciplinary ideas into travel demand modeling requires efforts along four dimensions:

- Inward-looking: Expanding the interdisciplinary knowledge of those core to the field.
- Outward-looking: Exciting researchers from non-core disciplines about travel analysis so that more brain power is poured into this topic.
- Collaborating: Incentivizing multidisciplinary collaboration among researchers.
- Training: Fostering multidisciplinary student profiles.

Positive cases

There are currently mechanisms in place to encourage multidisciplinary work in travel demand modeling. For example, the International Choice Modeling Conference (ICMC) explicitly targets choice modeling researchers from a large array of fields, including transport studies, marketing, environmental valuation, operations research, and health economics. The Tri-Annual Invitational Choice Symposium requires interdisciplinarity in the makeup of the small working groups assembled for the symposium (at least a couple of working groups each year have a transport flavor). Government funding organizations such as NSF, SHRP, NCHRP, TCRP, and the UTCs often reward collaborative proposals and many provide specific support for collaboration among researchers, consultants, and the public sector. For example, the NSF CRISP program (Critical Resilient Interdependent Infrastructure Systems and Processes) requires that any proposal must have at least one co-PI from each of the three disciplines: engineering, social science, and computer science. It requires significant contribution from each discipline instead of as an add-on.

Competitions are a different type of mechanism that have been used successfully in other fields to attract attention relatively easily and quickly. The annual ImageNet challenge (since 2010) has led to dramatic improvements in image recognition algorithms and is seen as "the catalyst for the AI boom the world is experiencing today" (Gershgorn, 2017; Russakovsky et al., 2015). The Hackathon tradition in computer science is another good example, where teams work intensively for several hours to days to tackle a particular problem. Kaggle is an online community for data science where competitions are hosted. One of the earlier competition examples on Kaggle (2011) is actually related to travel analysis. The transport agency from New South Wales of Australia wanted to forecast a motorist's travel time on a major highway from 24 hours to 15 minutes ahead of time. It offered competitors access to two years' historical data. Then-local start-up Kaggle (later moved to San Francisco) was hired to host the competition, which attracted over 300 teams from around the world, all vying for the $US 10,000 top prize.

Another example of model competition comes from academia in psychology. It was carried out in 2009 to predict choices from both one-shot and repeated choice experiments. Each competition was based on two experimental datasets: An estimation dataset, and a competition dataset. After collecting the experimental data to be used for estimation, the organizers posted them on the Web, together with their fit with several baseline models, and challenged other researchers to compete to predict the results of the second (competition) set of experimental sessions. Fourteen teams responded to the challenge. Merits and limitations of the competition are summarized in an article authored by the organizers and winning teams, published in a special issue of the Journal of Behavioral Decision Making.

In terms of educational initiatives, a strong example is the yearly summer school organized by the European Association of Environmental and Resource Economics (EAERE). Each year a specific topic is chosen, and professors from different fields within the topic are invited. These professors do give general lectures on their research, but the core of the summer school is the work of the students. Student application requires submission of the draft of one paper from the student's dissertation. Students present their paper at the summer school, get feedback from other students and the professors, and refine the draft to address the multiple views of the received feedback. Ricardo Daziano participated in this summer school in 2009 when the topic was: "Economics, Transport and Environment." Professors were all from economics, but representing different fields: microeconometrics, environmental economics, industrial organization, urban economics. There were students from economics, engineering, and social psychology.

Call to Action

The first step in drawing from other disciplines is to educate ourselves. Many researchers are already constantly looking into other disciplines, but we need to do more. Collectively, the community should maintain an updatable list of related conferences, textbooks, online courses, and research papers. Researchers in the field should commit to seriously engaging in at least one thing off this list each year, by attending an outside conference, reading a textbook, taking an on-line course, reading a set of research papers in a specific area.

We should be making more use of existing resources and infrastructure to further our agenda. Examples include: proposing a workshop related to advancing the science of travel demand modeling to the Triennial Choice Modeling Symposium, the International Choice Modeling Conference, or the International Association of Travel Behavior Research (IATBR) Conference; submitting a proposal to an interdisciplinary call from NSF; and cross-fertilizing fields by bringing our agenda to other conferences (e.g., organizing workshops in NIPS, AAAI[15], UrbComp) and bringing outside experts from other fields to workshops and invited sessions at our conferences (the annual meeting of the Transportation Research Board and the International Conference on Innovations in Travel Modeling). Working in both directions, the goals should include reaching at least two outside conferences a year as well as having a related-agenda item at each TRB and Innovations Conference. Even within TRB, there needs to be more engagement between the Standing Committee on Transportation Demand Forecasting (ADB40) and the big data and machine learning committees (e.g., the Standing Committee on Artificial Intelligence and Advanced Computing Applications, ABJ70) which are currently almost entirely disconnected.

[15] In the Machine Learning field, workshops are becoming increasingly prestigious, extremely high attendance and low acceptance rates. A concerted action between prominent ML-TDM researchers would be a fertile starting point.

Beyond making use of existing resources, we need to generate new resources, including the creation of a fund to support the collaboration of researchers from multiple disciplines to focus on travel demand modeling. The gold standard would be to establish a fund that would support co-PI's from multiple disciplines on large research projects. However, the creation of seed funding at smaller levels could also prove to be transformative. The seed fund could be used to support travel and preliminary research, which builds the foundation for larger multidisciplinary proposals to major funding agencies. It could support the cross-fertilization of researchers between our core conferences and related conferences in other disciplines. It could also be used to augment other funding (such as large investments for MPO model developments) to support the participation of interdisciplinary researchers or enable competition among different approaches (related to Theme 2).

We also propose that we host model competitions to attract teams from multiple fields. An impactful effort would require funds for the development and cash prizes, which could come either from a USDOT grant or from Zephyr resources. Before launching a competition, a survey needs to be conducted of competition in other (and our own) disciplines, and recommendations will be made regarding format, content, and ways to attract teams from multiple disciplines. Then, data sets, rules and platform need to be set up, followed by an announcement and execution of the competition.

In terms of education, the objectives are both to attract non-traditional students to the field and to broaden the perspective and skills of traditional students. On the first point: whereas we do not seem to have problems getting Civil and Environmental Engineering (CEE) students to be attracted to computer science or operations research in particular (everyone now seems to desire to become a data scientist), our sense is that the reverse is not necessarily true, or at least not at the same level. The first step is to collect data on the state of the field in this respect by doing a survey on whether universities are actively recruiting beyond traditional departments (and how) and the statistics in terms of "field of origin" of current graduate students. The next step is to develop a marketing plan. Although we are living in very exciting times in the field, prospective CEE students are not necessarily aware of this. We may need to outline an outreach plan where we emphasize that the problems in transportation are timely and challenging with large impacts, and one suggestion is to create a fellowship (or fellowships!) for graduate applicants with a non-traditional background.

We also recommend the organization of summer schools for interdisciplinary work such as the EAERE example described above. Since transportation has a clear energy and environmental component, and demand is an economics topic, the summer school could be organized under the EAERE umbrella; however, we suggest that TRB or Zephyr could do something similar in the US. In fact, another model is the summer school and conference of the International Transportation Economics Association (ITEA) where the summer school takes place right before the conference. Holding a winter school right before the annual meeting of TRB could be a possible implementation of this idea.

Theme 4: Strengthen links from research to policy/planning

Symposium participants universally agreed that there is a need to strengthen links from research to policy and planning. Most academics do not feel they have a strong understanding of, or personal connection to, practical uses of the models their work is meant to inform. Meanwhile policy makers and planners perceive that their needs are often not met by academic advancements in modeling methods. The available tools are often not particularly well-understood among policy makers and transportation planners, which limits the ways in which they can be applied and their effectiveness when used. Further, both academics and practitioners question whether the tools are flexible or sophisticated enough to account for a rapidly changing transportation environment. There is willingness and interest on both sides to more closely engage, beyond the strongest current link which is that the graduates of transport-focused programs go on to work at public agencies and the firms that support them.

In many states there are funding relationships between the state Department of Transportation and local universities, which could in theory provide a helpful link between research and practice. However, funded projects are often chosen to address immediate state planning needs which often do not deal with travel demand, and the resulting research agenda certainly does not constitute a programmatic approach to improving demand modelling methods over time to improve the connection between methods and application.

Aspirations

For academic modelers and applied academic planning researchers to become more relevant to the planning discussions in their regions, academics and consultants in travel demand modeling need to work together to make their tools and methods both more transparent and more relevant to today's problems.

It is important to encourage more direct interaction between faculty and students and their local metropolitan planning organizations and other agencies involved with transportation planning and travel demand forecasts. Convening meetings between academics and practitioners is a potentially powerful first step, and certainly an essential one. There are a number of questions to be addressed when doing so, including: Who should be in the room? How frequently should the meetings be held? Who is in the best position to initiate and plan the meetings? Can we articulate the benefits to each side of participating, so as to better motivate attendance?

Better reproducibility of academic research and more post-hoc testing of forecast accuracy (which are addressed elsewhere in this report) would also help strengthen the link from research to practice by making it clearer how and whether innovative advances in model and forecast methods have practical value.

In order to demonstrate the value of their models, academics should link the forecasts more clearly to real world planning decisions. This could involve reframing research questions to orient them to a broader policy environment rather than exclusively framing model improvements in terms of narrower questions such as technical measures of model performance. Similarly, on the practitioner side, clearer links between planning decisions and forecasts are needed. It is not always clear whether and how planning decisions are related to different forecasts, forecast uncertainty, and so on. Clearly there are many considerations that play an outsized role in public investments and plans, beyond ridership and traffic forecasts. Better understanding of how and whether forecasts inform decisions is important to helping academics make their models and forecast outputs relevant. For example, academics could and should carry out more research about how and whether forecasts are used in planning processes, even if this type of research is not something for which most academic modelers are trained.

We believe that the field should spend more time developing a track record of model successes and failures, as evaluated in terms of both accurate forecasts as well as actual use of the models to assist in policy decision making. Evaluating failures should be an area in which academics have the potential to do more than practitioners, who must deal with a much more highly political domain. But even for academics, evaluating failures honestly is difficult, due to factors such as "publication bias," in which descriptions of failures and problems with models are generally not written up and submitted for publication, and when they are, reviewers and editors may be less likely to accept them for publication.

The workshop participants identified at least two additional sets of important changes to forecast models that could result in a better bridge to practice (which are discussed elsewhere in this report). The first is to open models to practitioner users using such techniques as open validation, open software, and better software interfaces allowing practitioners to vary inputs for the models and repeatedly re-run them. The second is a general effort to make forecast models more adaptive to new interventions by increasing processing speeds with more efficient software/computational algorithms and by opening up model code to the academic community so that academics are more easily able to build upon previous improvements.

The symposium participants had a number of other ideas that would help make models and forecast outputs more practically useful. One is to take "tech transfer" more seriously by having a new norm of expecting participation by faculty and students in direct efforts to translate research results for planning agencies, and not delegating all of those efforts to research staff positions or university extension staff. Another is to spend more time conducting scenario-based forecasts and analyzing how decisions can be made more robust given uncertainty in forecasts. Academics could also spend more of their time focusing on better visualization of model forecasts. One final idea is to create "case books" of modeling applications that demonstrate for practitioners how behavioral modeling has been used in particular applications, with a focus on real-world complications and a frank assessment of the benefits and costs of applying the particular model in that particular context.

It is important to note that most or all of these ideas, however helpful or creative they may seem, require individual academics to alter their research directions and foci to adapt and incorporate them. Such changes are difficult to envision, and are best understood as aspirational, absent leadership by faculty that leads to changes such as institutional incentives, incorporation within syllabi at the major programs that teach doctoral students, major talks at high visibility conferences, and other changes consistent with the principles outlined above.

Positive cases

There have been a number of promising efforts to bridge travel demand model research and practical applications, largely in the form of model development partnerships between academics and government agencies. One of the most successful collaborations between academics and practitioners is the Oregon DOT's Transport-Land Use Model Integration Project (TLUMIP). This program began in the 1990's. It moved forward as a series of consulting contracts to create an integrated land use and transport model for the Oregon Department of Transportation that included a series of structured peer reviews carried out by an international panel of academic experts. The panel guided the development of the project, including scoping out the work. The panel met every quarter, in person, to review progress and plan next steps. This procedure is vastly different from the peer reviews that are commonly done at the end of a project, when there is little room to improve the model to reflect the panel feedback. Part of the success of the TLUMIP collaboration was that the bulk of the model development work was done by consultants. Academics likely cannot and should not expect the same level of timely production from their student research assistants, who have papers to write and classes to attend. Also, much of the effort that goes into model development may not be publishable. Another element of the success of the TLUMIP effort was having a champion within Oregon DOT who secured the funding, ensured the end product was useful to the agency, and took steps to demonstrate it. Securing such cooperation from the public sector in many cases will be absolutely essential for successful bridging of research to practice.

Another example is the Toronto Regional Travel Modeling Group (TMG) at the University of Toronto, which was funded by a consortium of planning agencies in the Toronto region, and provides technical assistance to local and provincial planning agencies on applied planning methods. TMG receives on-going funding to support a small technical staff that works with faculty and students on practical modelling problems, as well as larger model development work. The operational activity-based GTAModel V4.0 travel demand forecasting system started as a research project and was taken all the way to operational implementation by the TMG.

There are a number of other good examples of similar partnerships, including between the San Francisco Bay Area's Metropolitan Transportation Commission and Arizona State University on the FAST-Trips transit model improvement project[16]; the San Diego Association of Governments and an academic advisory board working the implementation of an activity based model system[17]; the Ohio Department of Transportation and a group of academics and consultants working on the Ohio Statewide Model; and Florida International University's partnership with the Florida Department of Transportation on a dynamic traffic assignment (DTA) model.

[16] http://fast-trips.mtc.ca.gov/

[17] https://www.sandag.org/index.asp?subclassid=120&fuseaction=home.subclasshome

Call to Action

In addition to further emphasizing the importance of academic-practitioner partnerships to develop more transparent and useful models, additional actions are needed to push forward some of the main aspirations we have identified. The field already has in place three communities that aim to bridge academia and practice in travel demand modeling. One is the TRB Standing Committee on Transportation Demand Forecasting (ADB40), which has since its creation (by design) had an approximately equal split between academics and practitioners. ADB40 has for several years now had an agenda to advance the science of travel demand modeling, and this workshop and report is one of the outcomes. The other is the biennial Innovations in Travel Modeling Conference, which was created to bring together academics and practitioners. The Innovations Conference in recent years has not had as much academic participation as desired, and modifications are being made for the upcoming 2020 Conference in Seattle[18] to attract more academics. The third is the newly created Zephyr Foundation[19], whose mission is to advance travel demand methods for the public good. These three communities are well- positioned to encourage stronger connections between academic model development and practical application.

To address all of these aspirations, our first recommendation is aimed at the TRB Transportation Demand Forecasting Committee (ADB40). The opportunity to present at a lectern session at the TRB Annual Meeting is a highly desired opportunity by practitioners and academics alike. We recommend that ADB40 designate a lectern session each year to first highlight and then motivate additional work that connects modeling directly to policy making, with a highly public call for papers that accomplish this goal. The call will provide a strong signal to the ADB40 community of the importance of activities in which models are used in the crafting of transport policy.

TRB Committee ADB40 could also more proactively promote "practice-ready" research by academics. One possibility is to dedicate an issue of TRR each year to "advancing the state of practice" papers, similar to the current practice of producing a special issue on travel behavior research in *Transportation*. The ADB40 committee could also focus resources and champion papers in the annual review process where research has already been put into practice, rather than being only "practice-ready." Members of the committee could encourage TRB to create and promote products more easily consumed and used by practitioners, such as better online access to any research or other products that have been identified as ready to put to immediate use. Travel Forecasting Resource[20] has the potential to be such a mechanism.

The mechanism to address some aspirations is unclear, thus the need for continued discussion within existing communities. There are four main understudied research topics that we believe need more attention: demonstrations and descriptions of innovative models in specific practice contexts; post-facto evaluation of model accuracy and relevance; direct comparisons of different modeling approaches; and research about how and whether innovative models are used in

[18] http://itmconference.com
[19] https://zephyrtransport.org
[20] http://tfresource.org/Travel_Forecasting_Resource

practice, including an evaluation of the efficacy of the simple models that are often relied upon in lieu of the most innovative techniques.

Finally, we believe one of the most important aspects of making connections between research and practice is to foster more interaction and discussion among academics (particularly faculty and students) and practitioners (particularly agency personnel). One suggestion is to challenge faculty involved with relevant TRB committees to meet at least once per year with their local agency staff to present and discuss their research, and dialogue about how and whether it could be made more accessible, helpful and/or relevant to planning processes. This interaction challenge could be recognized yearly in the relevant committees by identifying faculty members who have successfully held a meeting in the previous year, receive and summarize reports from committee members on those meetings, and report on the numbers of total committee members who have engaged in such meetings.

Theme 5: Develop the workforce

In order to have widespread benefit, advances in the field must be matched in pace by advances in the knowledge, skills, and coverage of the workforce. In order to meet this need, the field must further engage current professionals, nurture the next generation, and expand the pipeline and definition of what it means to be a “travel analyst” or “travel modeler”. Current issues include: once trained, many qualified individuals are recruited away to more lucrative careers leaving key positions under-filled; professionals often lack the time and resources to advance their knowledge and skills at the pace of technological innovation occurring in the space; the field is not regarded with respect commensurate with its qualifications and educational attainment; and there is a severe lack of diversity in that the demographics within the field do not come close to reflecting the demographics of the populations served by the tools and models.

Aspirations

The travel modeling field needs to **broaden its brand beyond models** to match the needs of decision-makers for all data-based insights, and attract talent that has many of the matching technical skills, but didn’t participate in traditional travel modeling education. To that end, the industry must coalesce around a more encompassing title, such as *travel analysis*, *travel systems science*, or similar.

Travel modeling should **have an organizational home** with a welcoming front door devoted to *recruiting* people to the industry, *educating* professionals in the space, *collaborating* across industries and boundaries, and *keeping* effective people in the field. This organization would be committed to rolling out the welcome mat for potential professionals as well as collaborators and stakeholders. This organization would also serve as a clearinghouse for teaching materials and non-traditional learning experiences. In other fields, these organizations are called *backbone organizations*[21]. Backbone organizations are a critical component of *collective impact*, a proven set of organizational principles to efficiently align multi-stakeholder initiatives towards achieving a common agenda (Kania and Kramer 2011[22]). The organizational home, or backbone organization, should coordinate a learning network, and fulfill or facilitate other key components of collective impact such as articulating and owning a common agenda, sharing measurement, communication, and trust. The backbone organization can take the lead on a number of the aspirations that follow.

In order to **recruit** the needed workforce, we need to broaden our pipeline of professionals by increasing awareness of the field starting in high-school and beyond traditional fields of study as well as provide clear pathways for career progression. This would involve the creation of meaningful exposure to the field to include prestigious internships at all levels (high-school through experienced professional) and appropriate exposure to forecasting and planning analysis

[21] https://ssir.org/articles/entry/understanding_the_value_of_backbone_organizations_in_collective_impact_1#
[22] https://ssir.org/articles/entry/collective_impact

to graduate students. Central to the focus will be on engaging people that are typically underrepresented in the travel modeling field.

We need to **educate** the travel modeling workforce by developing and maintaining a fundamental curriculum that is accessible from various entry-points to diverse ages, sectors and career-levels. In many cases, teaching has not kept up with research. We must undertake an effort to create, disseminate, maintain, and update a list of field "fundamentals" to enable educational institutions to benchmark their curricula and keep them up to date as well as provide continuing and cross-sector education opportunities. Fundamental curriculum components shall encompass not just technical knowledge but scientific inquiry and public policy. In order to attract entry to the field from adjacent fields of study, the curriculum should have clear entry-points such as "travel analysis for data scientists" or "travel analysis for planners". To supplement classroom learning and cross-pollination of ideas, we should develop a corps of trained speakers about practice and research as well as welcome and define experiential learning opportunities such as capstone projects, fellowships and internships.

We must help industry professionals **collaborate** across sectors and industries by conducting both active and passive network weaving exercises in the form of a learning network. Active network weaving should include match-making between practitioners and researchers or researchers across industries, calls for assistance to other research communities, in-person gatherings, and fellowship programs. Passive network weaving includes gathering and then broadcasting relevant news and information across silos through channels like social media, newsletters, blogs, and journal articles. As studied by Ehrlichman and Sawyer (2018), learning networks work best when front-facing resources (i.e. packaged research briefs, communications, and outreach) are matched with network facilitation activities and back-office infrastructure. We will be able to **keep** professionals in the field by making their work fun, interesting, worthwhile and respected. To that end, the community must be warm and welcoming while cultivating a culture of rigor and continued learning. In its interface with society, we should provide the means for the industry to cultivate success and guide it towards useful work. And finally, we should reward people, projects, and processes that exemplify success. Travel modeling does not historically have a venue for awarding non-academic success but this is a critical component to draw positive attention to the field externally as well as holding up those within the field as exemplars.

The final thing we must do is continuously measure ourselves and our progress through a regular survey of our workforce and its stakeholders in order to identify where we should be expending our efforts.

Positive cases

Many industries or industry subsectors have been able to increase their workforce performance. Specific programs and projects examined here include fellowships and experiential learning experiences, curriculum development, communications, rewarding excellence, and regular benchmarking to update goals and track progress.

Teach for America attracts talent that didn't traditionally think about a teaching career by providing a well-curated, high-profile experience akin to a fellowship that is layered on top of a job with direct impact and service. Upon completion, fellows often have their pick of careers in- or outside of teaching but bring with them an understanding of the sector that they would not have gained without the experience. Data Science for Social Good (University of Washington and University of Chicago) also uses the fellowship model to bring together a diverse background of applicants to work on a specific issue or problem. One of the successes of this model is that the finite amount of time to focus together helps manage distractions from other things and results in more effective collaboration across individuals.

Many universities use a capstone experience such as a studio project, professional report, or senior design project to provide a direct link between students and problems or issues identified by practitioners. Some of these experiences are opportunistic while other universities (such as the University of Texas and the University of Washington) have defined processes and open calls soliciting problem statements, some of them even allowing interdisciplinary teams.

Software Carpentry, a project of the NumFocus Foundation, has put together curricula for data science and basic software tools that have been replicated and expanded based on their basic format. Some companies have made their curricula and teaching tools open, like Google's Tech Dev Guide[23], which was developed in conjunction with academic faculty at several institutions.

There are several organizations within the transportation industry that are producing documents publicizing the industry and relevant topics to outsiders while also effectively transmitting information among industry insiders. TransitCenter produces a series of graphically-pleasing publications[24] based on ripe topics such as "The Data that Travelers Want" as well as documenting trends at regular intervals such as their "Who's on board" series. SPUR produces policy papers based on in-house technical research that is then approved by a policy body, such as "Solving the Bay Area's Fare Policy Problem" (Fleisher, 2019). The North American City Transportation Officials (NACTO) organization writes both design guides as well as policy-based recommendations such as "Guidelines for Management of Shared Active Transportation" (NACTO, 2018). These reports are written at a level that is appropriate for a policy-maker or citizen interested in the topic as well as technical experts who want to remain up-to-date. Other organizations (i.e. Shared Use Mobility Center, The Overhead Wire, Science News, Streetsblog), create reports or newsletters at regular, time-based intervals (daily, weekly, monthly). These complementary methods round out the basic research and information dissemination needs for an industry.

Industry awards are common, with Women's Transportation Seminar (WTS) standing out as rewarding individuals for service and leadership in addition to technical merit-based awards.

While a regular report on the state of the workforce for a specific industry seems rare, the Women's Transportation Seminar has put together a series of Glass Ceiling Reports to document

[23] https://techdevguide.withgoogle.com
[24] http://transitcenter.org/publications/

progress and remaining challenges for women in the transportation workforce (WTS, 2016). Salary surveys are common (and required for many public agencies), but are often not publicly released.

Call to Action

Attract additional talent

Academic institutions and professional communities play a large role in attracting talent to the travel modeling workforce. Academic institutions should attract would-be travel modelers coming from other disciplines by creating multidisciplinary degree programs and labs that draw from a multitude of academic backgrounds. In order to provide real-life context and engagement, coursework should include a variety of first-hand practitioner perspectives and encourage semester- to a year-long internships or projects where students have the opportunity to see through the lens of an industry professional.

We must cultivate a front door to the community and a brand for the field – welcoming would-be travel modelers and concerned stakeholders alike. To that end, organizations should develop a speaker corps of trained speakers, be a presence at *adjacent* industry events, and package and broadcast important information between sectors and industries via newsletters as well as synthesis of ripe topics.

Educate new and existing workforce

In order to educate the existing workforce, the Transportation Research Board (TRB) should continue its Spring conference cycles of Planning Applications and Innovations in Travel Modeling and seek to broaden their appeal beyond the usual suspects and approaches.

Current travel modeling practitioners should volunteer to develop a tutorial, review coursework for relevancy, speak at or teach a class, and participate in ripe topic synthesis and be compensated by their employers or an organization rather than sacrificing their livelihood.

Collaborate among ourselves

Travel modelers need catalysts to interact outside of our own sector- or industry-specific cul-de-sacs and should seek to do so at a minimum by putting data and research into the world in a manner that promotes public discourse rather than presuming they have settled something. To that end, the industry should embrace the principles of "open science[25]" and require meeting certain open science thresholds for funded research.

Fellowship models such as Data Science for Social Good provide funding and venues for active interaction and should be replicated in the travel analysis industry by starting with a few test institutions. Academic institutions can solicit collaboration with practitioners through capstone project requests for proposals and speaker requests. When publishing research and reports,

[25] https://en.wikipedia.org/wiki/Open_science

researchers should use open data in useful formats to the extent possible and be accompanied with sufficient information to reproduce the results. Practitioners should exercise an open-door policy for interested students and invite academics to learn about their work and participate in strategy as well as conspicuously showing up to events with students or would-be students.

Retain talent

In order to retain talent in our workforce we must deliver benefits (both tangible and less tangible) that are comparable to the opportunity cost of staying in the industry as well as recognize and reward good work.

Salaries and benefits should be scaled and informed by the labor and jobs markets by conducting and publishing a regular state of the workforce survey. Employers should develop job titles and salary ranges that consider the market for similar skill sets.

Because this sector is unlikely to be able to be competitive strictly on a monetary basis, it is critical that employers deliver job satisfaction through less tangible benefits such as compelling, important and exciting work, a happy and jovial workplace and professional community, and opportunities to broaden skill sets. If people view their job as important and of true service to the world, they are more likely to stay. Therefore, it is critical that travel modeling managers identify and pursue a workplan that is relatively free from low-value work as well as provide compelling information to policy-makers and the general public that demonstrates the value of their work.

Finally, we need to deliberately nominate travel modelers for broader industry recognition as well as recognize our own though awards and accolades. The Zephyr Foundation's inaugural set of awards distributed at the 2019 TRB Annual Meeting is a start, but needs to be broadened and replicated.

Theme 6: Continue conducting foundational research

Fundamental research is aimed at establishing a foundational body of theory, methodology, and factual knowledge on which to build a particular domain of intellectual/scientific inquiry. It defines the science underlying travel demand modeling. What constitutes fundamental research in travel demand modeling, and what are the key questions that are currently driving the development of the science in this highly multidisciplinary domain with fuzzy, porous boundaries?

Two caveats are in order. First, what is considered *fundamental research* in a given domain is often considered *applied* in another. What is *fundamental* to an engineer is often *applied* to a physicist or mathematician. Likewise, fundamental research questions to travel demand modelers may or may not be considered fundamental by a mathematical economist or behavioral psychologist. Second, fundamental research questions depend on the lens or measurement tool through which one is observing the system of interest. Observing behavior as a response to stated choice questions where the stimuli are written questions is different from a neuroscientist's analysis of brain MRIs stimulated by various sensory stimuli.

Articulating the most relevant or important fundamental research questions in travel demand modeling (TDM) is a challenge on multiple fronts, namely (a) the diversity of influences and disciplinary perspectives, (b) the scope of the domain itself, (c) the relatively ad hoc organization of the existing body of knowledge, reflected in the absence of a dominant field-defining textbook, and (d) the variety of motivating policy, planning and engineering applications of TDM. These challenges lend further urgency to the need for articulating and addressing the fundamental research questions undergirding the TDM domain.

The questions identified in this discussion are grouped into four different areas of investigation or applications of TDM:

1. Measurement and characterization of travel patterns and choice processes
2. Understanding travel and activity choice processes and their determinants
3. Developing mathematical and other formal representations of choice processes
4. Forecasting future demand and changes in response to policies, technologies and transportation system features.

These are discussed in turn hereafter. In addition to the substantive and methodological questions noted, additional background is provided on the priority (or lack of it) these questions may have received, why these are challenges, and related developments to address these issues and realize the opportunity when applicable.

1. Measurement and characterization of travel patterns and choice processes

The starting point of any scientific investigation is the observation, measurement and characterization of the processes of interest. Breakthroughs in scientific knowledge have often come from improvements in measurement capabilities—the better, more precise and powerful the ability to measure, the greater the ability to characterize and understand the underlying processes. In TDM, two types of measurement have generally been available—*passive*, in which the observed entity does not directly participate (and is often not aware of being observed), and *active*, specifically eliciting responses from the subjects of interest. The former is rooted in physics and engineering, such as traffic and traveler counts, while the second is rooted in the social sciences and survey research methods. A main limitation of the former is it only conveys the occurrence of certain behaviors, with no insight into purpose, context or motivation. The main caveat with the latter is the inherent biases in self-reported information—a social manifestation of the well-known Heisenberg Uncertainty Principle of statistical physics.

While considerable development has occurred in the past decade in methods related to both passive (e.g., GPS tracking, Bluetooth and wi-fi "sniffing") and active (e.g., interactive surveys, stated choice experiments) measurement of travel behavior, perhaps the most notable is the ability to track human trajectories over time and space—including activities performed and associated durations. With trajectories, the main manifestation of travel and activity behavior is captured, providing (a) objective answers to the *where*, *when* and *how long* aspects of this behavior, and over time *how much* (frequency); (b) a basis for reasonable inference of *what* (purpose, based on the nature of the locations visited) and *by what mode* (by inferring travel speeds); but (c) virtually no clue as to *why*, *with whom*, at what cost, and *relative to what* (alternatives not chosen).

Addressing the latter requires augmentation of passive tracking with some form of active traveler input in response to querying, which is likely most reliable when performed in real-time contemporaneously with the activity in question, though would still yield valuable insight after the fact. Furthermore, other sources of passive observations, such as financial transaction records (e.g., transit fare cards, credit cards, mobile payment) could add considerable, largely objective context and content to the space-time trajectories, provided it is possible to reliably fuse these disparate sources. Other, more subjective data streams include social media posts, which can further contribute to context inference and exogenous influential factors. However, more complete understanding and eventual modeling of the complex underlying decision processes generating these behavior traces require more engaged elicitation and elucidation processes.

Frameworks and methodologies to characterize and fully leverage the informational richness of space-time trajectories, augmented with various passive or active sources of additional data, remain, surprisingly, lacking. Techniques exist in geography and network science to compare space-time trajectories, and to depict certain characteristics of the underlying graph structure.

2. Understanding travel and activity choice processes and their determinants

The foundation of a domain consists of a set of observationally-verified and generally accepted facts and phenomena, as well as theories and principles that help explain and interpret these phenomena and their differences across contexts and cultures. The TDM domain has lacked a strong backbone of core knowledge in travel and activity behavior that would be common across the various disciplinary perspectives that have taken an interest in this domain. Economists tend to examine these processes from their own particular prism and formalism; likewise psychologists and sociologists, whereas planners and engineers take a generally more pragmatic view of tools designed to solve specific problems in particular contexts.

Nonetheless, the body of knowledge derived from travel surveys and travel modeling exercises has continued to grow over the years—with realizations that different travel time components may not be weighted equally or consistently, that reliability of travel time may be equally if not more important than mean trip time in evaluating alternative modes, that attitudes may help explain choice, and so on. More recent studies have shown concern with richer behavioral phenomena such as inertia, asymmetric preferences for gains vs. losses when evaluating uncertain prospects, and so on. And perhaps most importantly, our ability and desire to capture heterogeneity in preferences across individual travelers has led to new model developments and substantially more detailed model results. Without a broadly accepted and rigorous framework the core knowledge tends to dissipate, or become increasingly polarized amongst subcommunities with similar perspectives. It also becomes inefficient, as the continuing stream of new discoveries remains disconnected, or sometimes lives in its own bubble that may bifurcate from the core.

A key question that has occupied a segment of the travel behavior community is that of establishing causality, rather than mere statistical associations. Part of the motivation lies in the potential policy implications of the findings. A supposedly causal relationship between a determinant and an outcome would suggest that interventions on the determinant would in all likelihood result in a change or impact in the desired outcome(s). A well-known and highly controverted example is the effect of the built environment on travel behavior (Handy et al., 2005). Establishing causality in the behavioral sciences is especially challenging when relying on observational data, which may further be subject to self-selection biases, when multiple factors influence the response variables, and when the responses themselves are subject to considerable uncertainty. Statistical significance of model coefficients is not a sufficiently powerful basis for establishing causality. Essentially, causality in this context would have to reflect a scientific and professional consensus, when considering the totality of the empirical evidence. Only when well-designed controlled experiments are administered under certain conditions is there a credible basis for claiming some degree of causality, subject to that very limited set of conditions. However, conducting controlled experiments in the travel behavior domain is often impossible, due to ethical, practical, or financial infeasibility. In an era of big data and GPS trajectories, the ability to establish causality in a strong sense diminishes, however the observational basis for establishing reliable empirical relations is comparatively greatly enhanced.

In addition to core facts (characteristics) and phenomena, fundamental knowledge entails understanding the mechanisms underlying choice processes that determine travel and activity outcomes. Some of these questions include: How do people decide where to engage in out of home activities? Where to live? Where to work? What causes change in travel behavior (and home/work location) over time but also, change in how people make decisions about travel (and home/work location) over time? What are the respective roles of attitudes, habits and cultural changes? What are the relative roles of the economy, the built environment, attitudes, lifestyles in household and firm travel behavior and location choice?

From a modeling standpoint, it is essential to better understand the dynamics of user choices in a variety of travel and activity choice dimensions. While a large body of work exists on many aspects of user choice dynamics, modeling frameworks have yet to recognize that daily, repeated choices are different than infrequent, or first-time choices. Everyday decisions tend to exhibit a great deal of inertia, eventually becoming habitual, and could even be viewed in the same vein as "instinctive" choices—or at least choices that are not questioned and subject to revision on a daily basis. Everyday decisions also tend to be made in circumstances where the alternatives are better known than infrequent decisions, including the travel options available as well as typical congestion levels. Better understanding of the fundamental determinants of household travel behavior is a first step towards incorporating those into our models to (a) improve model forecasts, (b) identify areas of forecast uncertainty, (c) determine how to properly represent supply in the model system, and (d) inform policies ranging from infrastructure development and management to social marketing and education.

3. Developing mathematical and other formal representations of choice processes

Early travel demand models were aggregate in nature, capturing relations among statistical averages of direct demand quantities, drawing primarily on developments in social physics (e.g., entropy models; Wilson, 1970), with limited behavioral content, often masked behind averages of sometimes widely distributed quantities. The basic theories for TDM at the disaggregate (micro) level came from microeconomics, particularly consumer theory, and basic utility maximization. Travelers were modeled as rational economic agents, seeking to maximize their respective utilities, derived not from quantities consumed (travel by different modes) but from the attributes of these modes—referred to as indirect utility functions. Choice models were then built using both revealed and stated preference data, recognizing observation errors from various sources, formalized in random utility maximization (RUM). By assuming certain model forms for the distribution of these errors, different probabilistic choice model forms have provided the backbone of the past 40 years of travel behavior research and applications to demand forecasting (McFadden, 2001).

However, this framework has hit against several limitations in seeking to capture more realistic behavioral notions and phenomena often manifested in actual behavior. Inertia, habit formation, nonlinearities in valuation, thresholds, asymmetries, hierarchical/lexicographic features, complex heterogeneity patterns, and several others are pushing the boundaries of our tools. On the supply-side, not enough attention has been given to representing the characteristics of transportation supply and the choice contexts that influence behavior. For example, we use built environment variables to try to explain why residents of San Francisco and NYC don't own cars, instead of the simple fact that they live in dwelling units that don't have garages because this information is not readily available and perhaps not so easy to forecast. Given the mostly econometric perspective within which the dominant class of choice models has evolved, much effort has been devoted to error structures and resulting choice model forms, rather than to the fundamental choice processes and phenomena that do not conform with prevailing utility specifications (e.g., linear-in-parameters and simple polynomial forms). With greater reliance on simulated likelihood estimation techniques (Train, 2009), and efficient computational techniques for model estimation, virtually any error structure could be specified to reflect the characteristics of a wide range of data measurements and informational situations for model estimation.

To better capture some of the above behavioral phenomena, techniques from psychology and psychometrics have long been integrated with econometric choice models—e.g., structural equations and hybrid models—often making use of extensive additional data on subjective factors from survey respondents. While resulting in better model fit to the estimation data and/or providing more behavioral richness than simpler model structures, application of these models for forecasting is not straightforward.

A major likely disruptive phenomenon/change that is beginning to manifest itself is the greater availability of a wide range of data streams (so-called “big data”) from transactions and various tracking devices, which in turn call for a different set of tools, outside of the mainstream. While econometric models have primarily evolved in conjunction with relatively small samples, and the need for powerful and rigorous statistical inference using such samples, big data changes the game in that statistical significance is not the primary consideration, but rather the ability to identify meaningful patterns in the data, identify clusters of observations (market segments) on the basis of several variables, and establish relations among data variables. Accordingly, a set of techniques have evolved from mainstream statistics and computer science (namely Artificial Intelligence) to perform such analyses. While these techniques have typically been used more commonly in a “black box” manner, integrating their role in data discovery and pattern recognition with formal choice process representation is a critical fundamental methodological priority. One obstacle to such integration is a difference in model development cultures; econometric models typically expect the model specification to reflect strong a priori assumptions (resulting from some underlying theory), and the data to essentially refute or not refute those assumptions. On the other hand, data science analytics are typically data-driven, intended to allow the data to reveal what patterns and relations it might contain, without strong pre-judging. The opportunity here lies in combining new formalisms (e.g. Deep Learning Embeddings), that have shown ability to represent abstract concepts, with the theoretical foundations, that often arrive oversimplified to the actual model specification.

4. Forecasting future demand and changes in response to policies, technologies and transportation system features.

A major objective of developing travel and activity choice models is to be able to predict future demand under various possible scenarios, and explore how demand might change under different contemplated policy actions. While forecasting has been the primary application of TDM tools in practice, it has not received the level of attention it merits in the academic research community, where it has been relegated to a “necessary evil.” Development research tends to focus on estimating models with much less investment in how to use these models to develop forecasts that target policy needs and that recognize the inherent uncertainty of the process itself (Mahmassani et al., 2013).

Fundamental questions regarding forecasting methods as applied in the transportation domain address some issues encountered in any forecasting exercise—how "good" is the forecast, how good does it need to be to support effective decision-making? How do we explicitly recognize that the quality of the forecast typically degrades the longer the forecast horizon? How do we keep forecasts up-to-date in an adaptive process that incorporates the latest available data?

Methodologically, explicit recognition of forecast quality in model development and parameter estimation, e.g. through Bayesian methods (Geweke and Whiteman, 2006), would be an important direction for our models and their use in practice. Similarly, formal statistical learning techniques (e.g. online learning, probabilistic graphical models, ensemble methods) could provide a robust methodological framework for updating model parameters and/or obtaining consensus forecasts in a multi-method adaptive process over time.

However, the more daunting issues arise from the inherent uncertainty of unfolding future scenarios—i.e. values of the "input" variables for the contemplated future scenarios, as well as whether these scenarios affect the underlying behavioral mechanisms of travelers. The former point especially has been largely neglected, with very little emphasis on making predictions of the level of service data that feeds the models. The latter point relates to a largely unchallenged assumption in travel demand forecasting—that behavioral models remain valid over time while the attributes of the choice alternatives (and travel context) might change. This assumption can only be expected to hold when changes over time are relatively minor. However, emerging new technologies such as autonomous vehicles, urban personal mobility tools and new ways of delivering services, such as mobility-as-a-service, have the potential to transform the way people organize and schedule their activity patterns over time and space, expanding users' feasible set of choice alternatives, changing relative valuation of travel attributes (e.g. value of time spent in vehicle), and enabling more optimizing (relative to satisficing) behavioral mechanisms.

Connecting forecasting and model results with decision-making remains a key task for our community. In terms of impacting practice, much remains to be done in terms of extracting and communicating insight from model forecasts, and eliciting interaction between models and users in decision-support contexts. Blending the human behavior side with data and model predictions remains an art, with many challenges but incredibly rich opportunities.

Aspirations

In light of the above fundamental questions, several aspirational goals for the travel demand modeling community of scholars can be articulated.

Codify knowledge: As noted, absence of a recognized body of core knowledge is an impediment to the further advancement of the field of transportation behavioral modeling as a scientific domain as well as an area of professional practice. While occasional survey articles at the level of "handbooks" aimed at practicing planners provide tabulations of findings and factoids from model results, we envision a more fundamental and comprehensive undertaking that would define core knowledge, provide a framework for advancing and updating that knowledge, reflecting common themes and differences across various studies, lessons learned and best-practices, as well as identifying gaps that would serve to motivate further work aimed at filling those gaps.

Behavioral Directions: The wish list is quite long in terms of capturing richer behavioral features and phenomena in travel and activity choice models. Key elements on the list include:

- Incorporate behavioral dynamics: learning, evolving, memory, diffusion, role of experience and information.
- Incorporate non-linearities, thresholds, asymmetries, hierarchies, lexicography, cognitive heuristics in model specifications.
- Recognize risk perception, relative valuation and regret aversion in choices under uncertainty.
- Emphasize activity motivations, goal achievement, higher-order lifestyle orientations, and mobility- oriented market segments.
- Continue to develop better understanding of activities and utility of activity participation, and stronger linkages between activity and travel choices, especially in light of emerging technology developments (autonomous vehicles, new mobility alternatives).
- Better define choice sets/alternatives (lifestyle/mobility).
- Take agents seriously as a construct for capturing and delivering behavioral diversity and heterogeneity in model development and application.
- Recognize the role of other activities and other individuals as constraints in individual travel behavior.

Data: Related to the above discussion on measurement and observation of traveler choices and behavior, the need for reliable, relevant and representative data remains critical for most knowledge creation and model development activities of relevance to transportation demand modeling and forecasting. Our aspirational list includes:

- Leverage “big” passive data streams such as traveler trajectories, traffic counts, speeds, travel times, and farecard data for travel demand characterization and behavioral mapping over time and space.
- Merge non-traditional transactional data (apps, credit-cards) to form a more complete picture of travel and activity behaviors along with likely contextual variables.
- Blend small, deep (survey) data with big, shallow data (crosswalks).
- Develop and test robust methods for fusion of disparate datasets, and provide support to tasks such as external validity and extrapolation to different realities.

Modeling frameworks: To the extent that models provide the primary platform for both encoding domain knowledge and delivering that knowledge for forecasting to support planning and operational decision-making, this category addresses both fundamental and application-related concerns. Several goals for developing and applying modeling frameworks have been articulated, including:

- Reduce latency between calibration data observation, model estimation, and application for forecasting.
- Formalize adaptive forecasting frameworks, leveraging both real-time continuous data streams and targeted special-purpose online travel surveys to update models and forecasts, e.g. using Bayesian methods and statistical learning techniques.
- Deal with uncertainty in forecasts.
- Revisit the role of forecasting models in the context of decision-making, establishing stronger linkages between forecasts and decisions.
- Improve methods to forecast for conditions far away from current conditions, and to inform decision-making recognizing model capabilities and limitations.
- Make models more responsive to new policy interventions and technology scenarios.
- Develop a new class of responsive metamodels with efficient software/computational performance that would put models closer to stakeholders.
- Revisit model formulation and specification to make them more readily transferable geographically.

Positive cases

The travel behavior/demand modeling field has been dynamic and innovative, benefiting from an openness to cross-disciplinary influences and changing motivations and policy directives. On the other hand, travel demand forecasting in urban transportation planning practice has been less flexible and more rigidly specified, possibly due to federal requirements for standardized output and modeling approaches (National Research Council, 2007). The list of positive cases across the spectrum of topics addressed in this theme would be quite extensive; a few examples are selected below.

Codifying and transmitting knowledge: Discrete Choice Analysis textbook

Ben-Akiva and Lerman (1985) played a critical role in disseminating the tools of the trade from a handful of universities in the US and around the world to a large audience of graduate students in transportation systems planning and modeling. The scope, level, clarity and timing of this textbook enabled professors across the world to instruct legions of students and later practitioners and researchers in the art and science of discrete choice modeling— transforming travel demand modeling from an apprenticeship skill to a modern scientific core discipline. It helped promote random utility theory to a foundational position, standardize terminology and notation for later research contributions, and define a skillset that employers could expect in professional recruits. (At about the same time, Sheffi (1985) played a similar role in the related area of urban network modeling.)

Data and behavioral directions: Laboratory experiments to study user choice dynamics

Obtaining data to study choice dynamics in transportation has typically been limited by the difficulty of obtaining simultaneous observations of choices made by travelers along with the attributes of the choice alternatives faced by those individuals. Furthermore, traditional stated choice experiments with pre-defined experimental levels are not responsive to the choices actually made by participants. To circumvent these issues, laboratory experiments in which travelers interact in real-time with simulated traffic systems substantially advanced the ability to understand and model repeated choices of travelers in everyday situations, particularly route and departure time decisions (Mahmassani and Herman, 1990; Mahmassani, 2009). Behavioral frameworks built on the notion of Simon's bounded rationality (Simon, 1955) helped expand and advance the behavioral foundations of travel models for everyday choices (Mahmassani and Chang, 1987). These types of experiments were instrumental in modeling the effect of real-time information on travel choices long before the introduction of apps (eg. Waze) on mobile devices, and enable network-wide assessments of the impact of information-related management strategies on network performance. Subsequent developments introduced concepts from behavioral economics to better incentivize respondents (Selten et al., 2004). More recent work has introduced three new promising elements: (1) gamification and personalization through interactive platforms on mobile devices (Jariyasunant et al., 2015); (2) auction mechanisms for truthful elicitation of preferences, e.g. willingness to pay for congestion-managed lanes (Brownstone et al., 2016); and (3) virtual reality environments, e.g. for future technologies such as autonomous vehicles or fleet services (Farooq et al., 2018).

Model frameworks and behavioral directions: Hybrid choice models

Marketing researchers have long known that attitudes influence preferences and thus resulting choices. Several travel behavior researchers incorporated attitudinal variables in their RUM choice models; others used Structural Equations Models (SEM) to capture joint responses along multiple inter-related dimensions. However, a unified framework integrating these "softer" behavioral constructs with RUM-based discrete choice models, and providing methods and tools for joint parameter estimation, did not appear until nearly three decades after the initial spread of discrete choice models in travel demand modeling. Referred to as hybrid choice models, they enable integration of latent class constructs along with attitudes and perceptions in a coherent and internally consistent manner, while allowing consistent and efficient joint estimation of model parameters (Ben-Akiva et al., 2002). These models have been applied across a spectrum of choice situations, and have contributed substantially to improving the behavioral content and realism of travel choice models to support effective policy decisions, particularly in areas where overcoming inertia and negative perceptions are of the essence.

Call to action

It is not evident that any one event or action item could achieve the aspirations articulated with this theme. Inter-disciplinarity often entails relinquishing ownership and control over the evolution of a domain of scientific inquiry, and opening up to influences that leave their own mark. A diversity of application areas and clients for these applications also means that standards of practice may not always reflect the more advanced knowledge or methods in the field. The kind of evolution envisioned here could come about as a result of both internal and external interventions. Here are a few suggestions towards that goal that reflect the discussion in this and other themes.

Mind Reset: from small data to big data. This impacts methods as well as how we approach theory development and model building. Let the data tell more of its story, rather than fit it to rigid a priori theory. Exploration and visualization regain their essential role in research, and allow new questions and perspectives to emerge. Avoid doing the same things, just with more observations. Expand the toolkit and embrace machine learning techniques, and explore ways that the old model constructs can improve with new perspectives.

Get out of the box-- RUMinate no more. Cognitive scientists continue to give us a rich array of perspectives and models of how the mind works. Random utility maximization with linear-in-parameter specifications have served us well, but have long ago hit against the limits of marginal usefulness and imagination.

Quick experimentation vs. slow motion. Time frames for typical data collection in travel behavior research have typically been excruciatingly slow. Travel diaries at the level of a city or metropolitan area take months to plan and execute, and subsequently process and analyze into working models. Special-purpose studies similar require months of survey design, pre-test, administration, etc. Often the motivating questions have become obsolete. Just as political pollsters keep taking the pulse of public opinion for various issues and candidates, we should be able to monitor and track people's attitudes and usage of mobility options. There can be apps for that, too. Opinions, attitudes, awareness, what to do, incentives can all be measured and tested on short notice. Travel experiences are increasingly tracked and recorded by private providers, or background apps. Offer opportunities for quick-response experiments through auctions and other mechanisms. There is no justification for using a decade-old survey to study people's possible responses to contemplated policies.

Riding the long wave. While on-demand travel data and state choice responses could greatly improve planning practice and policy design and implementation, the need for monitoring, studying, documenting and uncovering long term trends at the scale of generational cohorts (eg. aging boomers and millennials) is critical, and an essential, now missing piece of the travel behavior and demand puzzle.

Sharing is caring. As noted in several of the thematic discussions, data sharing can greatly foster rapid development and innovation in the travel behavior domain. Considerable sharing has been the norm for a long time in the planning arena. The main sources for many studies rely on Census data and related Census Bureau surveys; most travel diaries collected by various metropolitan areas tend to be shared, if informally. Even small-scale surveys are typically shared on request. What we need going forward is different—we need big data streams to be collected on a continuing basis, and shared on a continuing basis, with minimal time lags. We need more collaboratories (NSF has started doing that but then appears to have moved away from them), observatories and the like.

Play in the sandbox (commons). The convergence of technology, data and policy opens an era ripe for experimentation in the study of travel and activity behavior. From virtual reality to gamified incentives for green choices, the opportunities for insightful and transformative research are richer than at any previous time since the recorded beginnings of the field. Following up on the preceding point, development of shared, easy to access resources at state or regional levels in the US and around the world would greatly contribute to enabling young researchers to do meaningful novel research at scale instead of working with self-contained homemade small prototypes. There is a role for fundamental research agencies such as NSF or mission agencies such as DOT or DOE to help set up such resources (similar ideas have been successfully applied in the traffic flow and operations domain).

Rewarding forecasts. Travel demand forecasters have had a relative free ride. Rarely are forecasts of ridership and costs for urban rail projects systematically compared to what actually materialized (Pickrell, 1989). On the other hand, many small successes remain unreported, largely because travel demand forecasting is not practiced as a continuing process but rather as one-time events. In the era of big data, forecasts should be readily assessed, ex post, over time—because the path towards a presumed final equilibrium state is often as important, if not more so, than the presumed final state. Thinking outside the box, why not gamify the rewards to incentive forecasters to produce their highest-confidence forecasts, and learn to improve them over time? Reward functions are explicitly built into Bayesian methods, but in transport these remain to be specified.

Cluster away clutter. Segmentation has always been an effective technique to capture the effect of interacting, correlated attributes. Latent segmentation was an elegant approach technically, but did not necessarily produce interpretable nor forecastable segments. Clustering techniques applied to big data streams help model building as well as contribute to forming communicable fundamental behavioral knowledge and interpretable theoretical constructs. Clustering deserves more respect in the travel behavior community, and could help conquer increasing complexity of factors that modelers seek to capture.

Rewrite the book. To codify knowledge, and build on shared foundations, the community of researchers needs to periodically confront its findings and integrate them into a coherent body of knowledge, possibly reflecting varying degrees of evidential basis. The International Association of Travel Behavior Research played this role, in part, through its triennial meetings and associated books with state-of-the-art assessment of major current topics; this practice was however abandoned by the end of the first decade of the current century. Other specialty conferences played critical roles in codifying and advancing knowledge in areas such as dynamic models and activity-based approaches, as well as time use research related to travel. There is currently a vacuum in this regard, that agencies such as the National Science Foundation could step in to address.

References

Abadi, M., P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D.G. Murray, B. Steiner, P. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, and X. Zheng. 2016. "TensorFlow: A System for Large-Scale Machine Learning." Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation, Savannah, Georgia. https://www.usenix.org/system/files/conference/osdi16/osdi16-abadi.pdf .

American Institute of Certified Planners. 2016. "AICP Code of Ethics and Professional Conduct." https://www.planning.org/ethics/ethicscode/ .

Andersson, M., K. Brundell-Freij, and J. Eliasson. 2017. "Validation of Aggregate Reference Forecasts for Passenger Transport." Transportation Research Part A: Policy and Practice 96: 101–18. https://doi.org/10.1016/j.tra.2016.12.008 .

"Announcement: Reducing Our Irreproducibility." 2013. Nature News 496 (7446): 398. https://doi.org/10.1038/496398a .

Aschwanden, C. 2017. "There's No Such Thing As 'Sound Science.'" FiveThirtyEight, December 6, 2017. https://fivethirtyeight.com/features/the-easiest-way-to-dismiss-good-science-demand-sound-science/ .

Axelrod, R. 2006. "Advancing the Art of Simulation in the Social Sciences." In Handbook of Research on Nature-Inspired Computing for Economics and Management, edited by J.-P. Rennard, 90–100. Hersey, PA: Idea Group.

Bain, R. 2009. "Error and Optimism Bias in Toll Road Traffic Forecasts." Transportation 36 (5): 469–82. https://doi.org/10.1007/s11116-009-9199-7 .

Batley, R., J. Bates, M. Bliemer, M. Börjesson, J. Bourdon, M.O. Cabral, P.K. Chintakayala, C Choudhury, A. Daly, T. Dekker, E. Drivyla, T. Fowkes, S. Hess, C. Heywood, D. Johnson, J. Laird, P. Mackie, J. Parkin, S. Sanders, R. Sheldon, M. Wardman, and T. Worsley. 2019. "New Appraisal Values of Travel Time Saving and Reliability in Great Britain." Transportation 46 (3): 583-621. https://doi.org/10.1007/s1111 .

Ben-Akiva, M., and S.R. Lerman. 1985. Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press.

Ben-Akiva, M., J. Walker, A. Bernardino, D.A. Gopinath, T. Morikawa, and A. Polydoropoulou. 2002. "Integration of Choice and Latent Variable Models." In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, edited by H.S. Mahmassani, 431-470. Emerald Group Publishing.

Brownstone, D., M. McBride, S.-Y. Kong, and A. Mahmassani. 2016. “Experimental Studies for Traffic Incident Management (No. CA16-2804).” Proceedings of the Transportation Research Board Annual Meeting, Washington, DC.

Cambridge Systematics, Inc. 2010. “Travel Model Validation and Reasonableness Checking Manual: Second Edition.” Federal Highway Administration.

Campbell, D.T., and J.C. Stanley. 1966. “Experimental and Quasi-Experimental Designs for Research.” In Handbook of Research on Teaching, edited by N.L. Gage, 171–246.

Casadevall, A., and F.C. Fang. 2016. “Rigorous Science: A How-To Guide.” MBio 7 (6): e01902-16. https://doi.org/10.1128/mBio.01902-16 .

Dixit, V., T. Montz, and B. Wolshon. 2011. “Validation Techniques for Region-Level Microscopic Mass Evacuation Traffic Simulations.” Transportation Research Record 2229 (1): 66–74. https://doi.org/10.3141/2229-08 .

Epstein, J.M. 2008. “Why Model?” Journal of Artificial Societies and Social Simulation. http://jasss.soc.surrey.ac.uk/11/4/12.html .

Erhardt, G., D. Schmitt, J. Hoque, A. Chaudhary, S. Rapolu, K. Kim, S. Weller, et al. 2019. “NCHRP 08-110: Traffic Forecasting Accuracy Assessment Research, DRAFT Technical Report.” National Cooperative Highway Research Program. Transportation Research Board.

Farooq, B., Elisabetta C., and A. Sobhani. 2018. “Virtual Immersive Reality for Stated Preference Travel Behavior Experiments: A Case Study of Autonomous Vehicles on Urban Roads.” Transportation Research Record, 2672, 35-45.

Fleisher, A. 2019. "Solving the Bay Area’s Fare Policy Problem: How Streamlined, Integrated Fares Can Help the Region Realize the Promise of Transit." SPUR white paper.
https://www.spur.org/sites/default/files/publications_pdfs/SPUR_Solving_the_Bay_Area%27s_Fare_Policy_Problem.pdf .

Flyvbjerg, B. 2007. “Policy and Planning for Large-Infrastructure Projects: Problems, Causes, Cures.” Environment and Planning B: Planning and Design 34 (4): 578 – 597.
https://doi.org/10.1068/b32111 .

Flyvbjerg, B., M.K.S. Holm, and S.L. Buhl. 2005. "How (In)accurate are Demand Forecasts in Public Works Projects? The Case of Transportation." Journal of the American Planning Association 71: 131–146. https://doi.org/10.1080/01944360508976688 .

Galilei, G. 1638. Dialogues Concerning Two New Sciences. New York: Macmillan.

Gershgorn, D. 2017. "The Data that Transformed AI Research--and Possibly the World." Quartz. https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/ .

Geweke, J., and C. Whiteman. 2006. “Bayesian Forecasting.” In Handbook of Economic Forecasting, edited by G. Elliott, C. Granger, A. Timmermann. 3-80. https://econpapers.repec.org/bookchap/eeeecofch/1-01.htm .

Gilet, C. n.d. “Ozone Depletion: Uncovering the Hidden Hazard of Hairspray.” Edited by A. Thanukos. University of California Museum of Paleontology. https://undsci.berkeley.edu/article/0_0_0/ozone_depletion_01 .

Govindaraju, R.S., M. Hantush, and X. Chu. 2019. “New Policy for Transparency of Data, Models, and Code.” Journal of Hydrologic Engineering 24 (3): 01618001. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001785 .

Handy, S., X. Cao, and P. Mokhtarian. 2005. “Correlation or causality between the built environment and travel behavior? Evidence from Northern California.” Transportation Research Part D: Transport and Environment 10 (6): 427-444. https://doi.org/10.1016/j.trd.2005.05.002 .

Hartgen, D.T. 2013. “Hubris or Humility? Accuracy Issues for the next 50 Years of Travel Demand Modeling.” Transportation 40 (6): 1133–57. https://doi.org/10.1007/s11116-013-9497-y .

Holt, R. 2017. “Act for Science.” Science 355 (6325): 551–551. https://doi.org/10.1126/science.aam9177 .

Jariyasunant, J., M. Abou-Zeid, A. Carrel, V. Ekambaram, D. Gaker, R. Sengupta, and J.L. Walker. 2015. “Quantified Traveler: Travel Feedback Meets the Cloud to Change Behavior.” Journal of Intelligent Transportation Systems 19 (2): 109-124. https://doi.org/10.1080/15472450.2013.856714 .

Kavanagh, J., and M.D. Rich. 2018. “Truth Decay.” Product Page. 2018. https://www.rand.org/pubs/research_reports/RR2314.html .

Lanza, M.L. 1990. “A Methodological Approach to Enhance External Validity in Simulation Based Research.” Issues in Mental Health Nursing 11 (4): 407–22. https://doi.org/10.3109/01612849009006526 .

Mahmassani, H.S. 2009. “Learning from Interactive Experiments: Travel Behavior and Complex System Dynamics.” In The Expanding Sphere of Travel Behavior Research, edited by R. Kitamura, T. Yoshii, and T. Yamamoto. Emerald Publishing. https://www.researchgate.net/publication/255950584 .

Mahmassani, H.S., and G.L. Chang. 1987. “On Boundedly Rational User Equilibrium in Transportation Systems.” Transportation Science 21 (2): 89-99. https://doi.org/10.1287/trsc.21.2.89 .

Mahmassani, H.S., and R. Herman. 1990. “Interactive Experiments for the Study of Trip Maker Behaviour Dynamics in Congested Commuting Systems.” In Developments in Dynamic and Activity-based Approaches to Travel Analysis, edited by P. Jones. Gower.

Mahmassani, H. S., F. Koppelman, C. Frei, A. Frei, and R. Haas. 2013. “Synthesis of Traveler Choice Research: Improving Modeling Accuracy for Better Transportation Decision-making.” Federal Highway Administration, US Department of Transportation.

Marchau, V.A.W.J., W.E. Walker, P.J.T.M. Bloemen, S.W. Popper, Eds. 2019. Decision Making under Deep Uncertainty. Springer International Publishing.

McFadden, D. 2001. “Economic Choices.” American Economic Review 91 (3): 351-378. [Nobel lecture].

Miller, J.S., S. Anam, J.W. Amanin, and R.A. Matteo. 2016. “A Retrospective Evaluation of Traffic Forecasting Techniques.” FHWA/VTRC 17-R1. Virginia Transportation Research Council. http://ntl.bts.gov/lib/37000/37800/37804/10-r24.pdf .

NACTO. 2018. "Guidelines for the Regulation and Management of Shared Active Transportation." https://nacto.org/home/shared-active-transportation-guidelines/ .

National Oceanic and Atmospheric Administration. 2010. “Hurricane Forecast Improvement Program: Five-Year Strategic Plan.” http://www.hfip.org/documents/hfip_strategic_plan_yrs1-5_2010.pdf .

National Research Council (US). Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, & Transportation Research Board. 2007. Metropolitan Travel Forecasting: Current Practice and Future Direction--Special Report 288. Transportation Research Board, Washington, DC.

National Society of Professional Engineers. 2018. “Code of Ethics for Engineers.” https://www.nspe.org/resources/ethics/code-ethics .

Nicolaisen, M.S., and P.A. Driscoll. 2014. “Ex-Post Evaluations of Demand Forecast Accuracy: A Literature Review.” Transport Reviews 34 (4): 540–57. https://doi.org/10.1080/01441647.2014.926428 .

Odeck, J., and M. Welde. 2017. “The Accuracy of Toll Road Traffic Forecasts: An Econometric Evaluation.” Transportation Research Part A 101: 73-85. https://doi.org/10.1016/j.tra.2017.05.001 .

Patterson, E.A., and M.P. Whelan. 2017. “A Framework to Establish Credibility of Computational Models in Biology.” Progress in Biophysics and Molecular Biology 129: 13–19. https://doi.org/10.1016/j.pbiomolbio.2016.08.007 .

Paszke, A., S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer. 2017. "Automatic Differentiation in PyTorch." 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

Parthasarathi, P., and D. Levinson. 2010. “Post-construction Evaluation of Traffic Forecast Accuracy.” Transport Policy 17 (6): 428-443. https://doi.org/10.1016/j.tranpol.2010.04.010 .

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanerplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. "Scikit-learn: Machine Learning in Python." Journal of Machine Learning Research 12: 2825-2830.
http://www.jmlr.org/papers/volume12/pedregosa11a/pedregosa11a.pdf .

Pickrell, D.H. 1989. “Urban Rail Transit Projects: Forecast versus Actual Ridership and Costs. Final Report.” Urban Mass Transit Administration. http://trid.trb.org/view/299240 .

Pickrell, D.H. 1992. “A Desire Named Streetcar Fantasy and Fact in Rail Transit Planning.” Journal of the American Planning Association 58 (2): 158-176, DOI: 10.1080/01944369208975791 .

Popper, K. 1935. Logic of Scientific Discovery. 2005 reprint. London: Routledge.

Richmond, J. 2005. Transport of Delight. Akron: University of Akron Press.

Rosen, R. 1999. Essays on Life Itself. 1500 edition. New York: Columbia University Press.

Rosenberg D.E., and D.W. Watkins Jr. 2018. “New Policy to Specify Availability of Data, Models, and Code.” Journal of Water Resources Planning and Management 144 (9): 01618001. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000998 .

Rossi, T.F. 2016. “Making a Model a Good Predictive Tool.” FHWA-HEP-17-048. Federal Highway Administration.
https://www.fhwa.dot.gov/planning/tmip/publications/other_reports/predictive_tool/fhwahep17048.pdf .

Rubin, D.K. 2018. “Arup Settles $1.7B Australia Toll Road Revenue Forecast Suit.” Engineering News-Record. https://www.enr.com/articles/43707-arup-settles-17b-australia-toll-road-revenue-forecast-suit .

Russakovsky, O., J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A.C. Berg, and L. Fei-Fei. 2015. "ImageNet Large Scale Visual Recognition Challenge."

International Journal of Computer Vision 115 (3): 211-252. https://doi.org/10.1007/s11263-015-0816-y .

Sant, Joseph. n.d. “The Scientific Method, Hypothesis, Prediction and Test.” Accessed May 28, 2019. http://www.scientus.org/Science-Method.html .

Sargent, R.G. 2011. “Validation and Verification of Simulation Models.” In Proceedings of the 2011 Winter Simulation Conference, 183–98. Winter Simulation Conference.

Saulwick, J. 2014. “Lane Cove Tunnel Forecasts Based on ‘Very Large Number of Unknowns.’” The Sydney Morning Herald, August 13, 2014. https://www.smh.com.au/national/nsw/lane-cove-tunnel-forecasts-based-on-very-large-number-of-unknowns-20140813-103kth.html .

Schmitt, D. 2016. "A Transit Forecasting Accuracy Database: Beginning to Enjoy the ‘Outside View.'" Transportation Research Board 95th Annual Meeting, Washington, DC.

“Science Journals: Editorial Policies.” 2018. Science | AAAS. January 31, 2018. https://www-sciencemag-org/authors/science-journals-editorial-policies#research-standards .

Selten, R., M. Schreckenberg, T. Chmura, T. Pitz, S. Kube, S.F. Hafstein, R. Chrobok, A. Pottmeier, and J. Wahle. 2004. “Experimental Investigation of Day-to-day Route-choice Behaviour and Network Simulations of Autobahn Traffic in North Rhine-Westphalia.” Human Behaviour and Traffic Networks. Springer, Berlin, Heidelberg.

Sheffi, Y. (1985) Urban Network Modeling: Mathematical Programming with Applications. Prentice-Hall.

Shuldiner, A.T., and P.W. Shuldiner. 2013. “The Measure of All Things: Reflections on Changing Conceptions of the Individual in Travel Demand Modeling.” Transportation 40 (6): 1117–31. https://doi.org/10.1007/s11116-013-9490-5 .

Simon, H.A. 1955. “A Behavioral Model of Rational Choice.” The Quarterly Journal of Economics 69 (1): 99-118.

Stacey, D. 2015. “AECOM Unit Pays $201 Million to Settle Australia Toll-Road Lawsuit - WSJ.” The Wall Street Journal, September 21, 2015. https://www.wsj.com/articles/aecom-unit-pays-us-201-million-to-settle-australia-toll-road-lawsuit-1442826365 .

Taylor, S.J.E., A. Khan, K.L. Morse, A. Tolk, L. Yilmaz, and J. Zander. 2013. “Grand Challenges on the Theory of Modeling and Simulation.” In Proceedings of the Symposium on Theory of Modeling & Simulation-DEVS Integrative M&S Symposium. Society for Computer Simulation International. https://d2f99xq7vri1nk.cloudfront.net/legacy_app_files/pdf/GC-TMS2013_submitted.pdf .

Teale, C. 2019. “1 Year in: Uber’s ‘rocket Shot’ Cincinnati Partnership.” Smart Cities Dive, February 11, 2019. https://www.smartcitiesdive.com/news/uber-cincinnati-partnership-one-year-later/547964/ .

Toepfer, F., E. Rappaport, F. Marks, V. Tallapragada, S.G. Gopalakrishnan, N.P. Kurkowski, and N. Lett. 2018. "Hurricane Forecast Improvement Program (HFIP) Plan to Enact the Weather Act." American Meteorological Society 98th Annual Meeting, Austin, Texas. https://ams.confex.com/ams/98Annual/webprogram/Paper329922.html .

Tolk, A. 2015. “Learning Something Right from Models That Are Wrong: Epistemology of Simulation.” In Concepts and Methodologies for Modeling and Simulation, 87–106. Simulation Foundations, Methods and Applications. Springer, Cham.
https://doi.org/10.1007/978-3-319-15096-3_5 .

Tolk, A., S.Y. Diallo, J.J. Padilla, and R. Gore. 2013. “Epistemology of Modeling and Simulation: How Can We Gain Knowledge from Simulations?” ArXiv Preprint ArXiv:1306.5215.

Tolk, A., B.L. Heath, M. Ihrig, J.J. Padilla, E.H. Page, E.D. Suarez, C. Szabo, P. Weirich, and L. Yilmaz. 2013. “Epistemology of Modeling and Simulation.” In Proceedings of the 2013 Winter Simulation Conference: Simulation: Making Decisions in a Complex World, 1152–1166. IEEE Press.

Train, K.E. (2009). Discrete Choice Methods with Simulation. Cambridge university press.

Van Alstyne, M.W., A. Di Fiore, and S. Schneider. 2017. "4 Mistakes That Kill Crowdsourcing Efforts." Harvard Business Review. https://hbr.org/2017/07/4-mistakes-that-kill-crowdsourcing-efforts .

Voulgaris, C.T. 2019. "Crystal Balls and Black Boxes: What Makes a Good Forecast?" Journal of Planning Literature. https://doi.org/10.1177/0885412219838495 .

Wachs, M. 1990. “Ethics and Advocacy in Forecasting for Public Policy.” Business and Professional Ethics Journal 9 (1 & 2): 141–57. https://doi.org/10.5840/bpej199091/215 .

Wardman, M. 2004. “Public Transport Value of Time.” Transport Policy 11 (4): 363-377. https://doi.org/10.1016/j.tranpol.2004.05.001 .

Welde, M., and J. O'Deck. 2011. "Do Planners Get it Right? The Accuracy of Travel Demand Forecasting in Norway." European Journal of Transport and Infrastructure Research 11 (1). https://doi.org/10.18757/ejtir.2011.11.1.2913 .

Wilson, A. 1970. Entropy in Urban and Regional Modelling. Routledge, UK.

WTS. 2016. "A Longitudinal Study Benchmarking Women in Leadership Roles."
http://www.wtsinternational.org/assets/84/22/WTS_Report_FINAL_VERSION.pdf .

Appendix: 2017 Workshop program & 2018 TRB podium session

NSF WORKSHOP

ADVANCING THE SCIENCE OF TRANSPORTATION DEMAND MODELING

April 20 and 21, 2017 @ UC Berkeley

CHALLENGE: To fundamentally rethink travel forecasting.
We will focus on travel demand models used for transportation planning where a key requirement is sensitivity to a wide-range of transportation policies and investments, with an emphasis on academia and research.

DELIVERABLE: A white paper that proposes actions to undertake for the next generation of travel demand models to:

(1) Be subject to rigorous, scientific testing,
(2) Effectively integrate researchers and ideas from different disciplines,
(3) Be germane to the looming transformation in transport (clean, connected, autonomous), and
(4) Be useful.

DAY 1 BUILDING BRIDGES

On Day 1, we'll brainstorm ideas to move the field forward.

8:30-9:00 Breakfast (on-site)

9:00-9:45 **Introduction of workshop and attendees**
Joan Walker (UC Berkeley)

9:45-11:45 **PANEL 1: What are the advantages and disadvantages of different approaches to travel demand modeling? (big data vs small data, machine learning vs econometric modeling, black box vs behavioral)**

MODERATOR:	Chandra Bhat (UT Austin)
RAPPORTEUR:	Maddie Sheehan (UC Berkeley)
PANELIST:	Ricardo Daziano (Cornell) ~ Econometrics/Economics
PANELIST:	Francisco Pereira (TU Denmark) ~ CS/AI
PANELIST:	Marta Gonzales (MIT) ~ Statistical Physics
PANELIST:	Eric Miller (U Toronto) ~ Transport/Land Use Modeler

11:45-1:00 LUNCH (on-site)

1:00-3:00 **PANEL 2: How critical is causality? And how can we make clear statements about it in travel demand models?**

MODERATOR:	Pat Mokhtarian (Georgia Tech)
RAPPORTEUR:	Feras El Zarwi (UC Berkeley)
PANELIST:	Rolf Moekel (TU Munich) ~ Modeler/Planner
PANELIST:	Alexey Pozdnukhov (UC Berkeley) ~ Computer Science
PANELIST:	Jinhua Zhao (MIT) ~ Behavioral experimentalist
PANELIST:	Elias Bareinboim (Purdue) ~ CS & Stats / Causal Inference

3:00-3:30 BREAK

3:30-5:30 **PANEL 3: How should travel demand models be tested, compared, and validated?**

MODERATOR:	Hani Mahmassani (Northwestern)
RAPPORTEUR:	Mustapha Harb (UC Berkeley)
PANELIST:	Gregory Erhardt (U of Kentucky) ~ Activity-based TDM
PANELIST:	Josie Kressner (Transport Foundry) ~ Machine Learning
PANELIST:	Nicholas Chim (Sidewalk labs) ~ Machine Learning
PANELIST:	Daniel Chatman (UC Berkeley) ~ Planning
PANELIST:	Kay Axhausen (ETH) ~ Data collection and simulation

5:30-6:00 **Conclusion of Day 1 and Prep for Day 2**

DAY 2 PATHS FORWARD

On Day 2, we'll "write" the white paper and develop other potential outcomes.

8:30-9:00 Breakfast (on-site)

9:00-9:30 **Setting the stage for Day 2**
Joan Walker (UC Berkeley)

9:30-10:30 **Dan McFadden (UC Berkeley) – Reflections on the field**

10:30-12:00 **Break out groups**
Define concrete ideas and their priorities for moving the field forward. Target ideas that aim to realign incentives for the field to progress more rapidly, scientifically, and usefully.

12:00-1:00 LUNCH (on-site)

1:00-2:00 **Break out groups (continued)**

2:00-3:00 **Break out group reports**

MODERATOR: Aruna Sivakumar (Imperial College London)
RAPPORTEURS: One assigned by each breakout group

3:00-3:30 BREAK

3:30-5:00 **CLOSING PANEL:**
Different perspectives regarding the key lessons from the workshop

MODERATOR: Song Gao (U Mass)
RAPPORTEUR: Giovanni Circella (UC Davis)

PANELIST: Elias Bareinboim (Purdue) ~ CS & Stats / Causal Inference
PANELIST: Elizabeth Sall (UrbanLabs) ~ Zephyr Foundation/Practice
PANELIST: Timothy Brathwaite (UC Berkeley) ~ Data Sciences
PANELIST: Stephane Hess (Leeds) ~ Discrete Choice
PANELIST: Moshe Ben-Akiva (MIT) ~ Transportation Systems

5:00-6:00 **Next Steps… WRITING & TASK ASSIGNMENTS!**
ALL

Lectern Session 669

Advancing the Science of Transportation Demand Modeling

Tuesday, January 09, 2018 3:45 PM- 5:30 PM
Convention Center, 145A
Lectern

Joan Walker, University of California, Berkeley View Presentation

Sponsored by:
Standing Committee on Transportation Demand Forecasting (ADB40)

This session presents recommendations from a Zephyr Foundation-initiated and NSF-sponsored workshop on Advancing the Science of Transportation Demand Modeling. The presentations are aligned along six themes that emerged, and each will propose actions to undertake for the next generation of transportation demand models to (a) be subject to rigorous, scientific testing; (b) effectively integrate researchers and ideas from different disciplines; (c) be germane to the looming transformation in transport (clean, connected, shared, autonomous, flying); and (d) be useful.

Title	Presentation Number
Advancing TDM: Developing the Workforce Chandra Bhat, University of Texas, Austin Elizabeth Sall, UrbanLabs LLC Timothy Brathwaite, Lyft, Inc. Siyu Chen, Massachusetts Institute of Technology (MIT) Nicholas Chim, Sidewalk Labs Clint Daniels, RSG Hani Mahmassani, Northwestern University Rosella Picado, WSP Madeleine Sheehan, University of California, Berkeley Jennifer L. Weeks, Transportation Research Board View Presentation	P18-20307
Advancing TDM: Strengthening Linkages with Policy and Planning Clint Daniels, RSG Eric Miller, University of Toronto Daniel Chatman, University of California, Berkeley Giovanni Circella, University of California, Davis Ricardo Daziano, Cornell University Gregory Erhardt, University of Kentucky Mustapha Harb, University of California, Berkeley Rolf Moeckel, Technical University of Munich Rosella Picado, WSP Elizabeth Sall, UrbanLabs LLC Aruna Sivakumar, Imperial College London Jennifer L. Weeks, Transportation Research Board	P18-20461

Advancing TDM: Advancing Knowledge in a Generalizable and Testable Manner Gregory Erhardt, University of Kentucky David Ory, WSP Kay Axhausen, Eidgenossische Technische Hochschule Zurich Giovanni Circella, University of California, Davis Song Gao, University of Massachusetts, Amherst Stephane Hess, University of Leeds Josephine Kressner, Transport Foundry Hani Mahmassani, Northwestern University Eric Miller, University of Toronto Rolf Moeckel, Technical University of Munich Alexei Pozdnoukhov, University of California, Berkeley Paul Waddell, University of California, Berkeley View Presentation	P18-20462
Advancing TDM: Developing a Collaborative Ecosystem Nicholas Chim, Sidewalk Labs Brian Gardner, Federal Highway Administration (FHWA) Kay Axhausen, Eidgenossische Technische Hochschule Zurich Elias Bareinboim, Purdue University Moshe Ben-Akiva, Massachusetts Institute of Technology (MIT) William Charlton, Technische Universitat Berlin Daniel Chatman, University of California, Berkeley Feras El Zarwi, Uber Technologies, Inc. Mustapha Harb, University of California, Berkeley Patricia Mokhtarian, Georgia Institute of Technology (Georgia Tech) Alexei Pozdnoukhov, University of California, Berkeley Madeleine Sheehan, University of California, Berkeley View Presentation	P18-20467

Advancing TDM: Drawing from Multidisciplinary Fields Ricardo Daziano, Cornell University Song Gao, University of Massachusetts, Amherst Elias Bareinboim, Purdue University Moshe Ben-Akiva, Massachusetts Institute of Technology (MIT) Timothy Brathwaite, Lyft, Inc. William Charlton, Technische Universitat Berlin Siyu Chen, Massachusetts Institute of Technology (MIT) Stephane Hess, University of Leeds Amine Mahmassani, University of California, Irvine Daniel McFadden, University of California, Berkeley Jinhua Zhao, Massachusetts Institute of Technology (MIT) Marta Gonzalez, University of California, Berkeley	P18-20469
Advancing TDM: Addressing Fundamental Research Questions Josephine Kressner, Transport Foundry Francisco Pereira, Danmarks Tekniske Universitet Chandra Bhat, University of Texas, Austin Feras El Zarwi, Uber Technologies, Inc. Amine Mahmassani, University of California, Irvine Patricia Mokhtarian, Georgia Institute of Technology (Georgia Tech) David Ory, WSP Aruna Sivakumar, Imperial College London Paul Waddell, University of California, Berkeley Jinhua Zhao, Massachusetts Institute of Technology (MIT) Marta Gonzalez, University of California, Berkeley View Presentation	P18-20471