System Dynamics Perspective for Automated Vehicle Impact Assessment

www.its.dot.gov/index.htm

Final Report – July 2020

U.S. Department of Transportation

Produced by Volpe National Transportation Systems Center
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
Intelligent Transportation Systems Joint Program Office

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA-JPO-20-809		

4. Title and Subtitle	5. Report Date
System Dynamics Perspective for Automated Vehicle Impact Assessment	July 2020
	6. Performing Organization Code V336
7. Author(s) Ian Berg, Hannah Rakoff, Jingsi Shaw, Scott Smith	8. Performing Organization Report No. DOT-VNTSC-FHWA-20-12
9. Performing Organization Name and Address John A. Volpe National Transportation Systems Center U.S. Department of Transportation 55 Broadway Cambridge, MA 02142	10. Work Unit No. (TRAIS) 11. Contract or Grant No. Intra-Agency Agreement 693JJ318N300035, HW9EA5
12. Sponsoring Agency Name and Address Intelligent Transportation Systems Joint Program Office U.S. Department of Transportation 1200 New Jersey Ave, SE Washington, DC 20590	13. Type of Report and Period Covered Final Report July 2018 – May 2020 14. Sponsoring Agency Code

15. Supplementary Notes

ITS JPO project manager is Kevin Dopart.

16. Abstract

System dynamics (SD) allows modelers and planners to take simple causal interactions within a complex system and build a model that can demonstrate not-so-evident dynamic behavior. It is a useful addition to the strategic modeling toolbox. This report presents a plan to use system dynamics to model the impacts of automated vehicle adoption. It identifies, at a high level, the causal factors and institutional relationships that would influence adoption of a transportation mode. Two models of mobility-on-demand services are presented, using existing modes as proxies. In the first, passengers would request an automated vehicle (AV) in a similar manner as one might order a ride with a transportation network company (TNC) today. The second is that of a dockless bikeshare service, where the system operator owns the fleet of vehicles, and is concerned with their utilization. The SD modeling identified four important building blocks for the analysis of a transportation mode: (1) the reinforcing cycle of technology adoption, where consumers adopt a new product, via word-of-mouth and other influencing factors, (2) business models of providing a financially sustainable transportation service, (3) reinforcing effects of services and users, where greater usage of a service justifies adding more service and/or higher quality service, and (4) balancing effects of congestion.

17. Keywords	18. Distribution Statement
Automated vehicles, scenarios, mobility benefits, equity, accessibility, transportation planning, system dynamics	

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	56	

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Acknowledgements

This project was funded by the Intelligent Transportation Systems Joint Program Office (ITS JPO). We thank Kevin Dopart from ITS JPO for continuing to sponsor research on the impact of automated vehicles.

The early system dynamics work was based on work by the trilateral (EU, US and Japan) Working Group on Automation in Road Transportation (ART WG). We thank all of the participants at the group's April 2019 workshop in Leeds, UK for their thoughtful contributions.

Lastly, we appreciate the thoughtful review and recommendations by our many Volpe colleagues, including Anne-Marie Chouinard, Andrew Eilbert, Jonathan Koopmann, Sean Peirce, and Joseph Stanford, as well as external collaborators.

Table of Contents

List of Tables

List of Figures

Executive Summary

System dynamics (SD) allows modelers or planners to take simple causal interactions within a complex system and build a model that can demonstrate not-so-evident dynamic behavior. Such techniques are ideal for gaining insight into potential impacts of major changes in the transportation system, because they help planners build on individual causal links to gain systematic insight into the behavior of a whole system. While the causal links may be relatively evident, the behavior of a whole system is much harder to infer. As such, SD is a useful addition to the strategic modeling toolbox. This report lays out a plan to incorporate a system dynamics approach into modeling the impacts of automated vehicle adoption.

In 2019, the authors collaborated with several researchers from academia and an independent research institute (Rakoff et al., 2020) to identify, at a high level, the causal factors and institutional relationships that influence adoption of a transportation mode. Roles include the end users of transportation (e.g., households, businesses and freight shippers), the entities that control availability of transportation to end users (e.g., public transport operators, mobility-on-demand, and freight carriers), and infrastructure and technology providers (e.g., highway operators and payment networks). The U.S. DOT Volpe Center team then built two models of mobility-on-demand services, each of which can serve, in its own way, as a proxy mode to shed light on automated vehicles (AVs) in a fleet-owned business model. The first model was of driver and passenger recruitment for transportation network company (TNC) operations. The second was that of a dockless bikeshare service, where the system operator owns the fleet of vehicles, and is concerned with their utilization. The SD modeling identified four important building blocks, likely to be applicable to any transportation mode:

- The reinforcing cycle of technology adoption, where consumers adopt a new product, via word-of-mouth and other influencing factors.
- The business model of providing a transport service, focusing on the availability of labor, vehicles and other factors of production, how customers pay, and financial sustainability.
- The reinforcing effects of services and users, where greater usage of a service justifies adding more service and/or improving the quality of the service.
- The balancing effects of use where congestion is a factor. As something (e.g., road space or space on a transit vehicle) becomes desirable and is used more, its use becomes less pleasant and therefore less desirable.

Future work will include expansion of the SD modeling to include pricing, competition among modes and equity impacts. The authors also plan to place the SD work in the context of emerging practices (such as robust decision making) in scenario planning and long-range strategic modeling.

Chapter 1. Introduction

This report summarizes the system dynamics work performed under interagency agreement 693JJ318N300035 (Volpe reference number HW9EA5), Impact Assessment for Automated Vehicle Operations. It is focused primarily on the travel behavior part of the framework (Figure 1) developed in earlier phases of this program (Smith et al., 2015, 2018).

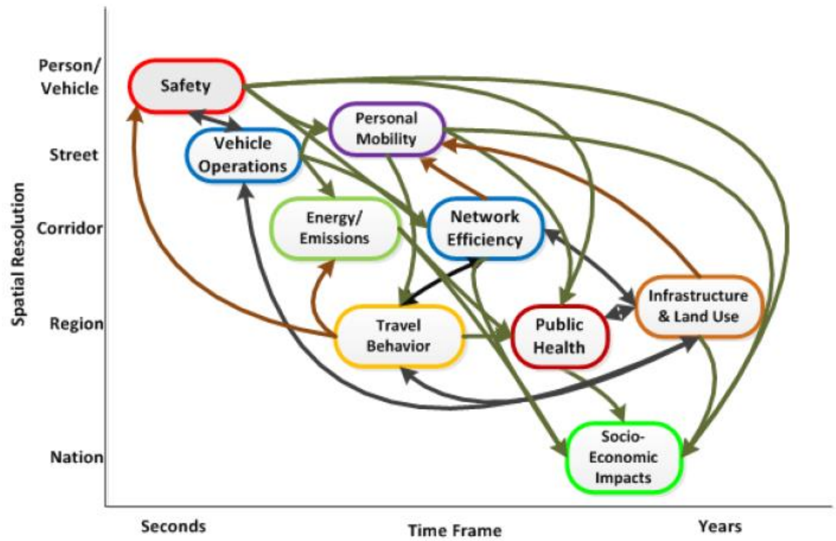

Figure 1. AV impact assessment framework

This report introduces the use of system dynamics to explore travel behavior as well as business models of transportation suppliers. Chapter 2 presents our work on the system dynamics of supply and demand for one automation use case: a shared-fleet mobility-on-demand system.

Chapter 3 proposes a way forward: using the building blocks from this report to create high-level models that can run quickly to allow users to test a number of different scenarios and possible policy levers.

Chapter 2. System Dynamics of AV Impacts

System dynamics (SD) allows modelers or planners to take simple causal interactions within a complex system and build a model that can demonstrate not-so-evident dynamic behavior. SD demonstrates that so-called unintended consequences, which may often be attributed to misbehavior of an actor within the system, or to uncontrollable externalities, can in fact arise endogenously from a system's structure (Sterman, 2000). The implications for policy design can be significant. SD techniques "explain behavior by providing a causal theory, and then…use that theory as the basis for designing policy interventions into the system structure which…change the resulting behavior and improve performance" (Lane, 2008). Such techniques are ideal for gaining insight into potential impacts of new modes on the transportation system, because they help planners build up on individual causal links, which may be relatively evident, to gain systematic insight into the behavior of a whole system, which is much harder to infer. SD allows for the examination of all of these causalities – and the interactions among them – simultaneously and holistically.

System dynamics emphasizes that the behavior of a system arises from its structure, the components of which interact according to decision rules of actors in the system (Sterman et al., 2015). For example, in the field of macroeconomics, the System Dynamics National Model Project, a large modeling effort at the Massachusetts Institute of Technology (MIT) in the late 1970s and 1980s dedicated to understanding cycles in the economy, succeeded in demonstrating that macroeconomic phenomena can emerge from ordinary day-to-day interactions in the system. By modeling detailed interactions between different sectors of the economy, the National Model was able to demonstrate inflation, short-term business cycles, longer-term cycles, and the so-called long wave of 50 year fluctuations in the economy, simply by representing "individuals acting, according to the information they have, subject to the limitations and motivations that go with their position" (Graham, 1984, p. 2), without assuming any macroeconomic structure. Its director of research, Dr. Alan Graham, wrote that "model structure comes more from model purpose and the observed structure of real organizations than from a prior theory on what creates the…behavior."(Graham, 1984, p. 2).

Key features of SD models, presented in the Journal of Operations Management by (Sterman et al., 2015) include:

- System dynamics emphasizes that the behavior of a system arises from its structure, the components of which interact according to decision rules of actors in the system. As with models in the behavioral operations traditions, SD models can be built to assume that decision-makers have bounded rationality, rely on heuristics and can be influenced by

emotions. While the system structure can be straightforward to determine, it can be surprisingly difficult to capture what drives decisions of the people in it.
- SD models do not assume that a system reaches an equilibrium, instead modeling how decision makers act given a state of the system at one point in time. Equilibrium, if it arises, is emergent rather than taken for granted.
- SD models also emphasize the importance of a broad model boundary. Mental models tend to have narrow boundaries, and may miss the big effects. Broadening a model's boundary allows the modeler to include feedback loops that a decision-maker may be unaware of but could have potential significant impacts.
- Finally, SD models are grounded in reality, with each component representing a real, testable thing, concept or relationship.

System dynamics is a useful addition to the strategic modeling toolbox. It helps modelers to take one step back from the data and identify the key causal relationships in a transportation ecosystem. It is one way to figure out which variables are likely to be highly influential on the state of the system. SD also encourages modelers to start by identifying the simplest fundamental mechanism that can generate the observed behavior, and add more details later if needed.

System dynamics and transportation modeling

Abbas & Bell (1994) discuss the usefulness of SD for transportation modeling, noting that "Transportation problems are holistic. They require integrating various forms of knowledge. They involve compensating feedback loops as well as counterintuitive behaviour. They comprise long-term/short-term trade-offs." (Abbas & Bell, 1994, p. 373).

A number of points from system dynamics resonate for travel demand modeling. Similar to agent-based modeling, system dynamics emphasizes that the behavior of a system arises from its structure, the components of which interact according to decision rules of actors in the system. In other words, SD models build up conclusions about a system from actions on the ground.

SD models can assume that decision-makers have bounded rationality. Travel demand models are similar, where a traveler's choice is influenced by both deterministic (e.g., cost, travel time) and random components.

Similar to travel models, SD models are grounded in reality, with each component representing a real, testable thing, concept or relationship. This resonates with the efforts of the travel modeling community to base its work on surveys of reported trips, mobile phone or app data collected from volunteers or anonymously, and other rigorous methods to build and validate models.

While SD can be a great addition to the strategic planning toolbox for transportation professionals, practitioners may need to broaden their thinking somewhat to incorporate it. For example, traditional travel demand models are used to search for a consistent agreement between the inputs and outputs of all modeling steps (trip generation, trip distribution, mode split and traffic assignment). The estimated travel demand patterns reflect the demand-supply interaction in a synthetic equilibrium. In SD modeling, equilibrium, if it arises, is emergent rather than taken for granted. This is an important concept for strategic modeling in transportation, particularly when dealing with rapidly changing travel demand and the appearance and sometimes disappearance of available travel modes, not to mention evolving business models of transportation providers. However, SD models do require that all equations are satisfied at each time step. So, while there is some difference between a traditional and an SD approach, the difference may be less than it initially appears.

SD models also emphasize the importance of a broad model boundary. Mental models tend to have narrow boundaries, and may have unstated assumptions that later turn out to be incorrect. Broadening a model's boundary allows the modeler to unearth feedback loops and hidden assumptions that a decision-maker may be unaware of but could have potential significant impacts. A broad model boundary may also help to reveal causes and effects that are not close to each other in space and time.

However, relying purely on SD concepts to model people's decision strategies can be somewhat limiting. Some SD researchers claim that feedback loops determined for SD models "must incorporate causal relations based on information on the decision rules used by the actors of the system, and not on correlations between variables observed in the historical data" (Saeed & Bach, 1992). This is a challenge for a practitioner looking at historical data for clues on how people make travel decisions, although again, the difference is less than it appears, since these clues are interpreted within a context of theory about how people make decisions (utility, for example). This report lays out a plan to incorporate a system dynamics approach into travel modeling, without necessarily insisting on rigid adherence to every aspect of SD theory.

What questions are of interest concerning user response to automated driving?

In the area of user response to automation, the following research questions are of particular interest:

- In which scenarios will the number of vehicles increase or decrease?
    - What is the effect on demand for parking?
- In which scenarios of AV implementation is VMT likely to increase, and in which is it likely to decrease?
    - What are the key parameters which govern whether a scenario falls into the first or second category? These variables may be particular foci for research that could allow modelers to make better predictions from analogous data in the non-AV world. They may also be important types of data to collect when AV implementations begin.

    - It may also be possible to gather useful data before full-scale adoption has occurred, either via data from smaller scale AV implementations, or from proxy modes (existing modes of transportation that are similar to AVs in some way)
    - Can the model be calibrated sufficiently to identify combinations of values of these key parameters which represent a possible "tipping point" between increased and decreased VMT?
    - How are impacts likely to vary by geography, especially by population density?
- What effect on VMT would actions by Federal, state, local and tribal governments to influence the availability and desirability of AV services have?
- How will potentially vulnerable user groups, such as people with disabilities or who are highly sensitive to cost, be affected by AV deployment and by the possible government actions?
- How will those who do and do not currently drive be affected by new modes?

Key to answering the above set of questions is that of understanding the viability of potential new modes of travel, which might include automated privately owned vehicles, automated mobility-on-demand, automated transit, or others. This report focuses on modeling directed at understanding automated mobility-on-demand.

Organization of this chapter

The remainder of this chapter is grouped into four sections:

- *Causal loop diagrams* provides a brief explanation of the diagrams that will be used in the remainder of the report
- *Impact linkages* articulates the important linkages between users, transportation providers and technology providers, that will influence the adoption of automation
- *Applying SD to investigate impacts of an AV mobility-on-demand service* introduces the specific automation application that is the focus in this analysis, and discusses the approach to developing the models that follow.
- *Modeling TNCs to investigate user response* presents an SD model that explores the user response side, using Transportation Network Companies (TNC) as a proxy mode to represent an on-demand automated vehicle service
- *Dockless bikeshare model of fleet management* presents an SD model that explores the transportation provider's side, using dockless bikeshare as a proxy mode to examine the impacts of utilization on viability of a system based on a fleet of vehicles that users rent on a short-term basis.

Causal loop diagrams

System dynamics models are often represented with diagrams, and simulated via computer. Figure 2 shows a simple causal loop diagram (CLD). Arrows represent causal links. The arrows with a plus (+) sign indicate that, all else equal, when the factor at the base of the arrow increases, the factor at the arrow's head also increases. This holds in the other direction as well: when the influencing factor decreases, the influenced factor, all else equal, moves in the same direction and therefore decreases (Lane, 2008).

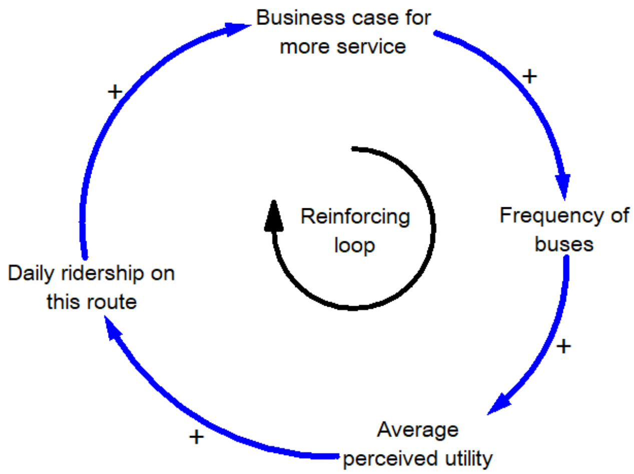

Figure 2. Example of reinforcing loop for bus service and ridership (source: authors)

A minus (-) sign (see Figure 3 and Figure 5, later in the report, for examples) means that a change in the influencing variable leads to a change in the opposite direction in the influenced variable (Lane, 2008). For example, if a product has a higher price, it will likely attract fewer users.

Impact linkages

Members of the project team joined several European researchers in organizing a group model building workshop, held in Leeds, UK, in April 2019 under the aegis of the trilateral (EU, US and Japan) Working Group on Automation in Road Transportation (ART WG). The group model building workshop was held in conjunction with the 2nd Annual Workshop on System Dynamics in Transportation Modelling, hosted by the University of Leeds Institute for Transport Studies and sponsored by the Transport Special Interest Group of the international System Dynamics Society. The full summary of the group model building workshop is given in (Rakoff et al., 2020). Material in this section is drawn directly from that paper.

The workshop focused on socioeconomic impacts, with one group looking at individual mobility, and the other considering societal issues. The scenario considered was that of a highly automated shared taxi service, operating in a geo-fenced area, providing local trips and trips to a commuter rail station.

One outcome of the workshop was a schematic of factors that might affect the number of trips in an AV (Figure 3). It is not a formal causal loop diagram. Arrows in Figure 3 indicate a link between a pair of items; links shown are not exhaustive but indicate the principal proposed impacts. Thin blue arrows have a clear proposed polarity. In accordance with accepted system dynamics notation, a plus sign means that the link is positive (or “reinforcing”): increasing the first item, all else equal, will lead to the second item being higher than it would otherwise be, and decreasing the first item will, all else equal, lead to the second item being lower than it would otherwise be. A minus sign means that the link is negative: an increase in the first item leads to a decrease in the second, and vice-versa. Around the outside of the diagram linked with thicker pink arrows there are the as-yet less-fully-defined groups of factors that can impact the system with a polarity that can be determined once the factor is better defined. For example, “traffic management objectives and strategies” is a placeholder for a more in-depth discussion that will lead to precise variables, with clear polarity, which can then be modelled and simulated. Similarly, “technology” will need to be defined more precisely as a level of technological capacity, in a measurable manner.

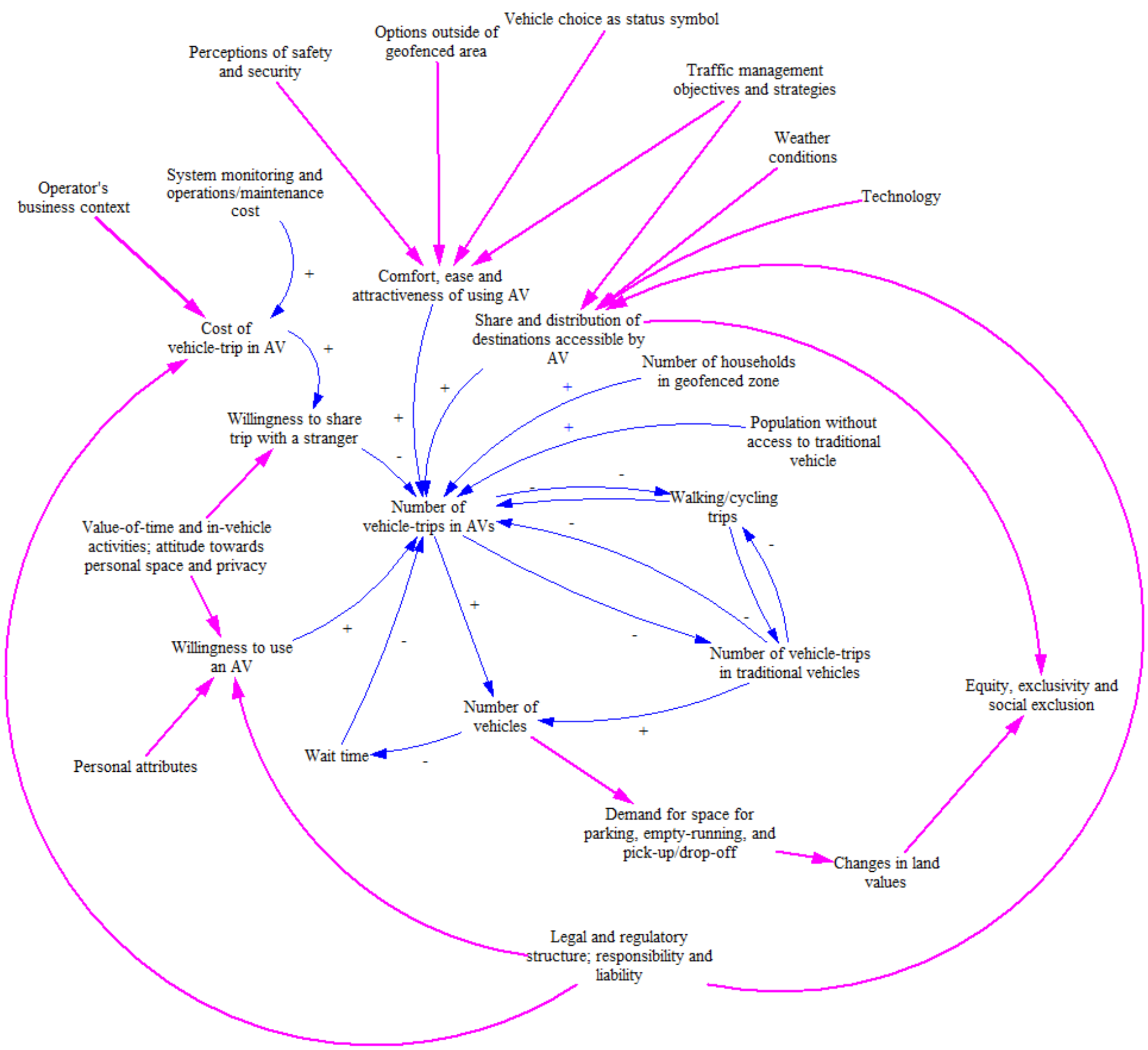

Figure 3. High-level schematic of the causal loop structure developed at the April 2019 workshop (source: (Rakoff et al., 2020))

In the months following the workshop, the authors of the workshop summary and other members of the ART WG created a higher-level framework, identifying the important roles which will influence the adoption of automation (Figure 4). The framework identifies the major generic roles within the transportation system and considers how they interact within the context of both traditional and new modes. Roles include the end users of transportation, the entities that control availability of transportation to end users, and the infrastructure and technology providers.

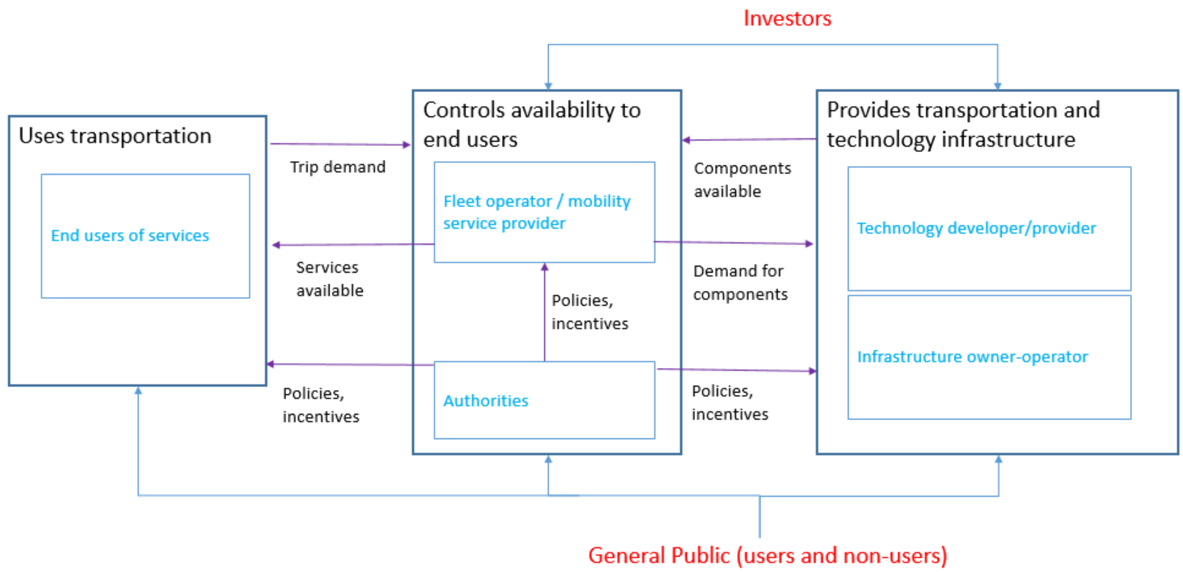

Figure 4. Diagram of major roles and how they influence each other (source: (Rakoff et al., 2020))

(Rakoff et al., 2020) then identifies agents within the system with specific relevance to AVs. For example, end users of services may include private individuals or households, businesses, and freight shippers. Examples of fleet operators/mobility service providers include public transport operators, private on-demand mobility services, freight carriers, and even travelers who are using their own vehicles. Authorities may be local, regional, national or even international in scope, and may be public or private (e.g., a university campus administration). Technology developers include vehicle-makers and suppliers of technologies to vehicle-makers, fleet operators or end users. Finally, the infrastructure owner-operator provides infrastructure-side needs for travel. This is typically road infrastructure, but may also include communications infrastructure.

Finally, the paper suggests the short- and long-term goals of the agents in each role, as well as how automation may affect the agents in ways relevant to their goals (Rakoff et al., 2020). This work provides a framework that will be useful for building future models.

Applying SD to investigate impacts of an AV mobility-on-demand service

One possible business model for AV deployment is through a mobility-on-demand service. In such a system, passengers would request an AV in a similar manner as one might order a ride with a transportation network company (TNC) today. However, unlike current TNCs, such a service may be fleet-based, with a single owner-operator. To gain insights on how much service users might demand of such an AV system, and how such a system would respond to demand for service, the system dynamics models described in this section provide insight into the growth dynamics of parallel systems that exist today.

There are several pairs of feedback relationships common to travel modes relying on shared vehicles, including conventional transit, TNCs and shared micro-mobility services (e.g. shared bikes and shared scooters).[1] Shared AVs are expected to have similar factors behind decision-making.

1. **Users and availability of shared service**
   The demand, such as the number of trips taken by users, depends upon the availability of the shared service. All else being equal, the higher the availability of the mobility service, the higher its utility, and the more users will use it. For example, a bus service with a 10-minute headway is more useful than a bus with a 60-minute headway. A shared AV service is more useful when many available vehicles are near the user's pickup location than if there are no available vehicles, the latter resulting in a long wait time. Meanwhile, if the amount of service is fixed, an increase in the usage of the mobility service will typically, in the short-term, lead to a reduction in its utility. For example, if shared AVs are used more, there will be lower availability of unoccupied shared AVs. And, for a given bus headway, an increase in use will lead to a higher likelihood of crowding onboard.

2. **Service providers and availability of shared service**
   The availability of the shared service depends upon a service provider's understanding of the demand and its strategies to meet the demand. For instance, a service provider could determine the service area, the level of the services (e.g. frequency, vehicle type, etc.), and cost. The higher the utilization of the service, the higher the revenue if all else is equal.

3. **Long-term decisions of service providers**
   Service providers make long-term decisions on the scale of their business. In particular, service providers could decide to increase vehicle supply, reduce supply or keep it the

---

[1] In this report, the term "shared vehicle" refers to a vehicle which more than one household has access to for making trips, such as a transit bus, TNC vehicle, or bikeshare bike. This does not necessarily mean that trips are "pooled" (i.e., persons from multiple households are in the vehicle at the same time), although the term does not exclude modes where pooled trips occur (e.g., public transit).

same. The criteria that a service provider uses to make long-term business decisions could be factors such as utilization of the service provided (e.g., trips per vehicle per day), revenue, or profit. At the growing stage of a business cycle, utilization of the service provided could be a key indicator for a service provider to validate its existing business model, and decide whether the company should expand, stay the same or exit. In this phase, therefore, the amount of service provided likely depends, after a time lag, on the usage of a service. For example, most transit agencies need a certain level of ridership to justify a 10-minute bus headway. A shared AV service may not be financially viable if its vehicles are waiting many hours for the next pickup.

Since it appears that the decision-making mechanism of choosing TNCs versus choosing a shared AV service is similar, it seems reasonable to expect that the same elements that determine the viability of a new travel mode today will influence the adoption of AVs:

- A new mode's utility to users, in terms of convenience, cost, travel time, and perceived safety.
- Access to desired destinations.
- Its financial sustainability: will fares plus any subsidy cover operating costs? How are capital costs covered?
- Its externalities (contribution to congestion, emissions, noise, etc.), and how/by whom those externalities are accounted for. This may determine whether the new mode receives political support and, possibly, a financial subsidy.
- How the elements above compare to those for other available travel modes.

The U.S. DOT Volpe Center team is taking an iterative approach to building SD models. The essence of this approach is to develop a working, but limited model, learn from it, and then use those insights to build a more elaborate model. This process is repeated, perhaps many times, until a fully elaborated model has been built. The following sections in this chapter present two models. These models are functional and provide useful insights. However, the authors recognize that they would benefit from further refinement and development.

A fleet-based AV mobility-on-demand service that can operate away from a guideway does not yet exist. Therefore, the models developed in this section do not model this service directly; data to directly validate such a model does not currently exist. Rather, the work takes existing and emerging modes, which have available data, and uses them as proxies to study potential impacts of an AV service. The first model in this chapter considers TNCs, as a proxy for the system from a user's perspective. Indeed, a TNC might be considered the “first taste” of an AV to a passenger. A passenger can order a TNC ride and it often shows up within minutes, or can be scheduled in advance. After the ride, it “disappears”, in the sense that passengers need not worry themselves with parking or arranging the vehicle's next trip. Because TNCs have users today, there are data to understand the key factors affecting the utilization of the TNC service. As modeling advances, the authors will examine the assumption that the factors affecting TNC usage will have similar influence on the usage of a shared AV system.

On the other hand, the current TNC business model (where individual drivers contract themselves, with their own vehicles, to arrange trips using the TNC's software platform) may not represent how an AV-based mobility service is structured. Due to the potential, particularly early on, for increased production costs for AVs, as well as the possibility that liability will not be easily managed within the current auto-insurance market, mobility service providers offering AV service may own and operate fleets of vehicles. In this case, emerging micromobility options, such as dockless bikeshare and electric scooters owned by the companies that offer the service, are a better parallel for investigating fleet management and business models. The second model in this chapter examines how a dockless bikeshare system manages its fleet.

In recent years, many state and local authorities have begun to collect trip-level data from operators of both of these services (Akhavan et al., 2019; City of Chicago, 2020). These data provide reference modes with which to compare the trends that the models here produce: a reference mode is a pattern of behavior over time which one aims to reproduce in SD modeling, even if the model is not quantitatively calibrated to align with the data's exact values (Ford, 2018).

Modeling TNCs to investigate user response

As discussed in the previous section, there are many factors that affect the viability of a new travel mode. The model discussed in this section focuses on one of those factors: utility for the traveler. Utility is based on the generalized cost of a trip, which combines the monetary cost (i.e., fare) of the trip and the cost of the time needed to take a trip (converted into dollars through value-of-time factors, which may vary between waiting time and in-vehicle travel time).

This model focuses on how user adoption based on utility can lead the TNC to provide more service, further increasing the traveler's utility, and thus driving demand for a mode. Figure 5 shows the major reinforcing loop that links users of a TNC system and drivers who provide service for the TNC. All else equal, more users in the system lead to more trips being taken on the mode. This generates more revenue, which can entice drivers into the system. A system with more drivers has lower wait times for the users (again, all else equal), thus reducing the generalized cost of taking a trip on the mode, which attracts more users to sign-up for the service.

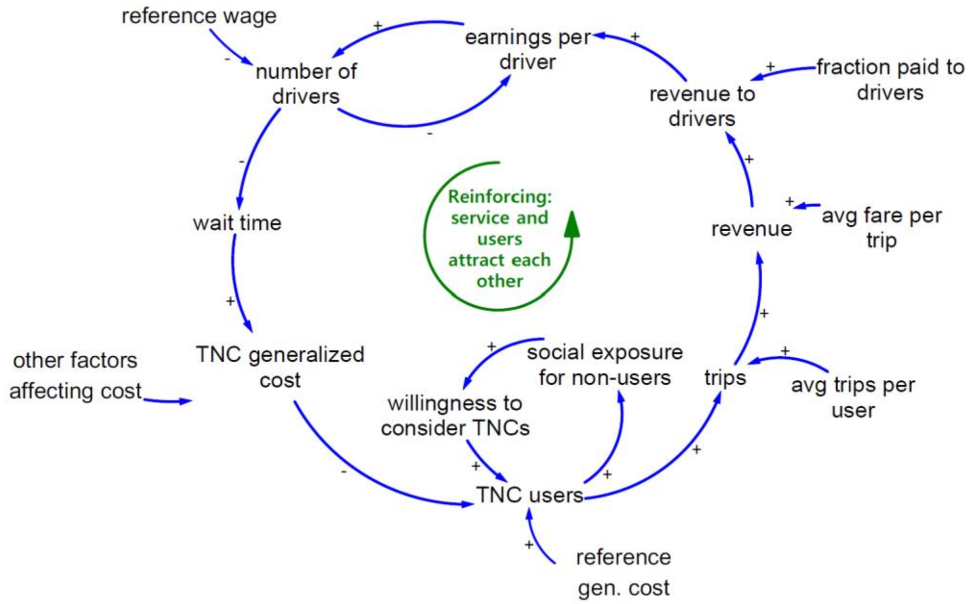

Figure 5. A reinforcing loop showing how user adoption drives driver recruitment, and vice versa

Other components of the model interact with this major loop. For example, there is a balancing loop reflecting the competition that drivers have for rides: as more drivers enter the system, per-driver earnings decrease, making driving a less desirable choice, thereby reducing the number of drivers entering the system. One key component implemented in this model is that of social exposure to the TNC system, which allows for more non-users to consider signing up for the service. These mechanisms are adapted from research on the adoption of alternative fuel vehicles (Struben & Sterman, 2008). Figure 6 describes the social exposure mechanisms implemented in the model. Note that while this figure focuses on users, a parallel structure is implemented for driver recruitment. Social exposure to the TNC system consists of marketing on one hand, and users spreading word-of-mouth on the other. These factors increase the fraction of the non-user population which is willing to consider signing up for the service.

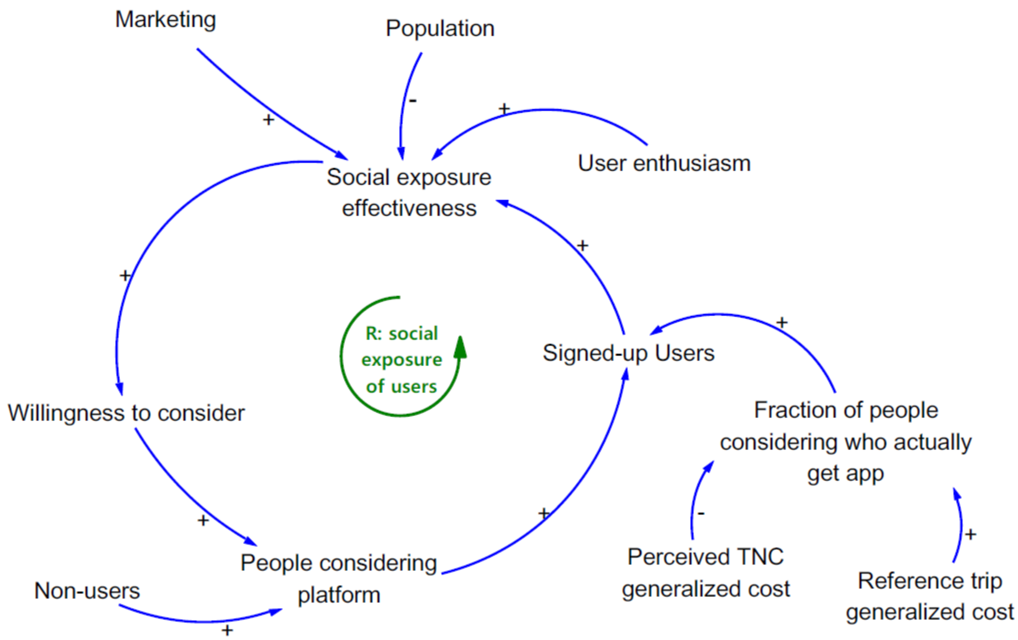

Figure 6. Causal-loop diagram showing social exposure structure, adapted from (Struben & Sterman, 2008)

To calculate the fraction of the people considering using TNCs who actually start using the mode, the potential user's perceived generalized cost of taking trips on the mode is compared with a reference cost, representing the cost of using another mode for these trips, and calculate the probability that someone would sign up to use the TNC service via Equation 1:

$$P(\text{sign up}) = \frac{e^{(\text{scaling factor})\times(\text{gen cost}_{\text{TNC}})}}{e^{(\text{scaling factor})\times(\text{gen cost}_{\text{TNC}})} + e^{(\text{scaling factor})\times(\text{gen cost}_{\text{ref}})}}$$

Equation 1. Function for calculating probability of a person signing-up for the TNC service

This function has an S-curve shape, with a scaling factor that is less than 0. The form of equation 1 is that of a logit model, often used in travel demand modeling (Koppelman & Bhat, 2006). The scaling factor multiplied by the generalized cost represents the utility of using the TNC mode, which is why the scaling factor is less than 0. If the cost of using the TNC is lower than the reference cost, it becomes more likely that the user will start using the TNC service. Figure 7 shows one such curve, calculated for a reference generalized cost of $15. Although these values are scaled to trips, note that the modeled decision is not a mode choice per trip; rather, it is modeling the inclusion of the TNC app in the traveler's choice set.

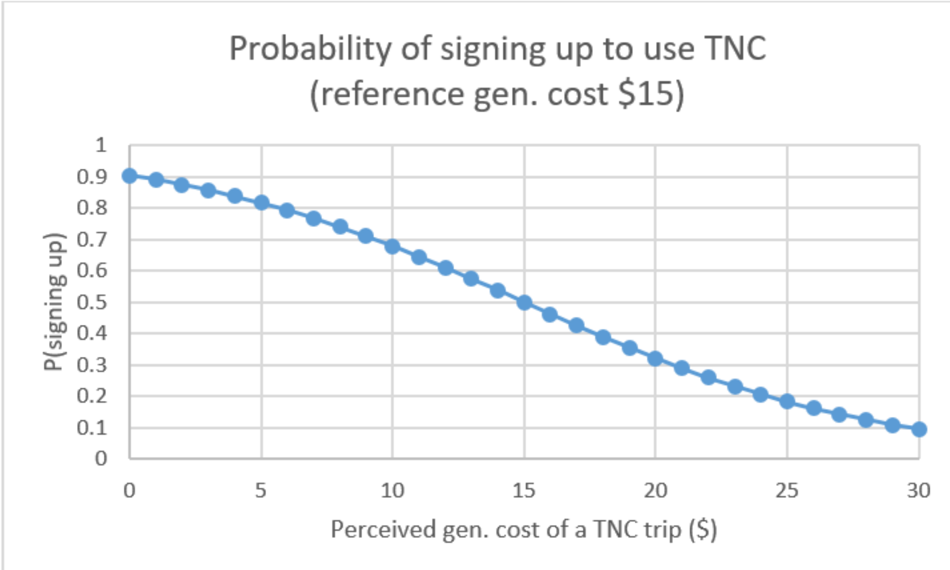

Figure 7. Graph. An S-curve comparing the perceived generalized cost of a TNC trip to the probability of signing up to use the TNC.

Not shown in Figure 6, but included in the model, are decay factors for both signed-up users and willingness to consider (WtC), which are reduced in proportion to the average length of time someone who has downloaded the app continues to use it (or, for someone who has not downloaded it, the time it takes to lose interest in doing so).

A full description of the model's parameters and equations is included in Appendix A. The initialization parameters shown in that appendix define an equilibrium state for the model that shows the TNC system steadily serving much of its potential user base. Approximately 71% of potential users and 90% of potential drivers are signed up to use the system. In this system, driver earnings are significantly higher than the reference wage ($47 vs $20). The system retains users although the generalized cost of a TNC trip is somewhat higher than the reference ($16 vs $10). Among non-users/non-drivers, willingness to consider a new mode is high.

Table 1. Parameters and initial values for the TNC model.

Parameter (units, if applicable)	Value (model begins at high equilibrium)	Value (system trends toward 0)	Value (model approaches high equilibrium)
Average time as user (months)	12	**6**	12
Average time as driver (months)	12	**6**	12

Parameter (units, if applicable)	Value (model begins at high equilibrium)	Value (system trends toward 0)	Value (model approaches high equilibrium)
Average time willing to consider among drivers (months)	12	**3**	12
Average time willing to consider among users (months)	12	**3**	12
Initial driver willingness to consider	0.75	**0.05**	**0.05**
Initial user willingness to consider	0.75	**0.05**	**0.05**
Initial drivers (people)	45	**10**	**10**
Initial users (people)	142	**50**	**50**
Initial expected wage ($)	47	**15**	**15**
Initial perceived generalized cost ($)	16	**15**	**15**
Reference wage ($)	20	20	**15**
Reference trip generalized cost ($)	10	**5**	10

Note: **bold** values highlight changes between the first column and either of the latter two.

Table 1 shows how changing some of these parameters at initialization can lead to differing results. While not a complete sensitivity analysis, these cases show how SD models can be used to provide a range of possible futures. Consider the case where 25% of potential users and 20% of potential drivers are signed up for the system. Varying other parameters (namely, the decay rates of users/drivers leaving the system, and the reference cost and wage) leads the system to behave in two divergent ways. With higher decay rates and a lower reference trip generalized cost, the system trends toward zero users and drivers. On the other hand, with lower decay rates and a lower reference wage, the system approaches the equilibrium defined by the first set of parameters. Figure 8 shows how the counts of signed-up users and drivers change over the three scenarios outlined in Table 1.

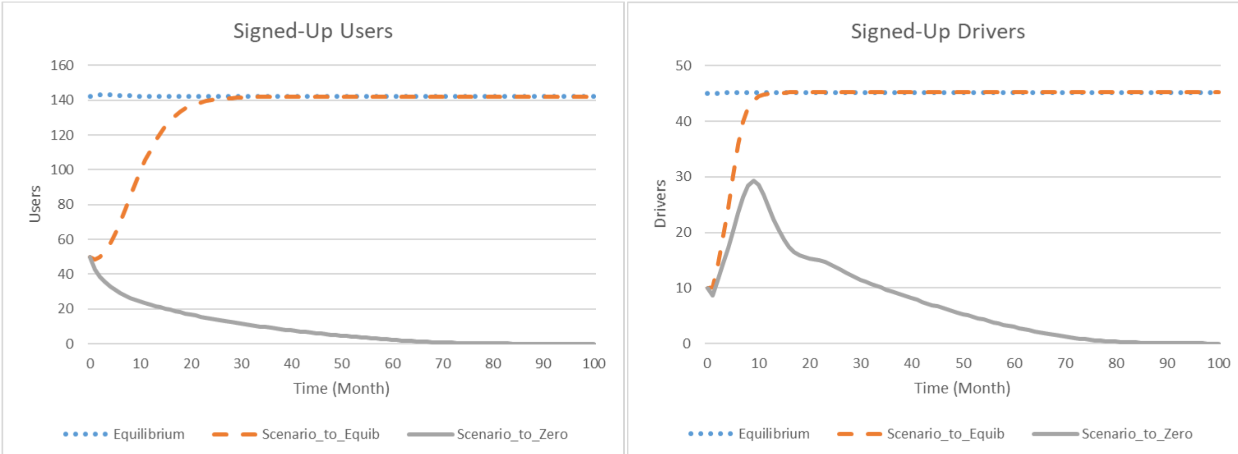

Figure 8. Graphs. Signed up users and drivers under the three scenarios defined in Table 1.

Future iterations of this model could address a variety of gaps in the current structure. This could include:

- More detailed modeling of passenger/driver decay and passenger wait times.
- Having trips per user, fares, and drivers' revenue share become an output of the model, rather than being treated as exogenous constants
- Variation across user or trip cohorts, including costs, values of time, and trip distances.
- Inclusion of multiple modes.

While some aspects of this model do not translate directly to a future automated mobility system, those pieces can still inform how to build model components to simulate such a system. For example, this model has structures for driver recruitment, which may not exist in an AV-based system. However, there will likely be some human role in maintaining fleet operations, in addition to a transitionary period where AVs and human-driven TNCs may both operate. Additionally, driver recruitment, like vehicle production and positioning, is a supply process with a lag, so the model can still provide insights.

But driver recruitment is not the only proxy for fleet management. In particular, vehicle production may be a longer, more expensive process than recruiting a driver to provide trips. Therefore, when discussing the potential impacts of automation, it is also prudent to draw from the experiences of other new fleet-based modes, such as micromobility. The next section will discuss a business model, dockless bikeshare, where the fleet of vehicles is owned and managed by the system operator.

Dockless bikeshare model of fleet management

In 2018, 14 inner-suburban Boston municipalities launched a dockless bikeshare system. For this system, data are readily available on:

- Cost to the user, both in 2018 (primarily manual bikes) and in 2019 (primarily e-bikes)[2]
- Overall trip patterns (Akhavan et al., 2019)

For one of the communities, additional information was available on:

- Number of bikes in the system at various times (a proxy for utility to users)
- Bicycle utilization (in trips / day), which indicates the usage of the service

In 2018, 150 manual bikes were deployed in one of the communities, later increasing to approximately 200 bikes. Although many trips were taken, the per-bike utilization was lower than desired by the vendor. In the summer / fall of 2019, approximately 60 e-bikes were deployed; very few manual bikes remained so the total number of bicycles available was lower. There was a corresponding decline in trips taken, and per-bike utilization remained low.

A simple working model of dockless bikeshare was built, using this data and the model framework illustrated earlier. The stock-flow diagram for the model is shown in Figure 9. As with the TNC model, a full description of its equations and parameters is included in Appendix A.

Bike utilization was one of the performance measures used during the deployment. This model does not explicitly consider costs. Rather, utilization is used as a proxy for the financial viability of the system: higher utilization rates mean that each bike is generating more revenue for the system.

[2] Manual bikes were priced at $1 for 30 minutes. E-bikes were priced at $1 plus $0.15 / minute, resulting in a total cost of $2.50 for a 10-minute ride.
https://boston.curbed.com/2019/4/9/18301751/e-bikes-boston-lime-bird

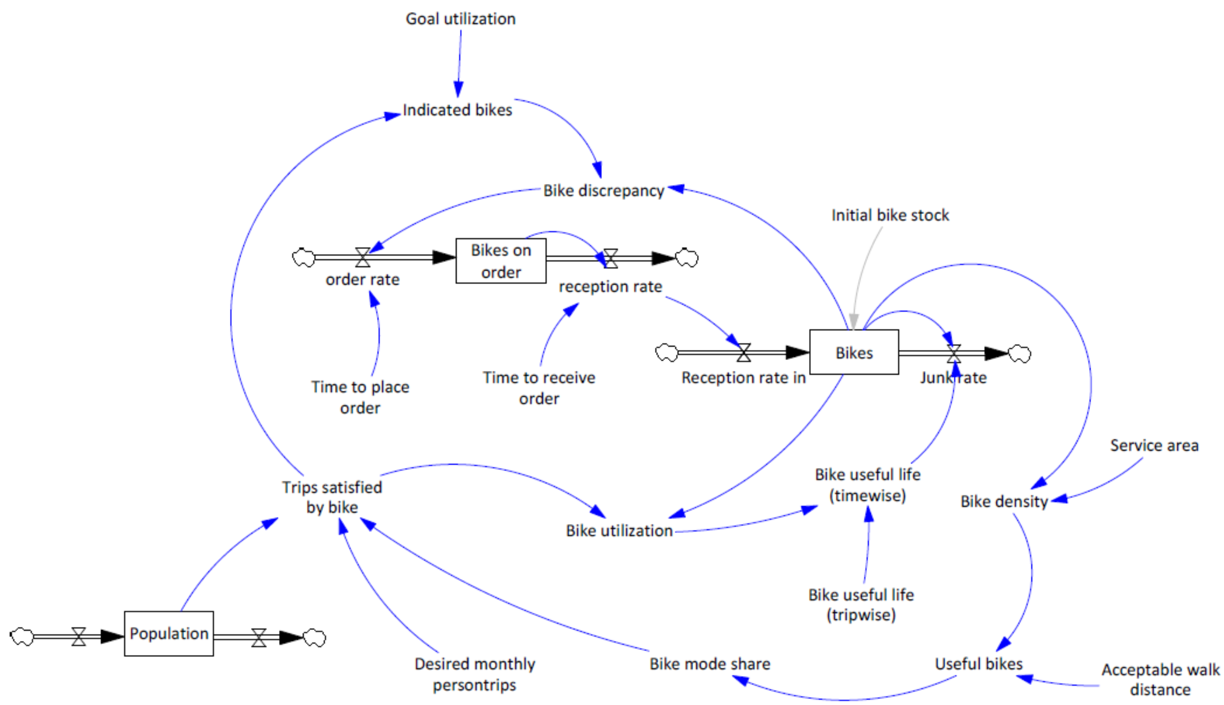

Figure 9. Stock-flow diagram for a dockless bikeshare system

The parameter values are inspired by the real case in the Boston metropolitan region, but the model is not calibrated to these data per se. As with the TNC model above, input parameters were varied to demonstrate SD's ability to model divergent futures. These two cases are a "declining" case where the bike stock is not sufficient to support a viable system, and a "successful" case, where the bike stock was sufficient, resulting in system expansion.

Table 2 shows the initial conditions for both cases, while Figure 10 shows the behavior of key system components with the "declining" case's initial conditions.

Table 2. Initial conditions for the two cases considered

Parameter	Value ("declining" case)	Value ("successful" case)
Population	1000 persons	1000 persons
Service area	16 km^2	16 km^2
Acceptable walk distance	0.5 km	0.5 km

Parameter	Value (“declining” case)	Value (“successful” case)
Desired monthly person-trips	100 trips/(person*month)	100 trips/(person*month)
Time to place order	2 months	2 months
Time to receive order	2 months	2 months
Goal utilization	60 trips/(bike*month)	60 trips/(bike*month)
Initial bike stock	85 bikes	**125 bikes**

Note: **bold** values highlight changes between the first column and the second.

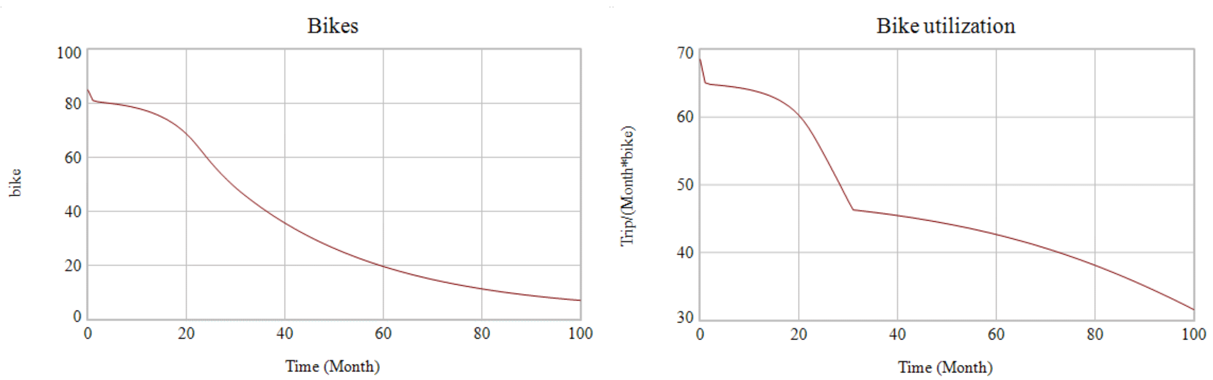

Figure 10. Graphs. Bike stock and bike utilization from the first parameter set in Table 2.

In this case, utilization is initially above the goal, so orders are placed to try to ensure that there are enough bikes in the system to keep up with demand.[3]

However, junk rate (the rate at which bikes wear out and have to be retired) is directly proportional to their utilization (measured in trips / bike). With the parameters in Table 2, the

[3] If the initial bike stock is not enough to achieve the goal utilization, no orders are ever placed, and the behavior is less interesting.

orders cannot keep up with the higher junk rate associated with this higher usage rate and the total bike stock never manages to increase.

The first inflection point on the bike utilization graph shows when the additional bikes first start coming in, after the initial delay for bike orders to be placed and received. Once utilization is below the goal, which occurs at about month 20, the decision rules say to stop purchasing, since, all else being equal, fewer bikes means more trips per bike. However, the system behavior shows two other factors at this point:

- All else does not remain equal: because the utility of the service goes down with fewer bikes, fewer trips are taken with the remaining bikes, further lowering the utilization rate. A sharper decline in bike utilization occurs between about months 20 and 30.
- Unfortunately for the service provider, because of delays for ordering and receiving bikes, it takes a few months for the stock of bikes to begin to decline faster, as shown on the left side of Figure 10.

Finally, because the remaining bikes take fewer trips, they last longer, so the system does continue to exist for a while even without any new bike orders, but at a slowly declining utilization rate well below the desired target. The current iteration of the model does not explicitly include operating costs; were these included, the service would probably run aground sooner.

Initial conditions for “successful” case are shown in the rightmost column of Table 2. The only difference between the two cases is that the initial bike stock is almost 50% higher. Results are shown in Figure 11.

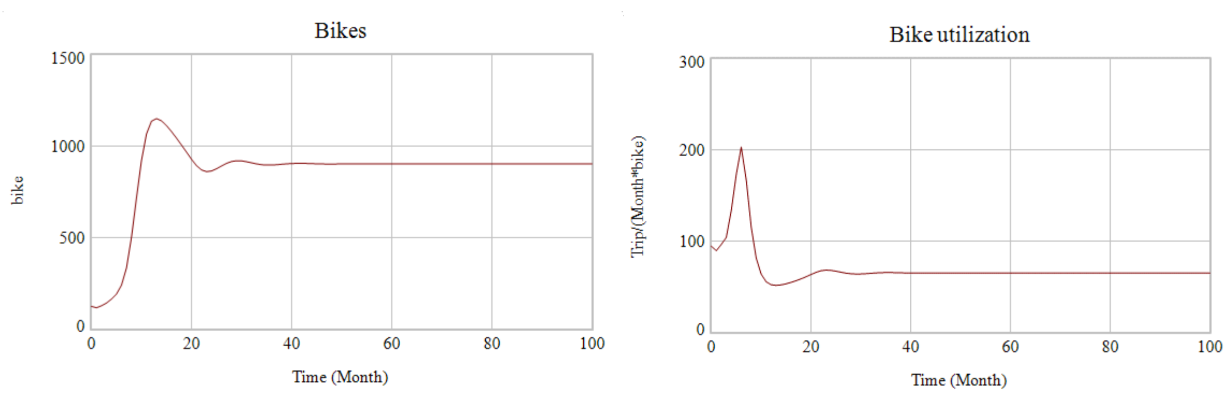

Figure 11. Graphs. Bike stock and bike utilization for the second parameter set in Table 2.

In this case, there are enough bikes in the system so that it starts with more utilization than in the first case. Initial utilization is well above the goal, so many more bikes are ordered; the system expands dramatically. As seen in Figure 11, the number of bikes grows to about 10 times the fleet's initial size. This also dramatically increases the utility of the service, which in the model is solely dependent on bike availability. After the dramatic push, bike ordering oscillates, due to the ordering overshoots that occur from delays in the order/reception process. Orders come to equilibrium at the same rate as bike retirements, since the service remains useful enough at its new scale to maintain utilization rates. Again, note that cost is not explicitly taken into account. The new equilibrium leaves the service provider with considerably more bikes to purchase and maintain, and utilization, while achieving the goal, ends lower than initial performance would suggest.

Chapter 3. Next Steps

To be useful, SD techniques need to be placed in the context of long-range strategic modeling and decision-making. They are part of the toolbox for identifying those near-term decisions that will make “good” outcomes more likely in the future. It may be useful to consider the “XLRM” framework (Lempert et al., 2003) from the field of robust decision-making (RDM) under deep uncertainty.

“X” refers to the external factors, or uncertainties. Examples that have been considered in the scenario-planning literature include technological development, economic growth, environmental changes (e.g., drought or sea level rise), attitudes of users, and attitudes of policy-makers, with resulting policy changes ((Lempert & Groves, 2010), (Netherlands Institute for Transport Policy Analysis, 2015),(Smith, 2019) and others). Depending on the modeling that is done, some of these factors might also become endogenous. They would change from external factors to relationships (the “R” in XLRM). For example, a conventional scenario planning exercise might treat user attitudes towards automation as an external uncertainty, while a SD model might treat it as endogenous, allowing other parts of the model to affect how user attitudes might change. Whether or when a particular event will happen is also a type of uncertainty. One could think about a cybersecurity breach that might destroy user confidence in automation, a sudden change in liability policy that changes the viability of a business model, or a pandemic that can change user willingness to share journeys.

“L” refers to possible policy levers, the actions that may be taken in the near term. Examples that may affect how automation plays out might include approaches to regulating AV testing and deployment, curb-space and land use regulation. In addition to regulation, levers may also include encouragement by provision of funding and discouragement via levying taxes or fees.

“R” refers to the relationships that are modeled. Examples of these relationships include

- Technology adoption: Consumer adoption of a new product, via word-of-mouth and other influencing factors. This is a commonly used concept in SD modeling, with obvious relevance to AV adoption.
- Business models: How the service provider structures its services and operations to make money. This depends on matching equipment (e.g., vehicles) and labor (e.g., staff to monitor service or intervene if problems arise) to demand. However, business models also change based on the source of revenue (e.g., selling a vehicle, selling a ride, selling advertising, or selling user data) and on the degree of competition and profitability.
- Reinforcing effects of services and users, where greater usage of a service justifies adding more service. For example, an area with high ridehailing demand may attract more ridehailing vehicles, thus leading to a reduction in wait times.

- Balancing effects of use: Congestion effects, where, as something is used more (e.g., road space), its use becomes less desirable.

"M" refers to performance metrics. The performance metrics are drawn from the long-term objectives for the region. Areas to consider, drawn from our previous work (Smith et al., 2018) include

- Safety – Is the system safe for users and non-users?
- Vehicle operations efficiency – How does the system make use of limited road space?
- Personal mobility – Does the system provide mobility for all types of users?
- Energy and emissions – energy consumption and air pollution impacts
- Network efficiency – What is the effect on overall transportation network efficiency?
- Travel behavior – How does travel behavior change? Are there more or fewer trips?
- Public health – aspects of public health include safety, access to medical care and other needs, air pollution, and the effect on physical activity via active transportation (walking and bicycling)
- Land use – How does the system affect curb space, parking needs and overall land use, including location and density of housing and other uses?
- Overall socio-economic impacts – The above impact areas, on both passenger and freight movements, will result in economic impacts. Automation may also have a substantial effect on labor markets.

(Innamaa & Kuisma, 2018) contains a comprehensive list of potential metrics for the impacts of automated driving.

It is also important to consider equity: the effect of AV adoption on different socio-economic and geographic subgroups.

Using the building blocks from this report, the next step is to create high-level models that can run quickly to allow users to test a number of different scenarios and possible policy levers. Although the next phase of work will primarily focus on this SD model development, building upon the aforementioned relationships, it will also be placed in the context of strategic planning, via the following activities:

1. Examining a selection of influential scenario studies that MPOs have developed, to identify the questions that they have asked and their approach to scenarios. The purpose is to better understand current MPO research and approaches on planning for how automation may enter into the complex surface transportation system, as well as the strengths and limitations of these studies. With these insights, our work can become more relevant to MPO research and modeling.
2. Seeking opportunities to work with an interested MPO partner, to provide greater realism and context for our SD modeling. It may make sense to pursue a partnership with one or

a small group of MPOs, in order to incorporate some of the SD approaches explored in this and future projects more deeply into their modeling.
3. Reviewing relevant emerging tools, such as VisionEval and the Travel Model Improvement Program – Exploratory Modeling and Analysis Tool (TMIP-EMAT) that may complement our work.
4. Looking at current and emerging data sources

These activities will also help prioritize what aspects to focus on in future iterations of the models, and will aid in demonstrating the relevance of SD modeling to potential users.

References

Abbas, K. A., & Bell, M. G. H. (1994). System dynamics applicability to transportation modeling. *Transportation Research Part A: Policy and Practice*, *28*(5), 373–390. https://doi.org/10.1016/0965-8564(94)90022-1

Akhavan, A., Gately, C., Gehrke, S., Hydrick, G., Partridge Guerrero, J., Reardon, T., Sadeghinasr, B., & Taylor, A. (2019). *First Miles: Examining 18 Months of Dockless Bikeshare in Metro Boston*. Metropolitan Area Planning Council. https://mapc.ma/firstmiles

City of Chicago. (2020). *Transportation Network Providers—Trips*. Chicago Data Portal. https://data.cityofchicago.org/Transportation/Transportation-Network-Providers-Trips/m6dm-c72p

Ford, A. (2018). Simulating systems with fast and slow dynamics: Lessons from the electric power industry. *System Dynamics Review*, *34*(1–2), 222–254. https://doi.org/10.1002/sdr.1595

Graham, A. K. (1984, May 26). *Introduction to system dynamics national model structure. Paper D-3573.* The 2nd International Conference of the System Dynamics Society, Oslo, Norway. https://proceedings.systemdynamics.org/1984/proceed/graha017.pdf

Innamaa, S., & Kuisma, S. (2018). *Key performance indicators for assessing the impacts of automation in road transportation: Results of the Trilateral key performance indicator survey* (VTT-R-01054-18). https://www.vtt.fi/inf/julkaisut/muut/2018/VTT-R-01054-18.pdf

Koppelman, F. S., & Bhat, C. (2006). *A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models*. Federal Transit Administration.

Lane, D. C. (2008). The emergence and use of diagramming in system dynamics: A critical account. *Systems Research and Behavioral Science*, *25*(1), 3–23. https://doi.org/10.1002/sres.826

Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. *Technological Forecasting and Social Change*, *77*(6), 960–974. https://doi.org/10.1016/j.techfore.2010.04.007

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the next one hundred years: New methods for quantitative, long-term policy analysis*. RAND.

Netherlands Institute for Transport Policy Analysis. (2015). *Driver at the wheel? Self-driving vehicles and the traffic and transport system of the future* (KiM-15-A07). Dutch Ministry of Infrastructure and the Environment.

Rakoff, H. E., Smith, S., Innamaa, S., Barnard, Y., Harrison, G., & Shaw, J. (2020). *Building feedback into modelling impacts of automated vehicles: Developing a consensus model and quantitative tool.* Transport Research Arena, April 2020 (conference cancelled), Helsinki, Finland. https://rosap.ntl.bts.gov/view/dot/48969

Saeed, K., & Bach, N. L. (1992). *Chaos out of stiff models*. International System Dynamics Conference, Utrecht, Netherlands.

Smith, S., Bellone, J., Bransfield, S., Ingles, A., Noel, G., Reed, E., & Yanagisawa, M. (2015). *Benefits Estimation Framework for Automated Vehicle Operations* (FHWA-JPO-16-229; p. 94). Department of Transportation. https://rosap.ntl.bts.gov/view/dot/4298/dot_4298_DS1.pdf

Smith, S., Koopmann, J., Rakoff, H., Peirce, S., Noel, G., Eilbert, A., & Yanagisawa, M. (2018). *Benefits Estimation Model for Automated Vehicle Operations: Phase 2 Final Report* (DOT-VNTSC-OSTR-18-01;FHWA-JPO-18-636). https://rosap.ntl.bts.gov/view/dot/34458

Sterman, J., Oliva, R., Linderman, K., & Bendoly, E. (2015). System dynamics perspectives and modeling opportunities for research in operations management. *Journal of Operations Management*, *39–40*(1), 1–5. https://doi.org/10.1016/j.jom.2015.07.001

Struben, J., & Sterman, J. D. (2008). Transition challenges for alternative fuel vehicle and transportation systems. *Environment and Planning B: Planning and Design*, *35*, 1070–1097.

Appendix A. Model Documentation

The models are implemented in Vensim Professional 7.2. A version viewable with the free Vensim Model Reader software is available.

TNC Model

Exogenous factors

Table 3. Exogenous factors in the TNC model.

Name in Vensim	Description (units, if applicable)	Example value
Average trip length in minutes	Average trip length (min)	30
Avg time as user	Average time as user (months)	12
Avg time as driver	Average time as driver (months)	12
Driver enthusiasm	Enthusiasm about system among drivers	0.25
User enthusiasm	Enthusiasm about system among users	0.25
Driver population	Population of potential drivers (people)	50
Population	Population of potential users (people)	200
Marketing	Marketing to drivers	0.1
DriverMarketing	Marketing to users	0.1
DriverWtC time to lose	Average time willing to consider among drivers (months)	12
WtC time to lose	Average time willing to consider among users (months)	12
Fraction of time each driver drives	Fraction of driver time spent making trips	0.2
Fraction paid to drivers	Fraction of TNC trip revenue paid to drivers	0.5
Initial user WtC	Initial driver willingness to consider	0.75
Initial driver WtC	Initial user willingness to consider	0.75
Initial drivers	Initial drivers (people)	45
Initial users	Initial users (people)	142

Name in Vensim	Description (units, if applicable)	Example value
Initial expected pay	Initial expected wage ($)	47
Initial perceived gen cost	Initial perceived generalized cost ($)	16
Monthly avg trips per user	Average monthly TNC trips per user (trips/month)	3
Price per trip minute	Price per trip minute ($/min)	0.3333
Reference monthly wage	Reference wage ($)	20
Reference trip generalized cost	Reference trip generalized cost ($)	10
Scaling factor users	Scaling factor for driver recruitment S-curve	0.3
Scaling factor	Scaling factor for user recruitment S-curve	-0.15
Time to change perception	Time to change perceived cost (months)	3
Time to change pay perception	Time to change perceived wage (months)	3
Value of minute traveling	Value of time traveling ($/min)	0.1667
Value of minute waiting	Value of time waiting ($/min)	0.3333

Endogenous factors

Table 4. Endogenous factors in the TNC model.

Name in Vensim	Description (units, if applicable)	Equation
Non-users	People who do not use the TNC service (people)	$\int -(\text{Net user recruitment})\,dt$
Signed-up users	People who do use the TNC service (people)	$\int \text{Net user recruitment}\,dt$
Net driver recruitment	Net users changing from potential drivers to signed-up drivers (People/Month)	$\text{driver gain} - \text{driver loss}$

Name in Vensim	Description (units, if applicable)	Equation
Driver loss	Decay rate of TNC drivers (people/month)	$$\frac{\text{Signed-up drivers}}{\text{Avg time as driver}}$$
User loss	Decay rate of TNC app users (people/month)	$$\frac{\text{Signed-up users}}{\text{Avg time as user}}$$
Driver gain	Rate of drivers switching from not driving for the TNC to driving (people/month)	$$(\text{Potential drivers considering platform}) \times (\text{probability of signing up to drive})$$
User gain	Rate of users switching from not using the TNC app to using it (people/month)	$$(\text{People considering platform}) \times \begin{pmatrix}\text{fraction of people considering} \\ \text{who actually get app}\end{pmatrix}$$
Fraction of people considering who actually get app	S-curve establishing probability of a user willing to download app of doing so	$$\frac{e^{(\text{scaling factor users})\times(\text{perceived generalized cost})}}{\begin{pmatrix} e^{(\text{scaling factor users})\times(\text{perceived generalized cost})} \\ +e^{(\text{scaling factor users})\times(\text{reference trip generalized cost})}\end{pmatrix}}$$
Probability of signing up to drive	S-curve establishing probability of a person willing to sign up to driver of doing so	$$\frac{e^{(\text{scaling factor})\times(\text{expected monthly driver pay})}}{\begin{pmatrix} e^{(\text{scaling factor})\times(\text{expected monthly driver pay})} \\ +e^{(\text{scaling factor})\times(\text{reference monthly wage})}\end{pmatrix}}$$
DriverWtC gain	Rate of WtC increase for drivers	$$(\text{DriverSocial exposure effectiveness}) \times (1 - \text{DriverWillingness to consider})$$
DriverWtC loss	Rate of WtC decay for drivers	$$\frac{\text{DriverWillingness to consider}}{\text{DriverWtC time to lose}}$$
DriverSocial exposure effectiveness	Effectiveness of social exposure and marketing for drivers; drives WtC increase	$$(\text{Driver enthusiasm} + \text{DriverMarketing}) \times \left(\frac{\text{Signed-up Drivers}}{\text{Driver population}}\right)$$
Potential drivers considering platform	People willing to drive for the TNC, who aren't already doing so (people)	$$(\text{DriverWillingness to consider}) \times (\text{Potential drivers})$$
Potential drivers	People (in the driver population) who do not drive for the TNC (People)	$$\int -(\text{Net driver recruitment})\, dt$$

Name in Vensim	Description (units, if applicable)	Equation
DriverWillingness to Consider	Willingness to consider among potential drivers	$\int (\text{DriverWtC gain}) - (\text{DriverWtC loss})\, dt$
Average available drivers	Number of drivers available to make a trip (People)	$(\text{Signed-up Drivers}) \times (\text{Fraction of time each driver drives})$
Average wait time (minutes) per trip	(minutes/trip)	$\min\left\{3 + \frac{15}{\text{average available drivers}}, 120\right\}$
Company monthly farebox	Total revenue from trips to TNC ($/Month)	$(\text{Monthly TNC trips}) \times (\text{price per trip minute}) \times (\text{Average trip length in minutes})$
Monthly TNC trips	Total trips across all users on TNC system (Trips/month)	$(\text{Monthly avg trips per user}) \times (\text{signed-up users})$
Net change in perceived generalized cost	($/Month)	$\frac{\left(\begin{array}{c}\text{trip generalized cost}\\ -\text{Perceived generalized cost}\end{array}\right)}{\text{Time to change perception}}$
Trip generalized cost	Combines the monetary cost (i.e., fare) of the trip, as well as the cost of the time needed to take a trip through value of time factors ($)	$(\text{Average wait time (minutes) per trip} \times \text{value of minute waiting}) + \text{Average trip length in minutes} \times (\text{price per trip minute} + \text{value of minute traveling})$
Net user recruitment	Net users changing from potential users to signed-up users (People/Month)	$\text{user gain} - \text{user loss}$
People considering platform	People willing to sign up for the app, who haven't already done so (People)	$\text{Willingness to consider} \times \text{Non-users}$
Perceived generalized cost	User perception of trip generalized cost (lagged over the time to change perception) ($)	$\int \begin{array}{c}\text{Net change in perceived}\\ \text{generalized cost}\end{array} dt$
Net change in expected pay	($/Month)	$\frac{\left(\begin{array}{c}\text{This month driver pay}\\ -\text{Expected monthly driver pay}\end{array}\right)}{\text{Time to change pay perception}}$

Name in Vensim	Description (units, if applicable)	Equation
Social exposure effectiveness	Effectiveness of social exposure and marketing on non-users; drives WtC increase	$(\text{User enthusiasm} + \text{Marketing}) \times \left(\frac{\text{Signed-up Users}}{\text{Population}}\right)$
Willingness to consider	Willingness to consider among potential users	$\int (\text{WtC gain}) - (\text{WtC loss})\, dt$
WtC loss	Rate of WtC increase for users	$\frac{\text{Willingness to consider}}{\text{WtC time to lose}}$
WtC gain	Rater of WtC decay for users	$(\text{Social exposure effectiveness}) \times (1 - \text{Willingness to consider})$
Drivers' share of fares	Pool of money paid out by TNC to drivers ($/Month)	$\text{Company monthly farebox} \times \text{Fraction paid to drivers}$
Expected monthly driver pay	Driver perception of wage (lagged over the time to change pay perception) ($)	$\int \begin{matrix}\text{Net change in} \\ \text{expected pay}\end{matrix}\, dt$
This month driver pay	Per-driver pay ($/(Month*Driver))	$\frac{\text{Drivers' share of fares}}{\text{Signed-up Drivers}}$
Signed-up drivers	People among the driver population who drive for the TNC (People)	$\int \text{Net driver recruitment}\, dt$

Outputs

These tables show outputs of the model for two key metrics: signed-up users (Table 5) and signed-up drivers (Table 6) for three scenarios. See Table 1 for a description of the input parameter values used to generate these outputs. These data are visualized in Figure 8.

Table 5. Signed-up users under the three scenarios described in Table 1.

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
0	45.0	10.0	10.0
1	45.0	10.2	8.7
2	45.1	13.8	11.3
3	45.1	18.7	14.1
4	45.2	24.4	17.2
5	45.2	30.4	20.4

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
6	45.2	35.8	23.5
7	45.2	39.9	26.3
8	45.2	42.4	28.5
9	45.2	43.8	29.3
10	45.2	44.5	28.6
11	45.2	44.8	26.8
12	45.2	45.0	24.6
13	45.2	45.1	22.3
14	45.2	45.1	20.3
15	45.2	45.2	18.6
16	45.2	45.2	17.3
17	45.2	45.2	16.4
18	45.2	45.2	15.9
19	45.2	45.2	15.5
20	45.2	45.2	15.3
21	45.2	45.2	15.2
22	45.2	45.2	14.9
23	45.2	45.2	14.6
24	45.2	45.2	14.3
25	45.2	45.2	13.8
26	45.2	45.2	13.3
27	45.2	45.2	12.8
28	45.2	45.2	12.4
29	45.2	45.2	11.9
30	45.2	45.2	11.5
31	45.2	45.2	11.1
32	45.2	45.2	10.8
33	45.2	45.2	10.4
34	45.2	45.2	10.1
35	45.2	45.2	9.8
36	45.2	45.2	9.4
37	45.2	45.2	9.1
38	45.2	45.2	8.8
39	45.2	45.2	8.5
40	45.2	45.2	8.2
41	45.2	45.2	7.9
42	45.2	45.2	7.5
43	45.2	45.2	7.2
44	45.2	45.2	7.0

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
45	45.2	45.2	6.7
46	45.2	45.2	6.4
47	45.2	45.2	6.1
48	45.2	45.2	5.8
49	45.2	45.2	5.6
50	45.2	45.2	5.3
51	45.2	45.2	5.1
52	45.2	45.2	4.8
53	45.2	45.2	4.6
54	45.2	45.2	4.3
55	45.2	45.2	4.1
56	45.2	45.2	3.9
57	45.2	45.2	3.6
58	45.2	45.2	3.4
59	45.2	45.2	3.2
60	45.2	45.2	3.0
61	45.2	45.2	2.8
62	45.2	45.2	2.6
63	45.2	45.2	2.4
64	45.2	45.2	2.2
65	45.2	45.2	2.0
66	45.2	45.2	1.9
67	45.2	45.2	1.7
68	45.2	45.2	1.5
69	45.2	45.2	1.4
70	45.2	45.2	1.2
71	45.2	45.2	1.1
72	45.2	45.2	1.0
73	45.2	45.2	0.9
74	45.2	45.2	0.8
75	45.2	45.2	0.7
76	45.2	45.2	0.6
77	45.2	45.2	0.5
78	45.2	45.2	0.5
79	45.2	45.2	0.4
80	45.2	45.2	0.3
81	45.2	45.2	0.3
82	45.2	45.2	0.3
83	45.2	45.2	0.2
84	45.2	45.2	0.2

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
85	45.2	45.2	0.2
86	45.2	45.2	0.1
87	45.2	45.2	0.1
88	45.2	45.2	0.1
89	45.2	45.2	0.1
90	45.2	45.2	0.1
91	45.2	45.2	0.1
92	45.2	45.2	0.1
93	45.2	45.2	0.0
94	45.2	45.2	0.0
95	45.2	45.2	0.0
96	45.2	45.2	0.0
97	45.2	45.2	0.0
98	45.2	45.2	0.0
99	45.2	45.2	0.0
100	45.2	45.2	0.0

Table 6. Signed-up drivers under the three scenarios described in Table 1.

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
0	142.0	50.0	50.0
1	142.7	48.2	43.0
2	143.0	49.8	38.7
3	143.0	53.2	35.6
4	143.0	57.9	33.0
5	142.8	63.6	30.9
6	142.7	70.2	29.2
7	142.6	77.3	27.7
8	142.5	84.6	26.4
9	142.4	91.9	25.3
10	142.3	98.9	24.3
11	142.2	105.5	23.4
12	142.2	111.5	22.5
13	142.1	116.8	21.7
14	142.1	121.3	21.0
15	142.1	125.2	20.2
16	142.1	128.5	19.5
17	142.0	131.2	18.8
18	142.0	133.4	18.1

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
19	142.0	135.2	17.4
20	142.0	136.6	16.8
21	142.0	137.8	16.2
22	142.0	138.7	15.6
23	142.0	139.4	15.0
24	142.0	140.0	14.5
25	142.0	140.4	13.9
26	142.0	140.7	13.4
27	142.0	141.0	12.9
28	142.0	141.2	12.5
29	142.0	141.4	12.0
30	142.0	141.5	11.6
31	142.0	141.6	11.1
32	142.0	141.7	10.7
33	142.0	141.8	10.3
34	142.0	141.8	9.9
35	142.0	141.9	9.5
36	142.0	141.9	9.1
37	142.0	141.9	8.8
38	142.0	141.9	8.4
39	142.0	141.9	8.1
40	142.0	141.9	7.7
41	142.0	142.0	7.4
42	142.0	142.0	7.1
43	142.0	142.0	6.7
44	142.0	142.0	6.4
45	142.0	142.0	6.1
46	142.0	142.0	5.8
47	142.0	142.0	5.5
48	142.0	142.0	5.2
49	142.0	142.0	5.0
50	142.0	142.0	4.7
51	142.0	142.0	4.4
52	142.0	142.0	4.2
53	142.0	142.0	3.9
54	142.0	142.0	3.7
55	142.0	142.0	3.4
56	142.0	142.0	3.2
57	142.0	142.0	3.0
58	142.0	142.0	2.7

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
59	142.0	142.0	2.5
60	142.0	142.0	2.3
61	142.0	142.0	2.1
62	142.0	142.0	1.9
63	142.0	142.0	1.8
64	142.0	142.0	1.6
65	142.0	142.0	1.4
66	142.0	142.0	1.3
67	142.0	142.0	1.1
68	142.0	142.0	1.0
69	142.0	142.0	0.9
70	142.0	142.0	0.8
71	142.0	142.0	0.7
72	142.0	142.0	0.6
73	142.0	142.0	0.5
74	142.0	142.0	0.4
75	142.0	142.0	0.3
76	142.0	142.0	0.3
77	142.0	142.0	0.2
78	142.0	142.0	0.2
79	142.0	142.0	0.2
80	142.0	142.0	0.1
81	142.0	142.0	0.1
82	142.0	142.0	0.1
83	142.0	142.0	0.1
84	142.0	142.0	0.1
85	142.0	142.0	0.1
86	142.0	142.0	0.0
87	142.0	142.0	0.0
88	142.0	142.0	0.0
89	142.0	142.0	0.0
90	142.0	142.0	0.0
91	142.0	142.0	0.0
92	142.0	142.0	0.0
93	142.0	142.0	0.0
94	142.0	142.0	0.0
95	142.0	142.0	0.0
96	142.0	142.0	0.0
97	142.0	142.0	0.0

Time	Equilibrium	Scenario to equilibrium	Scenario to zero
98	142.0	142.0	0.0
99	142.0	142.0	0.0
100	142.0	142.0	0.0

Bikeshare Model

Exogenous factors

Table 7. Exogenous factors in the dockless bikeshare model.

Name in Vensim	Description (units, if applicable)	Example value
Population	Population in service area (people)	1000
Service area	Size of the area in which the bikeshare service provides trips (km^2)	16
Acceptable walk distance	How far someone is willing to walk to find a bike (km)	0.5
Desirable monthly person-trips	Number of trips each person wants to take each month (Trips/(person*month))	100
Time to place order	Lag time from needing a bike to ordering that bike (months)	2
Time to receive order	Lag time from ordering a bike to receiving that bike (months)	2
Goal utilization	The company's desired trips taken per bike per month (trips/(bike*month))	60
Initial bike stock	Initial number of bikes put into the system (bikes)	125
Bike useful life (tripwise)	How many trips a bike can take before wearing out (trips/bike)	1500

Endogenous factors

Table 8. Endogenous factors in the dockless bikeshare model.

Name in Vensim	Description (units, if applicable)	Equation
Bike mode share	Share of trips taken on the bikeshare service	A lookup function with the following lookup values: When there are 0.122324 useful bikes, the mode share is 0.

Name in Vensim	Description (units, if applicable)	Equation
		When there are 2.32416 useful bikes, the mode share is 0.0219298. When there are 3.97554 useful bikes, the mode share is 0.0526316. When there are 5.50459 useful bikes, the mode share is 0.0964912. When there are 7.03364 useful bikes, the mode share is 0.149123. When there are 8.07339 useful bikes, the mode share is 0.219298. When there are 9.23547 useful bikes, the mode share is 0.315789. When there are 10.2141 useful bikes, the mode share is 0.399123. When there are 11.5596 useful bikes, the mode share is 0.482456. When there are 13.0275 useful bikes, the mode share is 0.52193. When there are 14.4954 useful bikes, the mode share is 0.54386. When there are 16.0856 useful bikes, the mode share is 0.557018. When there are 17.7982 useful bikes, the mode share is 0.570175. When there are 18.9602 useful bikes, the mode share is 0.574561. When there are 19.7554 useful bikes, the mode share is 0.578947. When there are 1000 useful bikes, the mode share is 1.
Bike useful life (timewise)	At current bike utilization rate, the length of time it takes for a bike to wear out (Month)	$\frac{\left(\text{Bike useful life (tripwise)}\right)}{\text{Bike utilization}}$
Reception rate	Rate of bikes being added to the system (Bikes/Month)	$\frac{\text{bikes on order}}{\text{time to receive order}}$
Reception rate in	Same as reception rate (repeated to demonstrate coflow) (Bikes/Month)	Reception rate

Name in Vensim	Description (units, if applicable)	Equation
Bike discrepancy	The difference between the number of bikes required in the system to achieve the goal utilization, and the current number of bikes in the system (Bikes)	$\text{Indicated bikes} - \text{bikes}$
Order rate	The rate of bikes/month ordered by the service (Bikes/Month)	$\max\left\{\frac{\left(\substack{\text{bike}\\ \text{discrepancy}}\right)}{\left(\substack{\text{time to}\\ \text{place order}}\right)}, 0\right\}$
Bikes on order	Number of bikes ordered but not yet received by the bikeshare service (bikes)	$\int(\text{order rate} - \text{reception rate})\, dt$
Bikes	Number of bikes currently in service (bikes)	$\int(\text{reception rate in} - \text{junk rate})\, dt$
Indicated bikes	Number of bikes required in the system to achieve the goal utilization at current number of trips taken (Bikes)	$\frac{\text{trips satisfied by bike}}{\text{goal utilization}}$
Junk rate	Rate of bikes wearing out by exceeding their useful life	$\frac{\text{Bikes}}{\left(\substack{\text{Bike useful life}\\ \text{(timewise)}}\right)}$
Bike utilization	Number of trips taken per bike per month (Trip/(bike*month))	$\frac{\text{trips satisfied by bike}}{\text{bikes}}$
Trips satisfied by bike	Monthly trips taken on all bikes in the system (Trip/Month)	$\text{bike mode share} \times \text{desired monthly person-trips} \times \text{population}$
Useful bikes	Assuming even distribution of bikes and people, the number of bikes within the acceptable walk distance of a person (Bikes)	$\pi(\text{acceptable walk distance})^2 \times \text{bike density}$
Bike density	Assuming even distribution of bikes, number of bikes per square kilometer (Bikes/km^2)	$\frac{\text{bikes}}{\text{service area}}$

Outputs

These tables show outputs of the model for two key metrics: number of bikes and bike utilization. See Table 2 for a description of the input parameter values used to generate these outputs. These data are visualized in Figure 10 (for Table 9, results from the first parameter set) and Figure 11 (for Table 10, results from the second parameter set).

Table 9. Outputs for the first parameter set in Table 2.

Time	Bikes	Bike utilization
0	85.0	68.6
1	81.1	65.1
2	80.6	64.9
3	80.4	64.8
4	80.2	64.7
5	79.9	64.6
6	79.7	64.6
7	79.4	64.5
8	79.1	64.3
9	78.7	64.2
10	78.3	64.1
11	77.8	63.9
12	77.2	63.7
13	76.6	63.5
14	75.9	63.2
15	75.0	62.9
16	74.1	62.5
17	73.0	62.1
18	71.7	61.6
19	70.3	61.0
20	68.7	60.3
21	66.9	59.4
22	64.8	58.4
23	62.5	57.2
24	60.3	55.9
25	58.1	54.6
26	56.0	53.3
27	54.0	51.9
28	52.2	50.5
29	50.4	49.1
30	48.8	47.6

Time	Bikes	Bike utilization
31	47.2	46.3
32	45.8	46.2
33	44.4	46.1
34	43.0	46.1
35	41.7	46.0
36	40.4	45.9
37	39.2	45.8
38	38.0	45.7
39	36.8	45.6
40	35.7	45.5
41	34.6	45.4
42	33.6	45.3
43	32.5	45.1
44	31.6	45.0
45	30.6	44.9
46	29.7	44.8
47	28.8	44.7
48	28.0	44.5
49	27.1	44.4
50	26.3	44.3
51	25.5	44.1
52	24.8	44.0
53	24.1	43.8
54	23.4	43.7
55	22.7	43.5
56	22.0	43.4
57	21.4	43.2
58	20.8	43.0
59	20.2	42.9
60	19.6	42.7
61	19.0	42.5
62	18.5	42.3
63	18.0	42.1
64	17.5	41.9
65	17.0	41.7
66	16.5	41.5
67	16.1	41.3
68	15.6	41.1
69	15.2	40.9
70	14.8	40.6

Time	Bikes	Bike utilization
71	14.4	40.4
72	14.0	40.2
73	13.6	39.9
74	13.3	39.7
75	12.9	39.4
76	12.6	39.2
77	12.2	38.9
78	11.9	38.7
79	11.6	38.4
80	11.3	38.1
81	11.0	37.8
82	10.7	37.6
83	10.5	37.3
84	10.2	37.0
85	10.0	36.7
86	9.7	36.4
87	9.5	36.0
88	9.3	35.7
89	9.0	35.4
90	8.8	35.1
91	8.6	34.8
92	8.4	34.4
93	8.2	34.1
94	8.0	33.7
95	7.9	33.4
96	7.7	33.0
97	7.5	32.7
98	7.3	32.3
99	7.2	31.9
100	7.0	31.6

Table 10. Outputs for the first parameter set in Table 2.

Time	Bikes	Bike utilization
0	125.0	94.6
1	117.1	89.6
2	128.1	96.4
3	143.3	104.1
4	164.5	133.4

Time	Bikes	Bike utilization
5	191.8	172.7
6	241.1	203.2
7	334.1	167.4
8	503.5	115.4
9	717.7	81.6
10	921.3	64.0
11	1067.9	55.5
12	1136.8	52.3
13	1151.4	51.7
14	1138.9	52.2
15	1112.8	53.4
16	1080.0	54.9
17	1043.8	56.8
18	1006.0	58.8
19	967.4	61.1
20	928.4	63.6
21	893.6	65.9
22	870.4	67.7
23	861.3	68.3
24	864.8	68.1
25	876.9	67.2
26	892.4	66.0
27	906.7	65.0
28	916.6	64.3
29	920.8	64.1
30	919.9	64.1
31	915.3	64.4
32	909.2	64.9
33	903.4	65.3
34	899.2	65.5
35	897.3	65.7
36	897.4	65.7
37	899.1	65.6
38	901.5	65.4
39	903.9	65.2
40	905.7	65.1
41	906.6	65.0
42	906.6	65.0
43	905.9	65.1
44	905.0	65.1

Time	Bikes	Bike utilization
45	904.0	65.2
46	903.3	65.3
47	902.9	65.3
48	902.9	65.3
49	903.1	65.3
50	903.5	65.3
51	903.9	65.2
52	904.2	65.2
53	904.3	65.2
54	904.4	65.2
55	904.3	65.2
56	904.1	65.2
57	904.0	65.2
58	903.9	65.2
59	903.8	65.2
60	903.8	65.2
61	903.8	65.2
62	903.8	65.2
63	903.9	65.2
64	904.0	65.2
65	904.0	65.2
66	904.0	65.2
67	904.0	65.2
68	904.0	65.2
69	903.9	65.2
70	903.9	65.2
71	903.9	65.2
72	903.9	65.2
73	903.9	65.2
74	903.9	65.2
75	903.9	65.2
76	903.9	65.2
77	903.9	65.2
78	903.9	65.2
79	903.9	65.2
80	903.9	65.2
81	903.9	65.2
82	903.9	65.2
83	903.9	65.2

Time	Bikes	Bike utilization
84	903.9	65.2
85	903.9	65.2
86	903.9	65.2
87	903.9	65.2
88	903.9	65.2
89	903.9	65.2
90	903.9	65.2
91	903.9	65.2
92	903.9	65.2
93	903.9	65.2
94	903.9	65.2
95	903.9	65.2
96	903.9	65.2
97	903.9	65.2
98	903.9	65.2
99	903.9	65.2
100	903.9	65.2

U.S. Department of Transportation
ITS Joint Program Office – HOIT
1200 New Jersey Avenue, SE
Washington, DC 20590

Toll-Free "Help Line" 866-367-7487

www.its.dot.gov

[FHWA-JPO-20-809]

U.S. Department of Transportation