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INTEGRATING DECISION FIELD THEORY WITHIN SYSTEM DYNAMICS FRAMEWORK FOR MODELING THE ADOPTION PROCESS OF RIDE SOURCING SERVICES

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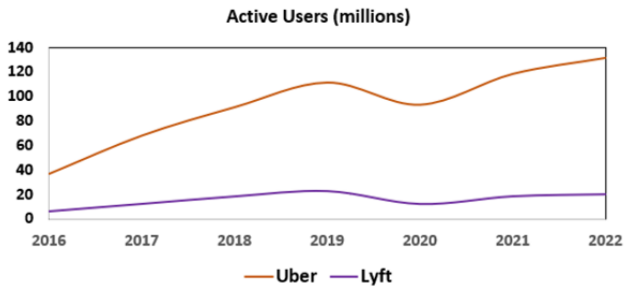
ABSTRACT

The rise of ride-sourcing services has changed the transportation industry, reshaping urban mobility services. This paper presents an integrated framework of the adoption of ride-sourcing services and its impact on transportation markets using a combined approach of System Dynamics (SD) and Extended-Decision Field Theory (E-DFT). Drawing on data from ride-sourcing platforms such as Uber and Lyft, the study investigates the temporal dynamics and trends of ride-sourcing demand. SD modeling is employed to capture the complex interactions and feedback loops within the ride-sourcing ecosystem at system-level. The integration of System Dynamics and extended DFT allows for a more comprehensive and holistic modeling of the ride-sourcing market. It enables exploration of various scenarios and policy interventions, providing insights into the long-term behavior of the market and facilitating evidence-based decision-making by policymakers and industry stakeholders while accommodating individual users' decisions based on changing preferences and environments.

1 INTRODUCTION

Over the past decade, the ride-sourcing market has experienced substantial growth and maturation, resulting in transformative changes in the transportation service industry (Wang and Yang 2019; Mitropoulos et al. 2021; Button 2020; Agatz et al. 2012; Tafreshian et al. 2020). Companies such as Lyft and Uber have been at the forefront of this evolution, driving advancements in technology, service quality, and market reach. The emergence of ride-sourcing services has revolutionized the transportation landscape, presenting individuals with convenient and flexible alternatives to traditional modes of transportation. Companies like Lyft and Uber have disrupted the industry, often referred to as transportation network companies (TNCs), offering on-demand transportation services that connect riders with drivers through digital platforms.

One notable growth in the TNCs is the significant expansion of service coverage. For example, in 2011, Lyft and Uber primarily operated in a handful of major cities in the United States. However, by 2021, Lyft reported providing services in over 650 cities across North America, while Uber expanded its operations to over 10,000 cities worldwide. This expansion has dramatically increased the availability and accessibility of ride-sourcing services to a broader population. In terms of numbers, ride-sourcing services have experienced substantial growth in terms of ridership and market penetration. For example, in 2019, Lyft reported providing over 1 billion rides globally, while Uber completed more than 6 billion rides worldwide in the same year. In terms of services, ride-sourcing companies have implemented various types of services and some of these are still successfully operated. For instance, Uber implemented a feature called "UberPool" in 2014, which allows riders heading in the same direction to share a ride and split the fare. This innovation reduces riders' costs, contributes to more efficient resource utilization, and alleviates traffic congestion. Lyft also introduced similar carpooling options, such as "Lyft Line," further expanding the availability of shared rides. These features have become popular choices for budget-conscious riders and have improved the overall efficiency of the mobility service market.



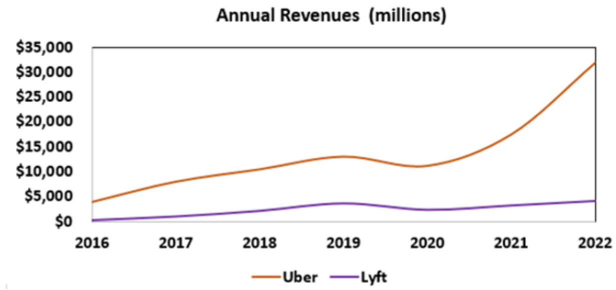


Figure 1: Annual growth of TNC.

Figure 1 illustrates the ride-sourcing services and TNCs with various players (drivers, travelers, platforms) in a complex environment (regulations, perceptions, technologies, etc.) dynamically evolve in the last few years, To understand and analyze the market wherein new services and technologies, Systems Dynamics (SD) can be a useful framework for recognizing the complex nature of ride-sourcing systems involving various players and environments. The research gap we identified is that traditional SD models, once calibrated, rely on fixed parameters that cannot adapt to evolving individual behavioral dynamics over time. This limitation restricts capturing how travelers' mode choice preferences change in response to shifting policies and/or market changes.

Therefore, the contribution of this paper is to demonstrate the necessity of the interaction to model transportation mode choice realistically. By capturing both individual-level psychological decision dynamics and system-level feedback effects, our hybrid framework addresses cross-level interactions that single-simulation methods cannot represent, offering a more comprehensive tool for evaluating policy interventions. The proposed new integrated framework based on SD and Extended Decision Field Theory (EDFT), which can provide a useful framework for understanding complex systems such as transportation and mobility systems. The proposed framework is expected to incorporate effects, causalities, and interactions between agents and environments via SD and the dynamics of individual travel behaviors via EDFT under uncertainty. We develop coordination methodologies to bridge the two modeling approaches, between two models using Bayesian updates. We aim to illustrate the adoption of ride-sharing, exploring the interplay between policy interventions and consumer behaviors to gain a deeper understanding of this evolving market.

2 LITERATURE REVIEW

SD has widely used to demonstrate dynamics of complex systems (Shepherd 2014; Aschauer et al. 2015). Since the SD approach incorporates effects, causalities, and interactions between agents and environments, it has been widely used in transportation applications (Jifeng et al. 2008; Suryani et al. 2020). Its flexibility enables to model, analyze, and interpret evolving complex systems, helping to develop sustainable transportation-related policies (Sayyadi and Awasthi 2020; Suryani et al. 2020). The SD modeling approach has been applied to specific applications including transit mode selection to minimize traffic congestion (Ahmed and Kwon 2012), public transportation investment decisions (Moradi and Vagnoni 2018), sustainable transportation policies (Sayyadi and Awasthi 2020), and transportation capacity requirements (Aurachman 2020). It is, however, widely recognized that travelers' behaviors also importantly determine the adoption and growth of these services (Ben-Akiva and Lerman 1985; Train 2009)., for which SD cannot fully capture. Therefore, it is important to consider agent-levels' behavior modeling and incorporate them into the SD framework.

As the rapid growth and widespread adoption of TNCs have sparked considerable interests among researchers, policymakers, and industry stakeholders, it is required to understand the dynamics of this evolving market from agent/group level's perspective, (Diao et al. 2021; Shaheen et al. 2020; Wang and Yang 2019), infrastructure perspective, including planning, operations, pricing, economics, supply (drivers) - demand (travelers) match, and their behaviors, etc., for different variations of operations and considerations, with different modeling techniques of optimization, data analysis, econometrics, economics, etc (Mitropoulos et al. 2021; Button 2020; Agatz et al. 2012; Tafreshian et al. 2020). (Wang and Yang 2019) presents a comprehensive review of the ride-sourcing markets, analyzing their demand and supply sides, whereas (Tafreshian et al. 2020) prioritized the operation parts of ride-sourcing, exploring operations management methodologies. As the methodologies and applications of ride-souring are widely extended, (Jin et al. 2018) clarified the relevant terminologies and studied different analysis methodologies. McKane and Hess (2023) examined ride-scouring's sustainability, including some spatial analysis.

Yan et al. (2020) focused on socioeconomic and demographic variables that are significant for ride-sourcing demand while demonstrating travel impedance and infrastructure could also be significant. Ridesourcing demand also can depend upon the travel distance, showing that less travel distance leads to more usage of ride scouring (Wu and MacKenzie 2021), reducing the energy consumption (Wenzel et al. 2019). (Sikder 2019) illustrates the causalities of household characteristics such as the number of children and elderly persons, decreasing the willingness of ride scouring usage, which are also confirmed by other researchers (Barbour et al. 2020). (Lavieri et al. 2018) focused on the relationship between income and ride-scouring usage, finding that people with different incomes utilize ride-sourcing services based on the purpose of the different trips. It is also well studied that younger generations are more likely to use ride-sourcing services (Dzisi et al. 2020; Goodspeed et al. 2019), while for the older generations, trust issues with random drivers were identified as a key factor, preventing from using the services (Sarker et al. 2022).

3 INTEGRATED SYSTEM DYNAMICS FRAMEWORK

Figure 2 demonstrates our framework, which captures both individual mode choice and transportation market dynamics. To predict people's choice of ride-sourcing services in the complex transportation market, it is imperative to consider both individual behaviors and market dynamics. We have selected and Extended Decision Field Theory (EDFT) to demonstrate individual choice behaviors while System Dynamics (SD) has been chosen to demonstrate the effect of the market on ride-sourcing service demand. After explaining those two models in the following two subsections, we will propose the integration approach of both models, which will provide a comprehensive understanding of ride-sourcing service demand over time.

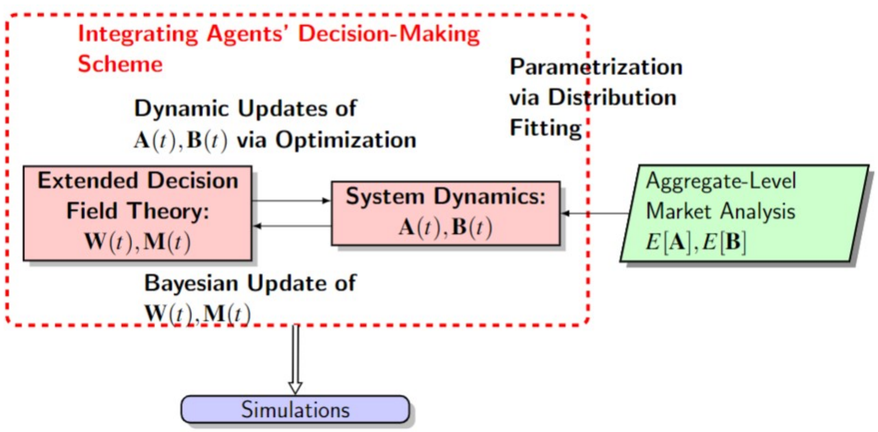


Figure 2: Integrated system dynamics framework.

As shown in Figure 2, the integration of System Dynamics and Extended Decision Field Theory (E-DFT) combines macro-level dynamics with micro-level decision-making to enhance the modeling and analysis. The integration helps to understand the complex interactions and feedback loops within a complex system. It allows the modeling of various components, such as user demand, driver supply, pricing mechanisms, and market competition. By incorporating these dynamics, the integration captures the overall behavior and evolution of the TNC system over time. DFT focuses on the micro-level decision-making processes of individuals within the TNC system. It considers factors such as individual preferences, social influences, and time-varying factors that affect decision-making. By integrating DFT, the modeling framework can capture the heterogeneity among users and how their choices impact the overall system dynamics.

As explained, we want to demonstrate the ride-sourcing service demand using our framework, and SD can be an appropriate modeling approach. For example, at the early stage of ride-sourcing services, travelers may not have felt comfortable using such services due to unfamiliarity or safety reasons. But as these services are more frequently described through word-of-mouth or media, travelers may become comfortable using them. Thus, the framework developed using SD can incorporate interactions among markets, policies, familiarity, etc, supporting the generation of long-term and strategic management plans. Developing an SD-based framework aims to generate decision-makers policy sets under environmental uncertainties and validate them in the simulation environment. Not only can one simulate and analyze the effects of marketing campaigns on ride-sourcing services, but one can also validate the model under different scenarios. The recent market-disrupting events, including the Covid breakout or crimes while using ride-sourcing services, SD can incorporate those incident events in evaluating demand dynamics. This aggregation procedure, indeed calibration, for the SD-based framework development is carried out at the macro level, typically via market analyses and surveys, including quantitative and qualitative approaches. It is noted that agents' decision-making processes or behavioral preferences are not directly captured in the SD framework as long as aggregate values that describe system-level performance are calibrated. Rather, agents' decision output is captured as positive/negative feedback at the aggregated level.

By doing so, the integration provides a more comprehensive understanding of the effects of interventions and policies in the TNC system. It allows policymakers to evaluate the potential impacts of different regulatory measures, pricing schemes, and incentives on user behavior, driver participation, and overall system performance. This can inform evidence-based policy decisions and contribute to the sustainable development of the TNC industry. Also, the integrated approach facilitates long-term forecasting and scenario analysis by considering both the macro-level dynamics and individual decision-making. This enables researchers and policymakers to explore various future scenarios, understand the potential consequences of different events or trends, and assess the resilience of the TNC system under changing conditions.

3.1 System Dynamics (SD) Modeling for Transportation Market Dynamics

As a highly abstract modeling methodology, SD simultaneously resolves the system-level problem by updating all relevant variables in small-time increments with balancing and reinforcing feedback considering interactions between agents and environments, and is therefore able to capture the evolution of systems. As we discussed in the literature review section, SD modeling approach has been recently recognized by the transportation research community (Shepherd 2014; Aschauer et al. 2015; Suryani et al. 2020; Suryani et al. 2020). Instead of focusing on the fine details of a system, such as an individual's characteristics or properties, products, or events, it produces a general representation of a complex system over time. Since the mode choice of new and emerging systems is highly dependent on the market, it is important to incorporate the market dynamics in mode choice.

One can develop a system dynamics model to simulate and forecast the demand for ride-sourcing services, as shown in Figure 3. The model would consider variables such as population demographics, urbanization trends, transportation infrastructure, pricing dynamics, service quality, and competing modes of transportation. The model can capture the dynamics and interactions that influence ride-sourcing demand by incorporating feedback loops, delays, and causal relationships among these variables. To develop a ride-sourcing demand model using system dynamics, you would first identify the key factors and variables that influence demand. These may include population growth, smartphone penetration, transportation network coverage, and factors that affect consumer preferences and choices. You would then define the relationships between these variables and represent them in the model.

This data can help establish the initial conditions and parameters of the model. It's important to note that developing an accurate system dynamics model requires a comprehensive understanding of the underlying

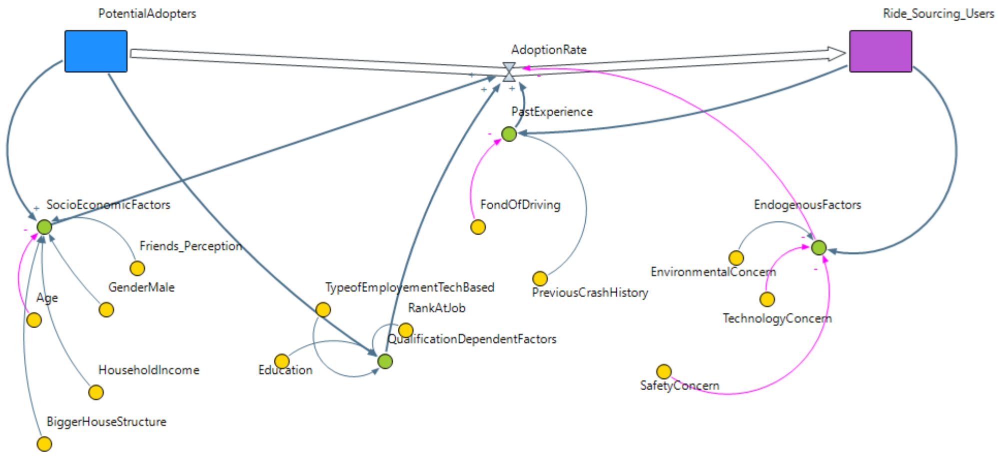


Figure 3: Illustration of system dynamics modeling (drawn in AnyLogic).

dynamics and careful consideration of data availability and quality. The model should be continually refined and updated based on new data and insights to improve its predictive accuracy. The model can estimate and predict ride-sourcing demand under different conditions and policy interventions by running simulations and scenario analyses. For example, you can assess the impact of changes in pricing strategies, market competition, or the introduction of new transportation policies on ride-sourcing demand. The model can be calibrated and validated using historical data on ride-sourcing demand and other relevant indicators.

As SD's their stock-and-flow structures are often represented using linear differential or difference equations that describe how system states evolve over time in response to inputs and feedback loops, SD models can be interpreted as a series of linear systems. System Dynamics have mainly used control dynamics, but now they have extended their applications in transportation, marketing, and socio-economic areas due to the advantage of incorporating dynamic behaviors of such systems. Assume that there are n numbers of transit modes, including ride-sourcing and m numbers of other transportation market variables. Then the corresponding SD model general model can be considered as follows:

$$\dot{\boldsymbol{x}} = \boldsymbol{x}(t+h) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t) \tag{1}$$

where $\boldsymbol{x} \in \mathbb{R}^n$ denotes people's choice on n different modes whereas $\boldsymbol{u} \in \mathbb{R}^m$ means the states of m different market variables. The way that we interpret the system is that the policy makers' decision only changes on μ as control variables, while $\boldsymbol{x}$ is state variables, which any decision/policymakers cannot control directly. SD can be considered as a linear combination of both variables $\boldsymbol{x}$ and $\boldsymbol{u}$. Thus, our research goal is to estimate reasonable and realistic matrix parameters $\boldsymbol{A}$ and $\boldsymbol{B}$, and update them when relevant data are available. To use fitting for prediction, it is important to consider the closed form of the system (Equation (1)).

$$\boldsymbol{x}(t) = e^{\boldsymbol{A}t}\boldsymbol{x}_0 + \int_0^t e^{\boldsymbol{A}(t-\tau)}\boldsymbol{B}\boldsymbol{u}(\tau)\,d\tau \tag{2}$$

Equation (2) represents the closed solution form of the SD model (1), where $x(t)$ indicates the number of people's choices on each transportation mode. Since $x(t)$ vector demonstrates the demand changes over time, we illustrate how to use the $x(t)$ vector to integrate the individual decision-making models in the following section.

3.2 Individual Choice behaviors via Extended Decision Field Theory

Decision Field Theory (DFT) is a cognitive decision-making model that incorporates time and therefore allows modeling of the dynamic evolution of preference over time (Busemeyer and Townsend 1993). It is a stochastic-dynamic model of decision-making behavior, which was expanded to include multi-attribute (Diederich 1997) and then multi-alternative decision-making (Roe et al. 2001), where it was renamed multi-alternative decision field theory. DFT has been utilized as a modeling framework in transportation applications, especially in mode choice (Qin et al. 2013; Hancock et al. 2018). Many researchers have utilized DFT as an individual-level decision-making framework in transportation (Stern 1999; Long et al. 2016; Hancock et al. 2018; Qin et al. 2013). For example, (Stern 1999) studied the role of time pressure in explaining the individuals' reaction to congestion under time pressure using DFT whereas (Qin et al. 2013) investigated the effect of deliberation time, deliberation threshold and initial preference for mode choice, especially in Park and Ride problem under the DFT framework. (Hancock et al. 2018) compared DFT to other decision-making models while showing that DFT provides a better representation of general decision-making in travel behavior modeling.

When an individual considers k number of alternatives with l number of decision criteria, DFT uses the partial differential equations to demonstrate her preference values (Busemeyer and Diederich 2002):

$$\mathbf{P}(t+h) = \mathbf{SP}(t) + \mathbf{CMW}(t+h) \tag{3}$$

$\mathbf{P}(t)$ and $\mathbf{P}(t+h)$ are k dimensional vectors, showing her preference values of all the k options at time $t, t+h$, respectively. The matrix $\mathbf{M} \in \mathbb{R}^l \times \mathbb{R}^k$ and the vector $\mathbf{W}(t+h) \in \mathbb{R}^l$ are two major parameters in DFT, implying the evaluation of options with respect to the decision criteria and weight values of the criteria, respectively. All the values of the matrix $\mathbf{S} \in \mathbb{R}^k \times \mathbb{R}^k$ are fixed ones that associate previous preference values at time t with updated preference values after time h has elapsed, while the scale matrix $\mathbf{C} \in \mathbb{R}^k \times \mathbb{R}^l$ guarantees that sum of all preferences values are set to zero (Busemeyer and Townsend 1993; Busemeyer and Diederich 2002). The vector $\mathbf{W}$, as a weight vector of the criteria, is highly dependent on the individual's demographics such as income, household, educational background, gender, and so on.

The evaluation matrix $\mathbf{M}$ should be dependent on the market status because the evaluation of a specific mode, with respect to some criteria, could change over time. For example, as gas prices increase, their evaluation results of two transportation modes - her own car or a ride-sourcing service- will be different. Thus, one can conclude that the evaluation matrix M can also be considered as stochastic processes over time $\mathbf{M}(t)$. The authors here propose an extended decision field theory to caputre chocie dynamics.

$$\mathbf{P}(t+h) = \mathbf{SP}(t) + \mathbf{CM}(t+h)\mathbf{W}(t+h) \tag{4}$$

In the original version of DFT, the choice probability at time $t+h$, denoted as $\mathbf{P}(t+h)$, is determined by the cumulative influence of two main components: the social influence term, representing the influence of others' choices, and the individual-specific decision-making term ($\mathbf{CMW}(t+h)$), which incorporates personal preferences and biases. However, several factors have emerged that can significantly impact individuals' decision-making processes. For example, safety concerns have become more prominent,

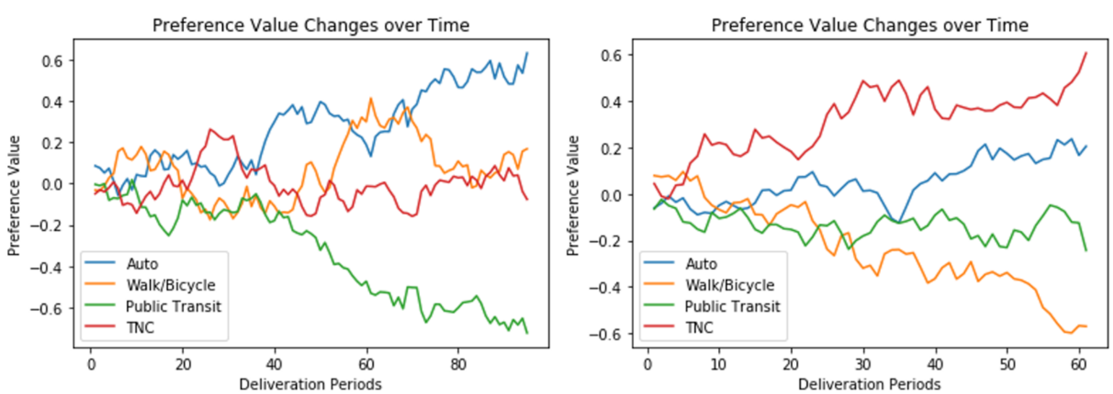


Figure 4: Preference evolution over deliberation.

leading to increased attention to health and hygiene considerations. As a result, the decision-making component **CM** can be expected to be influenced by these time-varying factors. Therefore, an extended version of DFT can incorporate the dynamic nature of these factors by considering **CM** as a function of time, denoted as $\mathbf{CM}(t+h)$. The increased importance of public transportation safety can further exemplify the impact of Covid-19 on ride-sourcing choices. With the ongoing pandemic, individuals may perceive public transportation as a higher-risk option due to the potential for crowded spaces and close contact with others. Consequently, ride-sourcing services may experience an increase in demand as people opt for individualized transportation that allows for better control over safety measures. The extended DFT framework can capture this dynamic relationship between the evolving safety concerns $(\mathbf{CM}(t+h))$

In this extension, we show that under the assumption of the independence between the weight vectors W and the evaluation vector $\mathbf{M}$, the expected value and the covariance structure remain the same as below. The first lemma below is important to calibrate this stochastic process to the traditional choice model or system dynamics models. The expected preference values and their covariance structures at each time period t are shown below. To address the evolution of our evaluation matrix $\mathbf{M}$ and $\mathbf{W}$, we introduce one covariance matrix $\Omega_i, i \in \{1, \cdots, l\}$, representing the covariance matrix of m_i&$\mathbf{W}$, m_i refers to the row vector of the matrix $\mathbf{M}$.

Theorem 1 Let $\boldsymbol{V}(t) = \boldsymbol{CM}(t)\boldsymbol{W}(t)$, where $\mathbb{E}[\boldsymbol{M}(t)] = \boldsymbol{\mu}_M$ and $\mathbb{E}[\boldsymbol{W}(t)] = \boldsymbol{\mu}_W$. Then, the closed-form expressions for $\mathbb{E}[\boldsymbol{V}(t)] = \boldsymbol{\mu}_V$ and $\mathrm{Cov}[\boldsymbol{V}(t)]$ are given by

$$\boldsymbol{\mu}_V = \boldsymbol{C}\boldsymbol{\mu}_M^T\boldsymbol{\mu}_W + \boldsymbol{C}\left[\mathrm{diag}(\boldsymbol{\Omega}_1), \mathrm{diag}(\boldsymbol{\Omega}_2), \cdots, \mathrm{diag}(\boldsymbol{\Omega}_m)\right]^T \tag{5}$$

$$\mathrm{Cov}[\boldsymbol{V}(t)] = \boldsymbol{C}\boldsymbol{\Sigma}_{MW}\boldsymbol{C}^\top. \tag{6}$$

Proof. Consider the product $\boldsymbol{M}(t)\boldsymbol{W}(t)$, where the i^{th} row of the product is $[\boldsymbol{M}(t)\boldsymbol{W}(t)]_i = \sum_{j=1}^{l} m_{ij}(t)w_j(t)$. Taking the expectation of the i^{th} row yields:

$$\mathbb{E}\left[\sum_{j=1}^{l} m_{ij}(t)w_j(t)\right] = \sum_{j=1}^{l} \mathbb{E}[m_{ij}(t)]\mathbb{E}[w_j(t)] + \mathrm{Cov}(m_{ij}(t), w_j(t)) = \boldsymbol{\mu}_i^\top\boldsymbol{\mu}_W + \mathrm{diag}(\boldsymbol{\Omega}_i).$$

Since this holds for all $i \in \{1, 2, \ldots, m\}$, we stack the rows and apply the transformation via $\boldsymbol{C}$:

$$\boldsymbol{\mu}_V = \boldsymbol{C}\mathbb{E}[\boldsymbol{M}(t)\boldsymbol{W}(t)] = \boldsymbol{C}\left(\boldsymbol{\mu}_M^T\boldsymbol{\mu}_W + \left[\mathrm{diag}(\boldsymbol{\Omega}_1), \cdots, \mathrm{diag}(\boldsymbol{\Omega}_m)\right]^T\right).$$

The expression for the covariance follows from the linear transformation of the product and is given as:

$$\mathrm{Cov}[\boldsymbol{V}(t)] = \boldsymbol{C}\boldsymbol{\Sigma}_{MW}\boldsymbol{C}^\top.$$

□

Theorem 2 Let $\mathbf{V}(t) = \mathbf{CM}(t)\mathbf{W}(t)$, where $\mathbf{C}$ is a constant matrix, and $\mathbf{M}(t)$ and $\mathbf{W}(t)$ are random matrices/vectors. Suppose $E[\mathbf{M}(t)] = \mu_M$ and $E[\mathbf{W}(t)] = \mu_W$. Then, the expected value and covariance of $\mathbf{V}(t)$ are given by:

$$\mathbb{E}[\mathbf{V}(t)] = \mathbf{C}\left(\mu_M^T\mu_W + \sum_{i=1}^{m} \mathrm{diag}(\Omega_i)\right), \tag{7}$$

$$\mathrm{Cov}[\mathbf{V}(t)] = \mathbf{C}\,\Sigma_{MW}\,\mathbf{C}^T, \tag{8}$$

where $\Omega_i = \mathrm{Cov}(\mathbf{M}_{i,:}, \mathbf{W})$ and Σ_{MW} denotes the covariance matrix of the random product $\mathbf{M}(t)\mathbf{W}(t)$.

Proof. Consider the matrix product $\mathbf{M}(t)\mathbf{W}(t)$, where $\mathbf{W}(t)$ is a column vector. The ith element of this product is:$[\mathbf{M}(t)\mathbf{W}(t)]_i = \sum_{j=1}^{l} m_{ij}(t)w_j(t)$ Taking the expectation of each term: $\mathbb{E}[m_{ij}(t)w_j(t)] = \mathbb{E}[m_{ij}(t)]\mathbb{E}[w_j(t)] + \mathrm{Cov}(m_{ij}(t), w_j(t))$ Summing over all j, we obtain:

$$\mathbb{E}\left[\sum_{j=1}^{l} m_{ij}(t)w_j(t)\right] = \sum_{j=1}^{l} \mu_{ij}\mu_{W_j} + \sum_{j=1}^{l} \mathrm{Cov}(m_{ij}, w_j)$$

This implies that the ith element of the vector $\mathbb{E}[\mathbf{M}(t)\mathbf{W}(t)]$ can be written as:$[\mu_M^T \mu_W]_i + [\mathrm{diag}(\Omega_i)]_i$ for row-wise covariance terms $\Omega_i = \mathrm{Cov}(\mathbf{M}_{i,:}, \mathbf{W})$. Stacking the results for all $i \in \{1, \ldots, m\}$ yields:

$$\mathbb{E}[\mathbf{V}(t)] = \mathbf{C}\left(\mu_M^T \mu_W + \sum_{i=1}^{m} \mathrm{diag}(\Omega_i)\right)$$

The covariance of $\mathbf{V}(t)$ follows standard rules for linear transformations of random vectors: $\mathrm{Cov}[\mathbf{V}(t)] = \mathrm{Cov}[\mathbf{C}\mathbf{M}(t)\mathbf{W}(t)] = \mathbf{C}\,\Sigma_{MW}\,\mathbf{C}^T$ where Σ_{MW} is the covariance matrix of the random product $\mathbf{M}(t)\mathbf{W}(t)$. $\square$

3.3 Integration of EDFT and SD

To integrate individual-level decision processes modeled by EDFT into the SD framework, we define the control input $\boldsymbol{u}(t)$ as a function of both the expected behavioral tendencies and their associated uncertainty. Let $\boldsymbol{V}(t)$ denote the stochastic output from the EDFT model, representing decision strengths across m alternatives or user segments. We compute the expected value $\mathbb{E}[\boldsymbol{V}(t)]$ and the covariance matrix $\mathrm{Cov}[\boldsymbol{V}(t)]$. To ensure dimensional consistency and interpretability, we adopt a diagonal adjustment scheme wherein only the variance terms are incorporated into the input calculation. The resulting input is defined as

$$\boldsymbol{u}(t) = \boldsymbol{u}_0(t) + \boldsymbol{K}_1\mathbb{E}[\boldsymbol{V}(t)] - \boldsymbol{K}_2\,\mathrm{diag}\left(\mathrm{Cov}[\boldsymbol{V}(t)]\right),$$

where $\boldsymbol{u}_0(t)$ denotes baseline input from policy or external interventions, and $\boldsymbol{K}_1$, $\boldsymbol{K}_2$ are gain matrices encoding the influence of expected decision strength and uncertainty, respectively. The diagonal operation ensures that uncertainty penalization is applied independently to each decision dimension, thereby moderating the influence of highly variable or inconsistent decision patterns on the macro-level system evolution. The input our EDFT model, $\boldsymbol{u}(t)$, is then propagated through the SD model to update the system state via

$$\boldsymbol{x}(t) = e^{\boldsymbol{A}t}\boldsymbol{x}_0 + \int_0^t e^{\boldsymbol{A}(t-\tau)}\boldsymbol{B}\boldsymbol{u}_0(\tau)\,d\tau + \int_0^t e^{\boldsymbol{A}(t-\tau)}\boldsymbol{B}\boldsymbol{K}_1\,\mathbb{E}[\boldsymbol{V}(\tau)]\,d\tau - \int_0^t e^{\boldsymbol{A}(t-\tau)}\boldsymbol{B}\boldsymbol{K}_2\,\mathrm{diag}\left(\mathrm{Cov}[\boldsymbol{V}(\tau)]\right)\,d\tau$$

effectively creating a closed-loop feedback mechanism that links micro-level decision-making with macro-level system dynamics.

On the other hand, to incorporate system-level feedback from the SD model into the EDFT framework, we adopt an affine transformation-based measurement model inspired by the formulation (Busemeyer and Diederich 2002). We treat the system state vector $\boldsymbol{x}(t)$, computed from the SD model, as a noisy but informative observation of the preference state $\boldsymbol{P}(t)$ in EDFT. Following the measurement equation

$$\boldsymbol{x}(t) = \boldsymbol{G}\cdot\boldsymbol{P}(t) + \boldsymbol{F} + \boldsymbol{E}(t),$$

where $\boldsymbol{G}$ and $\boldsymbol{F}$ are known transformation matrices and $\boldsymbol{E}(t)$ is a measurement error term, we estimate the internal preference state as

$$\hat{\boldsymbol{P}}(t) = \boldsymbol{G}^{-1}\left(\boldsymbol{x}(t) - \boldsymbol{F}\right).$$

This estimated state is then substituted into the standard EDFT preference evolution equation to yield the update rule:

$$\boldsymbol{P}(t+1) = \boldsymbol{S}\hat{\boldsymbol{P}}(t) + \boldsymbol{v}(t) = \boldsymbol{S}\boldsymbol{G}^{-1}\left(\boldsymbol{x}(t) - \boldsymbol{F}\right) + \boldsymbol{v}(t),$$

where $\boldsymbol{S}$ is the state transition (memory decay) matrix and $\boldsymbol{v}(t)$ is the valence vector representing external stimuli or decision inputs. This formulation enables a closed-loop integration where the macro-level system behavior captured by SD informs the micro-level cognitive dynamics of EDFT. It is worthwile to note that we address the discrete–continuous integration by running EDFT decision ticks four times within each annual SD time step, treating them as quarterly sub-steps. The input $u(t)$ is assumed constant over each EDFT tick within the year, reflecting stable policy or market conditions during that quarter.

Bayesian Updates Before presenting the case study, we explain how Bayesian updating is used to evolve the EDFT parameters, specifically the evaluation matrix $M(t+h)$. The M matrix represents travelers' evolving evaluations of different transportation mode options across multiple criteria (e.g., cost, convenience, safety). To model adaptive learning in response to changing conditions and observed behaviors, we assume that each matrix element initially follows a Normal prior distribution with mean μ_{prior} and variance σ^2_{prior}. During the simulation in the integrated framework, these elements are updated in real time based on inputs from the SD model. For example, significant increases in gas prices over discrete time intervals can be modeled as Normal likelihood distributions with observed mean changes and associated variance. Using Bayesian updating, the posterior distribution for each M element is also Normal, with an updated mean and variance $(\mu_{posterior}, \sigma^2_{post})$ that combine prior beliefs and observed SD-driven evidence. This Bayesian updates enables the EDFT model to represent real-time, data-driven adaptation of traveler choice dynamics at each simulation step, bridging individual decision processes with system-level trends such as price changes, service reliability, policy incentives, and congestion levels.

4 SIMPLE CASE STUDY

We have tested our models and framework with the San Francisco Municipal Transportation Agency (SFMTA) Travel Decision Survey Report (San Francisco Municipal Transportation Agency. 2019). SFMTA conducts surveys every other years to gather data on travel behavior, preferences, and decision-making in San Francisco Metropolitan Region. These surveys aim to understand how people choose and use different transportation modes, including ride-sourcing services, public transit, walking, biking, and private vehicles. The SFMTA Travel Decision Survey Report provides valuable insights into the factors influencing travel choices and the usage patterns of various transportation modes and also provides a realible data set that captures changes over time. It includes information on demographics, trip purposes, mode choices, trip distances, frequency of use, reasons for mode selection, and factors affecting mode preferences but does not include trip-specific details such as travel time, origin and destination, etc. We use data sets from 2012, 2013, 2017, 2015, 2017, 2019, 2021. The numbers of travelers surveyed ranges from 750-850 (752, 764, 767, 762, 804, 841, 756 in years 2012, 2013, 2014, 2015, 2017, 2019, respective). These years provide statistics on interesting growth and development of ride-sourcing markets before the Covid-19 break in 2020 which opens a door for further analysis.

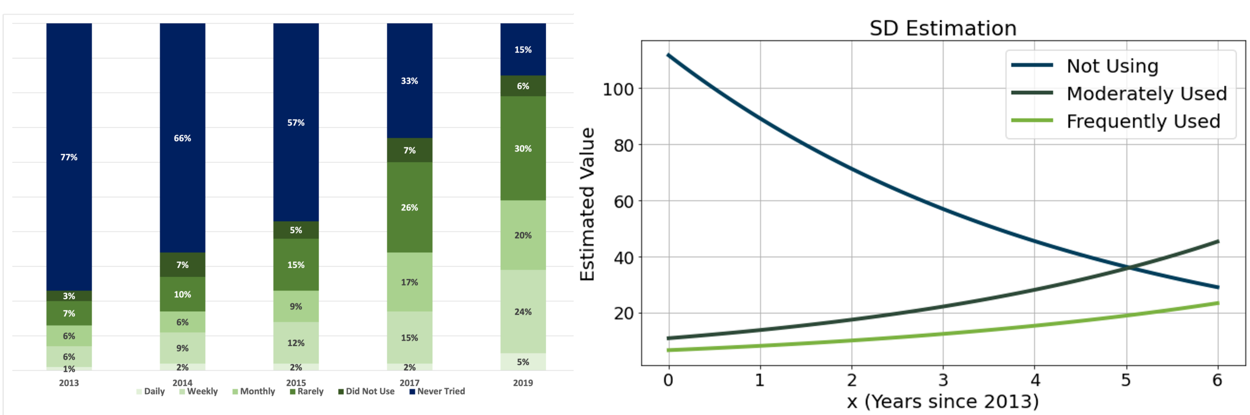


Figure 5: Transportation network company (TNC) usage.

Figure 5 (left) illustrates the evolving frequency of Transportation Network Company (TNC) usage among respondents from 2013 to 2019, based on the SFMTA Travel Decision Survey (San Francisco Municipal Transportation Agency. 2019). Over this six-year period, there is an evident decrease in the share of individuals who reported they had “Never Tried” using TNCs - dropping from 77% in 2013 to just 15% in 2019. This suggests a significant increase in awareness and acceptance of TNC services such as Uber and Lyft. At the same time, usage frequency across all other categories rose noticeably. The share of “Daily” users increased from 1% to 5%, and “Weekly” and “Monthly” usage grew to 24% and 20%, respectively, by 2019. It is noted that the “Rarely” category also expanded considerably, from 6% in 2013 to 30% in 2019, indicating that even occasional use became more common. The data reflect a clear behavioral shift, with TNCs becoming a more normalized and integrated part of urban mobility over time.

The right side of Figure 5 uses these observed historical trends (left side) as a basis for SD model calibration and forecasting. By estimating the parameters that reproduce the 2013–2019 changes in category shares, the SD model projects potential trajectories to 2025 under the assumption that similar behavioral dynamics persist. This project helps illustrate how the continued decline in non-users and rise in frequent and moderate users might evolve if the same exponential growth and decay patterns hold, directly linking empirical trends to the simulation model’s assumptions and outputs.

Using the trend data, the authors grouped the original six categories into three broader groups: *frequently used* (daily and weekly), *moderately used* (monthly and rarely), and *not using* (did not use and never tried). Based on these categories, we estimated the parameters of a system dynamics model using Equation (1). The matrices below present the estimated results for the system matrices **A** and **B**. The observed usage trends from 2013 to 2019 were well-approximated by exponential functions, which are naturally captured by a diagonal matrix A representing independent exponential growth and decay processes. The authors assumed that the matrix A is diagonal (which is bit strong), but it is effective to model early stage of process. The estimated A the corresponding simulation results are presented in Figure 5 (right).

$$\mathbf{A} = \begin{bmatrix} 0.798 & 0 & 0 \\ 0 & 1.2706 & 0 \\ 0 & 0 & 1.2369 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0.1 \\ 0.1 \\ 0.1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0.1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0.05 \\ -0.05 \\ 0.05 \end{bmatrix}, \begin{bmatrix} -0.05 \\ 0.05 \\ -0.05 \end{bmatrix}, \begin{bmatrix} 0.05 \\ 0.05 \\ 0.05 \end{bmatrix}$$

As the **B** matrix is designed to be a 3 by 1 matrix, that captures the effect of external inputs to three different levels of TNC. These external inputs can be price incentives, service quality improvements, marketing campaigns, or regulatory interventions, influencing each mode-choice group’s relative attractiveness.As shown in Figure 6, five different configurations of the matrix **B** were used to conduct a ”what-if” analysis. These are considered small variations with different actions, induced by individual preference changes (from EDFT). As shown, the slight modifications are well incorporated without violating the overall patterns. This analysis also highlights that, in the absence of the COVID-19 pandemic, these configurations could represent the projected percentage of PNC usage in San Francisco. However, due to the pandemic and

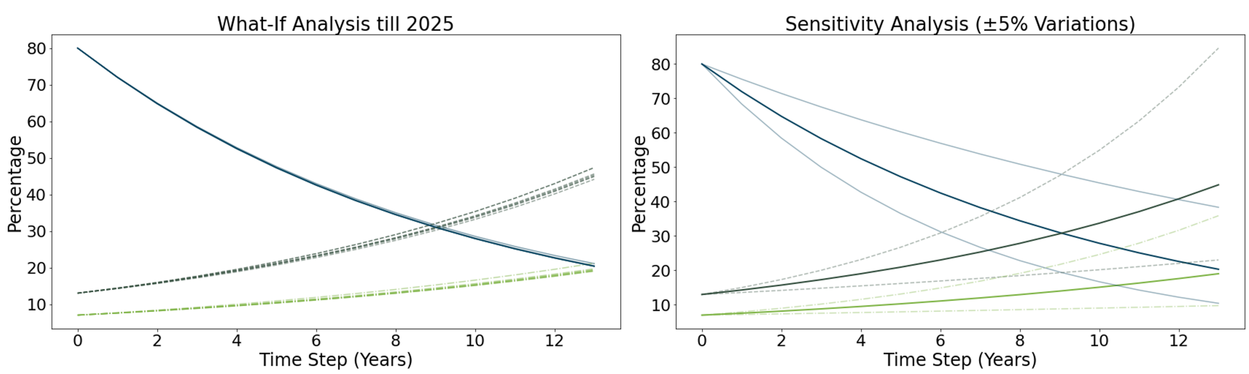


Figure 6: Validation via a case study: What-if analysis (left); Sensitivity analysis (right).

associated quarantine restrictions, the actual adoption rates were significantly lower. Thus, the results also reveal the gap between the idealized scenario and the observed lagged by COVID-19 disruptions.

As shown in Figure 6(b), we also performed a local sensitivity analysis by varying the diagonal terms of the system matrix A by $\pm 5\%$ to reflect uncertainty in internal growth and decay rates. This analysis reveals that small changes in these parameters can produce significant shifts in absolute mode shares, particularly when one option represents a large share. However, as the overall trend patterns remained consistent under these perturbations, Figure 6 supports the model's robustness for scenario-based planning.

5 CONCLUSION AND FUTURE WORK

This research proposes a new framework integrating individual choice models and system dynamics to capture individual heterogeneity, stochasticity, and market dynamics. By using cognitive decision-making models, EDFT, we can incorporate an individual's perception of transportation mode choice while easing to integrate of a system-level SD model. With the integration, the proposed framework will increase accuracy and provide a comprehensive understanding of ride-sourcing service choices. Both SD and EDFT in the proposed system will be used as crucial components in modeling complex systems, thereby increasing their impacts and widening their range of applications. Also, integration and coordination of micro-level (via EDFT) and macro-level (via SD) are achieved via dynamic or Bayesian updates. As a case study, we investigated San Francisco's SFMTA data demonstrating how individual cognition-based travel behaviors and all the market dynamics evolve together, affecting the ride-souring service choices in the community. Therefore, our future work will incorporate rare event simulation methods by integrating non-parametric approaches. We will also include an explicit noise term in the SD layer to demonstrate uncertainty quantification, while investigating the variance structure that determines the equilibrium conditions.

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