Strategic Capital Investment Analytics: An Agent Based Approach to California High-Speed Rail Ridership Model

Mark Abdollahian(✉), Yi Ling Chang, and Yuan-Yuan Lee

School of Social Science, Policy and Evaluation, Claremont Graduate University, Claremont, CA, USA
{mark.abdollahian, yi-ling.chang, yuan-yuan.lee}@cgu.edu

Abstract. In this paper, we present an agent-based model (ABM) of multi-dimensional transportation choices for individuals and firms given anticipated aggregate traveler demand patterns. Conventional finance, economic and policy evaluation techniques have already been widely adopted to more evidenced based decision-making process with the aim to understand the financial, economic and social impacts on transportation choices. Prior scholars have examined common practices used to measure profitability for investment appraisal including internal rate of return (IRR), net present value (NPV) and risk analysis approaches, incorporating the concepts of time value of money and uncertainty to assess potential financial gains with different transportation projects. However, using conventional capital budget planning or static scenario analysis alone cannot capture significant, interactive and nonlinear project, demand and market uncertainties. Here we build an agent-based model on the current California High-Speed Rail (HSR) to provide insights into firm investment decisions from a computational finance perspective, given the coupling of individual choices, aggregate social demand, and government policy and tax incentives. Given individual level choice and behavioral aspects, we combine financial accounting and economic theory to identify more precise marginal revenue streams and project profitability over time to help mitigate both project and potential, system market risk.

Keywords: Computational finance · Complex adaptive systems · Transportation projects · Agent based modeling · Risk mitigation · Social learning

1 Introduction

Aggregated demand models for public transportation projects are often lacking due to the inability in accounting individual decisions, changing project scope, firm interests and government receptivity. Hence, assumption-based planning approaches [1] can amplify errors across static or dynamic models when using average consumer demand as the indicator to overestimate rates of return or other financial, economic or government scenarios considered during planning. Fluctuation in consumer demand in the

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transportation industry increases due to the variety of options available, whether by emergent shared-platforms, travelers' socio-demographic preferences, individual specific scenarios, where are they traveling from and to as well as unexpected time related traffic patterns. In fact, prior scholars [2] have suggested that travelers by developing heuristics, may only be able to 'satisfice' and identify feasible, but not always optimal solutions to the choice problem subject to their particular set of constraints. This bottoms up demand estimation challenge significantly contributes to the level of difficulty in deciphering demand and consider all other relevant financial, economic and regulatory factors into a single spreadsheet approach. Other researchers [3] often use statistical modeling techniques in creating a form of integrated model with strict assumptions, compliant with similar to microeconomics principles. Though statistical methods can provide reliable results, their validity can be called into question since the approach inevitably is due to the significant assumptions and scenarios across the range of financial, economic, project and government uncertainty.

Modern techniques of an agent-based structure incorporate flexibility to observe emergent behaviors, creating computational advantages in modeling complex adaptive systems [4]. Our approach advocates an integrated computational finance simulation of understanding the interactive effects of individual choices, firm investment decisions and market outcomes across all scales of human behavior. Obviously, individual micro level choices are constrained and incentivized by the context of their operating environments. Given that individuals act, react and interact socially, networks of behavior can emerge at the meso level. The patterns of these social interactions can produce norms, rules and guide individual behavior. The aggregate results of these create the macro economic, financial and political outcomes surrounding this behavior. Of course, there are dynamic, nonlinear feedback loops across the micro, meso and macro scales which necessitates a complex adaptive systems approach [5].

In general, an agent-based model consists of three elements: agents, an environment, and rules. Agents are assigned characteristics and following behavioral rules define how agents act in the environment and interact with each other. In this specified environment we monitor agents' activities, and interactions to reveal patterns in helping us identify transportation ridership forecast. Our public transportation ridership model is a creation of an integrated model incorporating individual, economic, and financial human behavior with information diffusion theories in network analysis, in which individual agents are categorized into types of travelers, i.e. businessmen and tourists. Simple behavior rules are based on learning and knowledge transfer, shown to prove agents' capability of acting within their tolerance and constraints towards time and cost. Hence, maximizing their benefit from choosing a specific type of transportation to fit their needs. Quantifying the causal effect of human interactions in decision making process requires not only identifying influencers and information receivers, but also of whether individuals are then willing to change their decisions based on the information received.

Our research develops a dynamic agent based modeling framework (Fig. 1) adopting conventional financial accounting calculation as foundation to help predict the outlook of California High-speed Rail project, offering an alternative travel solution from San Francisco to San Diego. We are especially focused in tackling the existing challenges in identifying cost recovery time frame for this capital-intensive project

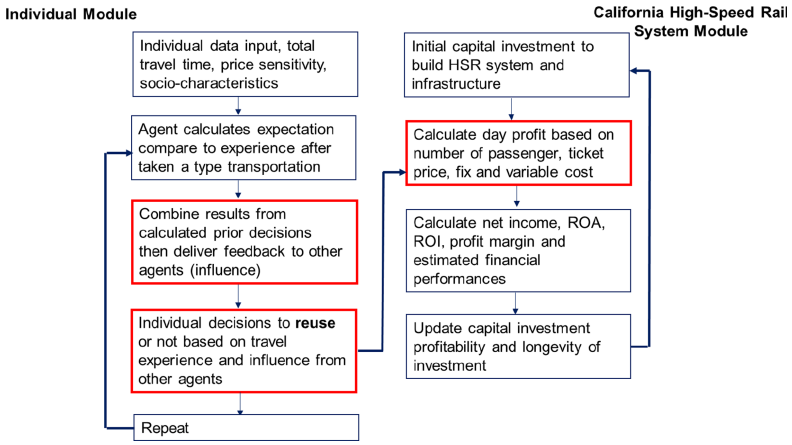

Fig. 1. Proposed California high-speed rail ridership model framework with ABM.

using rider adoption rate extracted from simulating individual travelers' decision making process with available transportation options including plane, bus, train and the upcoming high-speed rail. To increase model fidelity, we incorporate and examine the spread of information based on closeness centrality[1] in addition to choices made from personal travel experience to estimate adoption rate since peer influence plays a critical role in behavior phenomena, from the dissemination of information, to the adoption of new experiences or technologies.

In Sect. 2, we summarize prior related work on travel demand simulation, theoretical approaches, and dynamic interactions between travelers. Section 3 describes our methods, including a description of behavioral choice model and our modification of the theory into behavioral rules agents follow in choosing transportation methods, an additional layer of information spread over dynamic social networks via closeness. The experiment model we design uses data extracted from existing transportation options available in the market matching case study distance between San Francisco to San Diego, along with comparable financial accounting information from Taiwan High Speed Rail Company as a baseline in hopes to mimic closer to reality environment and constraints. The simulation experiment we conduct, the results, and scenario analysis are presented in Sect. 4. An experiment validation process is exemplified through sensitivity analysis described in Sect. 5. Finally, we conclude and discuss valuable implication for capital investment analysis specifically for transportation industry with future direction in Sect. 6.

[1] Closeness centrality: In network analysis, closeness centrality measures each individual's position in the network via a different perspective from the other network metrics, capturing the average distance between each vertex and every other vertex in the network.

2 Related Work

2.1 Towards Integrating Macro and Micro Economics with Computational Finance

Capital budget planning is a key determinant driving corporate direction and opportunity for future growth. This is usually performed using easily understood assumption based planning techniques, including average demand, aggregate demand and project finance approaches given various assumptions about how the markets will react, government subsidies or other know scenarios. However, these conventional approaches are often criticized for ineffectiveness in the face of uncertainty. Individual ratio numbers do not provide direct information unless compared with industry averages, and even then, there are significant information left uncaptured with shifts in micro consumer demand coupled with changing macroeconomic market conditions.

For example, many early macroeconomics analyses attempt to understand aggregate relationships, as one of the foundational principle Keynesian consumption function demonstrates the relationship between total consumption and gross national income. The implication of the theory is that consumption is determined by the change in income, therefore under the assumed stable equilibria, there is a relationship between disposable income, aggregated savings, and GDP overtime. Subsequently, many economists have criticized the original model due to behavioral factors, unemployment uncertainty, overall lack of micro factors that can create drastic changes in distribution of income and wealth, thus creating versions of consumption functions. On the other hand, microeconomic theories focus on the study of individual consumer behavior where supply and demand theories have produced rich information on market structure, but with strict assumption based on rationality and utility maximization. Many recent relevant projects we see discuss the benefits of developing multi-model transportation management system to integrate passenger demand uncertainty and unpredictability of traffic, focuses on the impact on travel time, delay, fuel consumption [6].

Here we see an interesting modeling arbitrage opportunity to integrate both macro market theories and data with the microeconomic theories of individual level consumer behavior, much like Schelling's seminal work [7]. Our computational finance model explicitly simulates individual choice sets and social learning with financial accounting operating in dynamic, macro behavioral environments surrounding a project. This helps firms to better identify marginal revenue streams and profitability overtime and hopefully a more reliable and valid assessment of systematic project demand forecasting. We apply our model to the current California High-speed Rail (HSR) project to explore how firms, investors, government and individuals can help mitigate unanticipated risks, such as through changes in individual demand, social learning or macroeconomic shocks.

2.2 Agent-Based Computational Practices with Interactive Agents

As discussed previously, ABMs can provide distinct added value as compared to conventional approaches. First, descriptively for increased model fidelity as agents can interact locally, transfer knowledge and learn in imperfect market conditions which most microeconomic models have difficulty with. Second, adaptability as modeling

allows researcher explore potential emergent behavior in a designed environment that is not achievable using traditional methodologies. These advanced techniques have increasingly captured global attention, especially after 2008 financial crisis, with "an agent-based model exploring the systemic consequences of massive borrowing by hedge funds to finance their investments. In their (Economist John Geanakoplo and physicists Doyne Farmers) simulations, the funds frequently get locked into a self-amplifying spiral of losses—much as real-world hedge funds did after August 2007." [8] There is a definite need for a responsive systematic model that can incorporate diverse principles across economics, socio-science and finance practices using individual level information to generate situational macro-solutions.

Recent publications have marked milestones in activity-based approach in traffic simulation and travel analysis, though success is often limited to clear, pre-defined conditions, the results shed light on high dimensional human decisions [9–11]. Lee et al. [12] classified these models theoretically into three major categories: an economics-based approach, a psychology-based approach, and a synthetic engineering-based approach. However, each approach exhibits strengths and limitations. In economics-based models, assumptions are a necessary component in allowing the models to accurately reflect the simplified process dissect from the complex system. "Models of the economics-based approach have a solid theoretical foundation, based mainly on the fundamental assumption that the decision makers are rational, one major limitation, however, is the lack of capability to capture the nature of the human cognition process [13–15]." In an attempt to overcome these limitations, researchers then propose and discuss psychology-based and engineering-based models, exploring ways to replicate human decision-making process and learning mechanism. Although these models account for human cognition, they generally examine human behaviors under simplified and well-controlled laboratory conditions, let alone integrated scale behavior in a complex adaptive system.

Travel behavior is a relevant research topic due to the nature of complexity, travelers' preferences, needs and available resources, combined with available choices and dynamic environmental factors that all of which interacting and contributing to emergent dynamics. "The traditional top-down approach studies what is the performance of a complex transportation system, whereas the bottom-up ABMS approach tries to understand why travelers make those decisions and how does transportation system perform in such a circumstance." [16] In our work here, we build a cognitive roadmap to understand agent's travel decisions, identifying four important stages and intuitively dividing the process of choosing types of transportation into three parts: before-trip, within route and post-trip. In general, travelers' route choice behavior involves learning from previous experiences, heterogeneity of travelers, incomplete network information, and communications among travelers. Those behaviors, which are difficult to model through the conventional equilibrium methods or discrete choice models, are perfect for agent-based modeling techniques. Moreover, using experimental techniques, well-defined decision scenarios can be reproduced, and strategies that humans actually use in dealing with complex situations may be revealed. An ABM approach offers a way to capture the heuristics of decision making in a model which is grounded in empirical data [17]. Our framework combines various theories to combat challenges seen with High Speed Rail projects, including overestimation in ridership,

appropriate ticket price based on consumer's sensitivity to cost, and the unknown cost recovery time period for investors.

3 Operational Prototype

Our research relies on two critical theories as the logical foundation to our integrated HSR model.

3.1 Route Choice Behavior Model Theory

In the original Route Choice Behavior Model, the travelers are modeled as agents, who choose a route based on their knowledge of the network prior to each trip (en route choice is not considered in this example). In the route choice model, a traveler agent first decides which route to travel when their trip starts. The traveler could decide to stay on the same route as the previous trip or could decide to change to an alternative route. Behavior rules described as following:

Rule 1 Set Initial Decision then the traveler agent does not change route on n + 1th day.

$$If\left(TT_j^n = TT_{min}^n\right) \tag{1}$$

Rule 2 Threshold, then the traveler agent does not change route on n + 1th day, where ε is a threshold related to the perception error.

$$If\left(TT_j^n - TT_{min}^n\right) \leq \varepsilon \tag{2}$$

Rule 3 Learned From Experience agent changes route with probability (4) and the choice probability is based on the posterior probability given the route choice and previously experienced travel time

$$If\left(TT_j^n - TT_{min}^n\right) > \varepsilon \tag{3}$$

$$\frac{\left(TT_j^n - TT_{min}^n\right)}{TT_j^n} \tag{4}$$

3.2 Modified Behavior Rule for HSR

In our framework (Fig. 2), we are interested in capturing the process of choosing a specific type of transportation tool based prior trip experience or memory. To align with our computational finance goals, we redesign an existing behavioral model to replicate the described decision-making process with an additional element on agents' sensitivity to time and cost. Moreover, to create more realistic scenarios, we are curious

how delay plays a role with people's choices and experience. This modification intensifies and speeds up the decision-making process, allowing agents to make frequent dynamic changes according to their memory and constantly updating their learning outcomes.

Rule 1 Set Initial Decision

$$If\left(TT_k^n - TT_{k\,min}^n\right) = time\ threshold,\ \text{then agent chooses k as transportation with an expected total travel time (TT = Total Travel Time)} \tag{5}$$

$$If\left(TC_k^n - TC_{k\,min}^n\right) = cost\ threshold,\ \text{then agent chooses k as transportation with the expected total travel cost (TC = Total Cost)} \tag{6}$$

Rule 2 Dynamic Behaviors From Experience

$$If\left(TT_k^n - TT_{k\,min}^n\right) > time\ threshold,\ \text{the agent will change other types of transportation option available} \neq k \tag{7}$$

$$If\left(TC_k^n - TC_{k\,min}^n\right) > cost\ threshold,\ the\ agent\ will\ change\ other\ types\ of\ transportation\ option\ available \neq k \tag{8}$$

Rule 3 Impact of Delay on Travel Experience

$$If\ \frac{\left(Tc_k^n - Tc_{k\,min}^n\right)}{\left(TT_k^n - TT_{k\,min}^n\right) * probabilty\ of\ delay_k} > \frac{\left(Tc_k^n - Tc_{k\,min}^n\right)}{\left(TT_k^n - TT_{k\,min}^n\right)},\ the\ agent\ will\ change\ other\ types\ of\ transportation\ option\ available \neq k \tag{9}$$

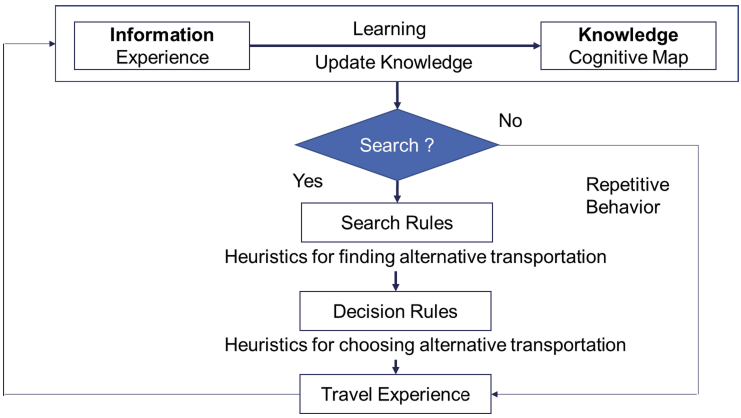

Fig. 2. Flowchart diagram of our micro-level behavior choice model

3.3 Information Diffusion and Social Learning

Agent-based modeling and network analysis have been used as complementary approaches; the former is a method of computationally representing micro-level interactions from which social patterns emerge; the latter is a technique that involves the characterization and structural analysis of socio-demographical patterns which yield inferences on degree of connectivity and how information propagate through the network over time and space. Figure 3 is a representation of our proposed network structure, includes three diffusion processes and three external factors [18].

We apply this approach to the context of transportation ridership. The network in our case is a social network of travelers; i.e. business people as well as tourists (nodes) and the information being diffused is their traveling experience using a specific type of transportation, options include train, bus, plane and high-speed rail system. First, the contacts amongst travelers form a network structure as a basis for diffusion and interaction. Here individuals form expectations around sensitivity to travel length and cost. Second, experiences are shared through direct contacts among individuals (the middle layer). The reach of information spread is based on degree of connectivity using closeness centrality as linkage. Third, the travelers process the information received which become influential to their decision-making process to switch or reuse their current type of transportation (bottom layer), thus accelerating the diffusion by repeating step one to three.

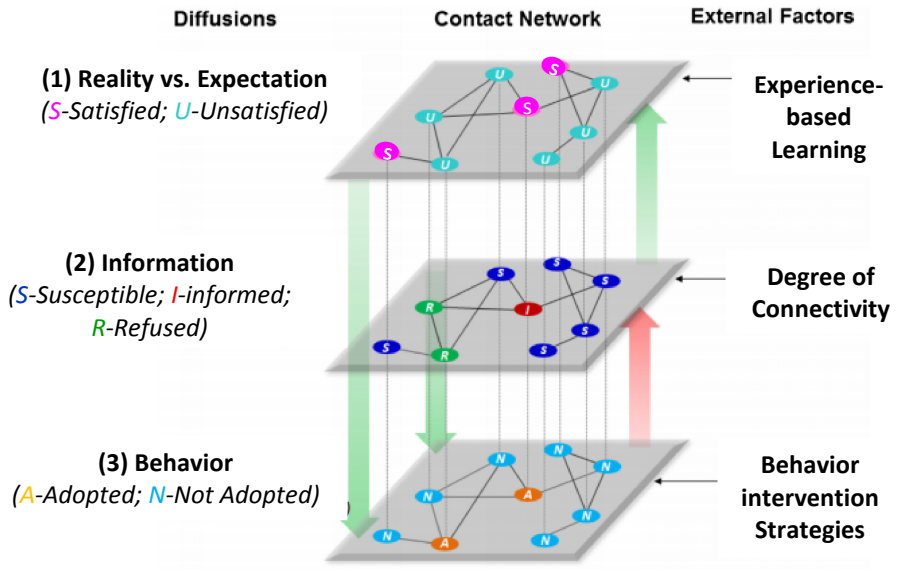

Fig. 3. Conceptual framework of our diffusion model through network structure.

4 Experiment Design

4.1 Descriptive Information

In order to populate our model, we use the current to California High-speed Rail project to *prima facie* provide insights towards validity with individual demand, using real cost and travel time comparable to traveling between San Francisco and San Diego, empowering agents i.e. businessmen and tourists the flexibility to choose among current population alternative transportation options in addition to the hypothetical high-speed rail. By monitoring the emergent phenomena our computational finance ABM generates from the bottom up, we offer alternative insights to project financing and risk mitigation.

The individual behavioral choice rules that are described in the previous section are the only sets of pre-defined calculation embedded in the system. The two types of agents, business people and tourists, are placed in the system to represent the different types of people; businessmen who need to travel may place their focus on efficiency, while tourists who are traveling on a budget constraint would prefer to save cost on transportation. Individual behavior exhibits memory, path-dependence, and hysteresis, non-stochastic behavior, or temporal correlations, including learning and adaptation, hence why we have chosen to use ABMs to understand the non-linear human behavior in transportation ridership problem. Another implied benefit is that the technique is best used when the appropriate level of description or complexity is not known ahead of time and finding the circumstances requires some calibration. "Aggregate differential equations tend to smooth out fluctuations, not ABM, which is important because under certain conditions, fluctuations can be amplified: the system is linearly stable but unstable to larger perturbations" [19]. Knowing consumer preferences for transportation system makes it possible to create virtual agents with similar characteristics mirroring human decision-making process to simulate close-to-reality scenarios.

4.2 Scenario Analysis – Consumer Level

1. **Baseline**

In Table 1, we include a list of our initial conditions for baseline scenario, representing when high-speed rail first enters the transportation market. Overtime, we observe the fluctuations in demand and a steady increase for each type of transportation that each transportation demand with consumer's first choice as plane, followed by High-speed rail, bus then train (Fig. 4). In Fig. 5, we provide a detailed breakdown among total passengers, 11 businessmen and 5 tourists have changed their preferred type of transportation due to differences incurred in cost and travel time between actual experience and expectation – following our designed behavioral rules. The dynamic movement we have monitored through the bar-chart shows closeness in the two groups of passengers.

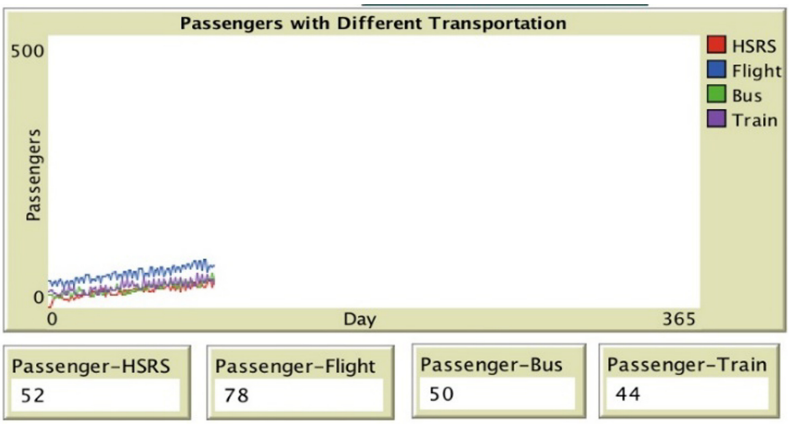

Fig. 4. The number of passengers for each transportation method under initial condition

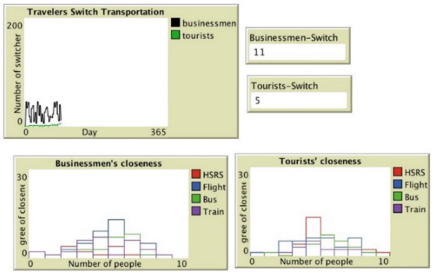

Fig. 5. Number of travelers switch transportations

Table 1. Initial condition

Number of passengers	
Businessmen	50
Tourists	50
Percentage of usage	
Plane	34%
Train	33%
Bus	33%
Arrival time by transportation type	
No delay	

2. Variety of Options

Changing only one parameter from the baseline, in Table 2, we present the HSR system as one of the initial transportation options to observe potential changes in travelers' behavior. Figure 6 captures the exact time length as the baseline, with 78 flight takers and 63 High-speed rail system users and an equal amount of customers choosing between bus and train. From Fig. 6, we can see that the High-speed rail system is a direct competitor to flight, suitable for consumers who are seeking lower price transportation choices and still allow them to arrive at their destination faster than taking the bus or/and train. In addition, we see relatively more consumers are switching (Fig. 7), 20 businessmen and 11 tourists, which further indicate that High-speed rail system has raised an interest among tourists who are price sensitive.

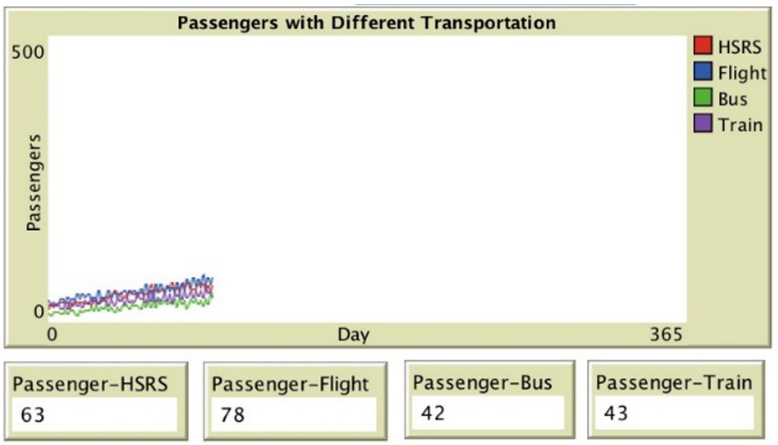

Fig. 6. The number of passengers per transportation type when presented with HSR system.

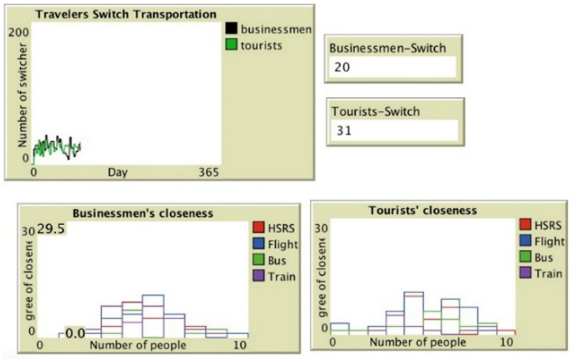

Fig. 7. Number of travelers switch transportation in scenario with variety of options.

Table 2. Variety of options

Number of passengers	
Businessmen	50
Tourists	50
Percentage of usage	
Plane	25%
Train	25%
Bus	25%
High-speed Rail	25%
Arrival time by transportation type	
No delay	

3. The Effect of Delay

In this scenario, we are interested to investigate consequences of transportation delay, and understand the overall effect towards consumer's decision making process. According to data collected by Bureau of Transportation Statistics, we incorporate the average percentage of delay into our model design (Table 3). The pattern emerged from simulation result reveal an interesting fact that with aircrafts having an average of 20% change of delay, there are more traveler demand switching over to High-speed rail system with a total number of 105 passengers surpassing the 81 flight passengers (Fig. 8). As shown in Fig. 9, the probability of delay can cause an increase in frequent switching between the two types of travelers.

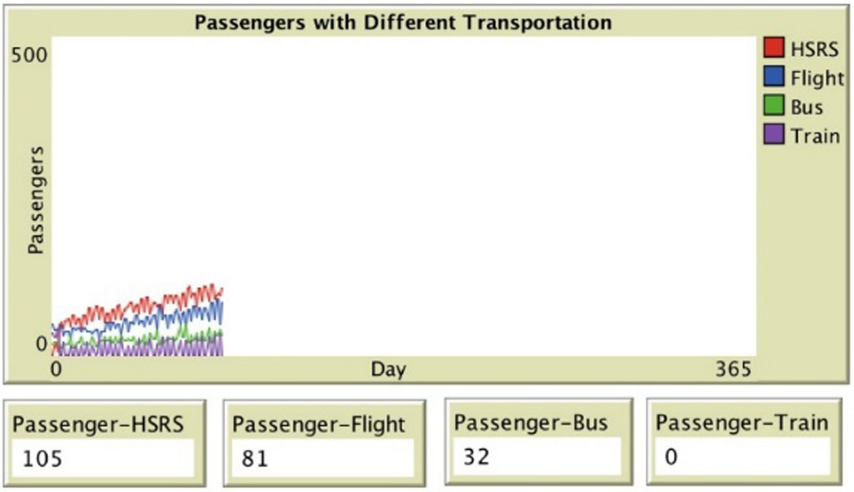

Fig. 8. The number of passengers per transportation incorporating probability of delay

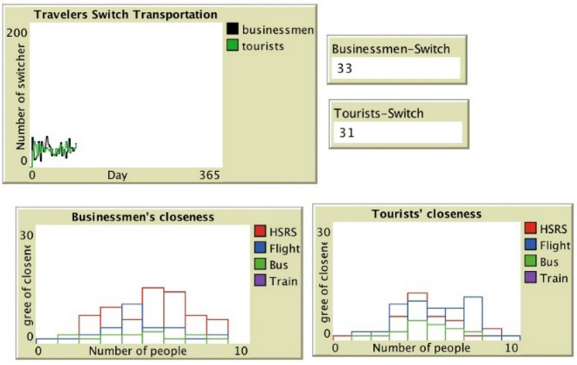

Fig. 9. Number of travelers switch transportation with the probability of delay.

Table 3. The effect of delay

Number of passengers	
Businessmen	50
Tourists	50
Percentage of usage	
Plane	25%
Train	25%
Bus	25%
High-speed Rail	25%
Percentage of Delay by transportation type	
Plane	20%
Train	25%
Bus	20%
High-speed Rail	5%

Overall, the three designed experiments open the possibility to analyze environmental factors, incorporate human network with information spread and better predict aggregated travelers' demand with changes in preferences.

5 Sensitivity Analysis

Next, we conduct a sensitivity analysis using data generated from model simulation results with the goal to understand how do HSR ticket price and corporate tax effect the overall profitability of the project. The result in Table 4 provides sensitivity assessment for investors to plan whether the long-term investment indeed can generate the estimated profit and the cost associated in making these decisions.

Table 4. Two-factor sensitivity analysis heat map from proposed ABM simulation result.

	(Net income in thousands)	Ticket Price				
	$604,123.13	433	438	442	450	458
Tax	28.00%	$582,556	$589,312	$594,717	$605,526	$616,336
	28.50%	$593,004	$599,880	$605,382	$616,384	$627,387
	29.00%	$603,451	$610,449	$616,046	$627,242	$638,437
	29.50%	$613,899	$621,017	$626,711	$638,100	$649,488
	30.00%	$624,347	$631,585	$637,376	$648,957	$660,539

6 Concluding Remarks

In our model, travelers are modeled as virtual agents, who choose a type of transportation based on their knowledge and satisfaction from prior experience, which is defined by if their expected cost and travel time match with their actual experience. At first, travelers may have little or no information on the transportation and purely form their expectation at random. Then from experience, travelers can accumulate knowledge to help find a best transportation to fit within their constraints. In our designed behavioral rules, best choices are evaluated by travel cost and total travel time. Travelers form a scale-free network, allowing them to exchange information of their experience of using a specific type of transportation. The two interactive mechanism realistically model human behavior in decision making process.

Traveler demand varies in each designed scenario and displays three distinctive patterns illustrating the complexity behind interaction on individual level and process of choice-making. In this research, we input actual financial data, allowing individual to have different levels of price and travel-time sensitivity based on market available transportation type including airplane, train, and bus, setting a comparable travel distance between San Francisco to San Diego with the current proposed HSR system. The three designed experiments represent possible scenarios that travelers may adopt to a newly introduced transportation option, providing the HSR investing partners a closer-to-reality estimation on project profitability and length of investment return. The benefit of agent-based modeling simulation is the ability to incorporate variation among demand, incorporating agents' interaction on information diffusion by utilizing network analysis to accurately capture the true consumer demand and adoption rate. The promise of our proposed modeling approach allows for better corporate risk mitigation by reducing errors from assumption-based planning approaches. The challenge with traditional capital valuable methods in making large financial decisions rests without complete knowledge of the unknown future consumer preference and industry trends, with a majority of companies going through trial and error costly processes.

7 Future Research Directions

1. **Individual agent's socioeconomic attributes**

Socio-economic attributes reveals key information on the micro level. In future research, we plan to include income status, education level, age and gender to help us better calibrate our simulation result to reflect a larger population within a specific region. In addition, combining socio-economic status and attributes, we would be able to generate deeper insights allowing companies to target specific consumer preferences and market behaviors. In turn, investing companies can better forecast demand, formulate strategies against risky capital intensive projects.

2. **Public-private partnership (PPP) financial accounting to complete build–operate–transfer (BOT)**

Many public transportation projects have been successfully deployed and constructed by BOT, including the Taiwan High-speed Rail and the Channel Tunnel between UK and France. These projects have taken multiple trials and extensive investment from multiple parties. Traditional capital budgeting methods often evaluate large investment for public transportation risky, thus decreasing forecasting accuracy on turnover, capital recovery and adoption rate. Traditionally, contracting companies often overestimate the number of passengers in order to present a promising outlook to stay competitive against other companies bidding in the same government contracted projects. This suggest significant room for growth and innovate computational finance approaches that capture individual level choice behavior and the interactive market effects.

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