Research Article

Improving the Sustainability of Integrated Transportation System with Bike-Sharing: A Spatial Agent-Based Approach

Abstract

Bike-sharing systems have rapidly expanded around the world in recent years. However, bike-sharing research focusing on East Asia is limited. The impacts of bike-sharing on travelers' usage of other transport modes in an integrated transportation system remain unclear. This study develops a spatial Agent-based model to simulate the use of bike-sharing services and other transport modes in Taipei city, considering their interactions through the modeling of the modal split based on the heterogeneous mode choice behaviors of travelers. Two scenarios are proposed for the development of a bike-sharing system: 1) bike infrastructure extensions; and 2) bike-sharing incentives. Two scenarios are evaluated along with the corresponding environmental and social impacts. The simulation results indicate that free use of bike-sharing to connect the transit system can be most sustainable with 1.5 million US dollars in transportation damage cost saved per year, and 22 premature deaths further prevented per year due to mode shift to cycling and walking based on the business as usual (BAU) scenario. However, bike-sharing has limited influence on the use of motorcycles, which is nearly invariable. This model can be a powerful tool to help policy-makers improve the sustainability of a multi-modal transportation system with bike-sharing.

Keywords: Bike sharing, Agent-based modeling, Environmental impact, Human health, Mode choice

1. Introduction

The rapid growth in world population and increasing demand for transportation is putting great pressure on the transportation and fuel sectors, resulting in heightened traffic congestion, increasing fuel prices, and degraded air quality. In response, worldwide consciousness has risen on land use management, environmental emissions abatement, and climate change alleviation. It has become essential to develop new modes of transport and adapt existing ones to move people in more sustainable and economically feasible ways (Bauman, Crane, Drayton, & Titze, 2016; DeMaio, 2009; Shaheen, Guzman, & Zhang, 2010).

Bike-sharing, or public bicycle programs, is emerging as a partial solution. Bike-sharing allows people to rent a bicycle from one of many stations that are situated throughout a city, then ride and return it at any one of these stations. Bike-sharing services have grown in Europe, North America, South America, Asia, and Australia (Liu, Jia, & Cheng, 2012). Today over 500 cities in 49 countries have well-established bike-sharing programs that in aggregate provide more than 500,000 bicycles. Bike-sharing systems have evolved, often beginning as free-to-use bike services that later became coin-deposit systems. Today's bike-sharing services are typically IT-based systems, with some city services including demand-responsive and multi-modal functionalities with real-time information, among other enhancements (Shaheen et al., 2010). Bike-sharing can be characterized as a "three-S" system: a Sustainable transport mode that can Substitute for short trip modes and Seamlessly connect with public transit (Hu & Liu, 2014). The reported benefits of bike-sharing include reduced greenhouse gas (GHG) emissions; reduced fuel consumption; enhanced accessibility; increased public transport use; decreased traffic congestion and noise; lower travel cost; increased physical activity and consequently improved health and physical fitness; and improved image of the urban environment (Bauman, et al., 2016; Caulfield, O'Mahony, Brazil, & Weldon, 2017; DeMaio, 2009; El-Assi, Mahmoud,

& Habib, 2017; Faghih-Imani, Hampshire, Marla, & Eluru, 2017; Kumar, Kang, Kwon, & Nikolaev, 2016; Pal & Zhang, 2017; Shaheen, et al., 2010; Shaheen, Martin, & Cohen, 2013)

However, some studies show that the benefits of bike-sharing are overstated. The mode shift to bicycling has clear health benefits, but it also may lead to a reduction in walking for some short-distance trips, while walking has greater health benefits (Fishman, Washington, & Haworth, 2014; Woodcock, Tainio, Cheshire, O'Brien, & Goodman, 2014). The effects of bike-sharing on public transit are not consistent; in a dense urban area bike-sharing may replace rather than supplement public transit use and offer quicker, cheaper, and more direct connections for short distances. In suburban areas, where public transit can be sparse, bike-sharing may provide better access to enhance the use of the existing public transit system (Martin & Shaheen, 2014). One promoted benefit of bike-sharing, namely reduction in carbon emissions, is often overstated given the limited mode share of bicycling (Ricci, 2015). Médard de Chardon, Caruso, and Thomas (2017) also found that bike-sharing has only a limited positive impact on health and modest impact on carbon dioxide emissions.

It should be noted that every urban area has its distinct attributes and thus the benefits of bike-sharing can vary from city to city. Research on the impacts of bike-sharing in East Asia is particularly limited. Current studies also generally do not assess the interactions between bicycling and other modes with methods that incorporate the influence of passenger behaviors. Thus, it would be valuable to explore the effects of bike-sharing in an integrated transportation system in Asian cities.

The objectives of this study are to understand how bike-sharing changes user travel behaviors and minimize the environmental and social impacts of an integrated transportation system. This study draws upon spatial agent-based modeling to observe how travel behaviors change in response to different bike-sharing strategies. Two kinds of behavior theories that are widely used in travel behavior modeling and prediction, which are random utility maximization and bounded rationality, are applied to study passenger mode choice behaviors. The key factors influencing passenger mode choices, including travel cost, travel time, accessibility level, and automobile ownership, are evaluated and integrated into the model. After defining travel behaviors, two scenarios are constructed to simulate different strategies for bike-sharing, including bike infrastructure extensions and bike-sharing incentives. These scenarios are evaluated by environmental and social impacts. The greenhouse gas (GHG) emissions, and air pollution emissions, such as SOx, NOx, and CO emissions of each mode are calculated to set benchmarks. The human health benefits from physical activity including cycling and walking are investigated. **Figure 1** shows the model framework based on a Taipei City map. As the model responds to real parameters, the user may amend basic input information to generate an optimum outcome and understand the required parameters, e.g., the most sustainable transportation scenario that has the minimum environmental impacts.

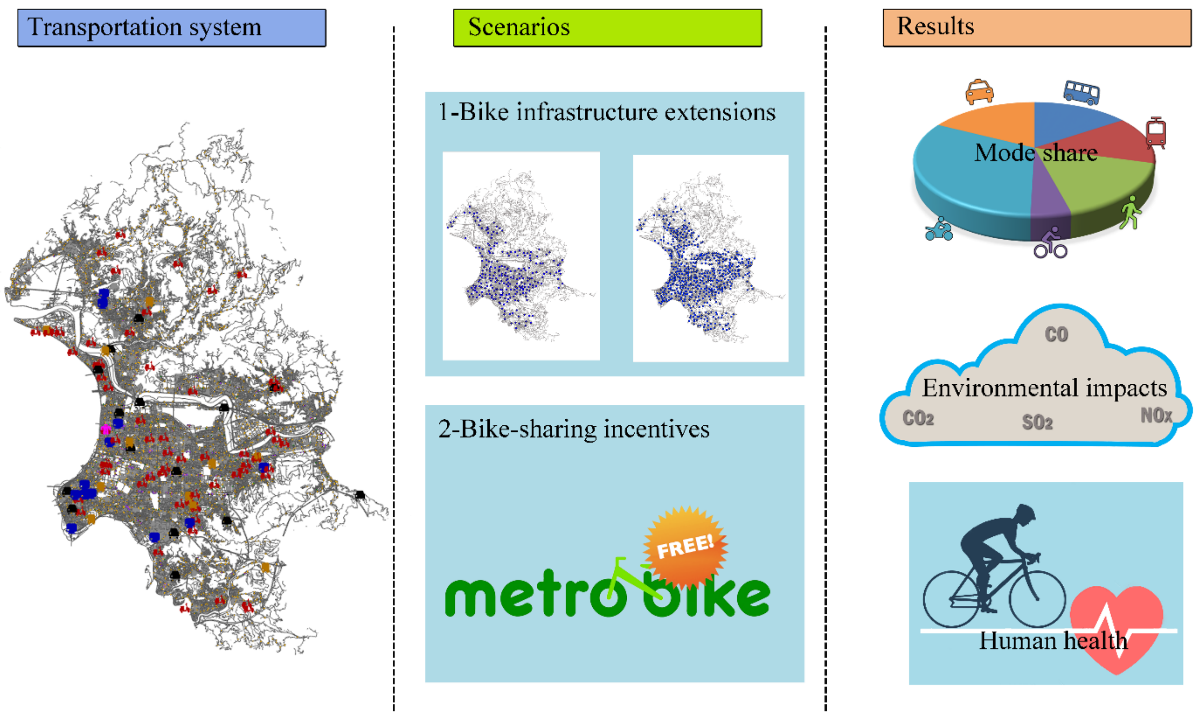

Figure 1. Model framework

2. Related work

Some studies have evaluated the environmental and cost impacts of bike-sharing separately. Montreal's Bixi has claimed that its program has saved over 3 million pounds of GHG emissions since its launch in May 2009 (DeMaio, 2009). Lyon (2009) stated that its program, which began in 2005, had cut the equivalent of 18.6 million pounds of CO_2 emissions from the atmosphere. Meanwhile according to the Earth Policy Institute, each shared bike user in Washington DC saves $800 in transportation costs per year on average (Davis, 2014).

The environmental impacts of bike-sharing can instead be investigated more accurately when taking into consideration its mode share in an integrated transportation system. Some studies indicate that bike-sharing mainly acts as a competitor to private modes. As Martin and Shaheen (2014) stated, bike-sharing has been found to decrease driving. A survey conducted by Shaheen, et al. (2013) revealed that 41% of respondents in Montreal, Canada reported using public transit with bike-sharing to complete a trip that would have previously been made by car. Faghih-Imani, Anowar, Miller, and Eluru (2017) also found that during weekdays bike-sharing for over half of trips less than 3 km is either faster or comparable to taxi service. The impacts of bike-sharing on shifts in public transit have been mixed. Campbell and Brakewood (2017) found that for routes in Manhattan and Brooklyn, every thousand bike-sharing docks along a bus route were associated with a 2.42% decline in daily unlinked bus trips. Martin and Shaheen (2014) found that bike-share members living in Washington D.C.'s high population density urban core were more likely to report reductions in bus use as a consequence of bike-sharing, while members living in lower-density regions in the urban periphery were more likely to report additional bus use. However, this pattern did not emerge in the results for Minneapolis, where respondents reported rising and falling usage in almost equal proportion regardless of residence in the urban core or periphery. Modal shifts identified in Hangzhou bike-sharing can act as both a competitor and complement to other available public transport options (Shaheen, Zhang, Martin, & Guzman, 2011). Some studies also found that bike-sharing has a greater impact on transit in these competitive relationships. Fuller, Gauvin, Morency, Kestens, and Drouin (2013) found that bike-sharing was associated with a small (0.3 – 0.4%) modal shift away from car use, but most of the apparent behavioral shift was seen from public transport, walking or private bike use. Similarly, Pai (2012) also reported that in Taipei, with the introduction of YouBike, 35.97% of YouBike trips shifted from bus traveling and 34.60% of YouBike trips shifted from walking. Only 8.72% of YouBike trips shifted from riding a private bike and 6.81% from riding a motorcycle. In order to more accurately evaluate the impacts of bike-sharing, the mode shares between bike-sharing and other transpiration modes were explored during the first stage of the current study.

The key factors that influence mode share choices have been investigated. Heinen, Maat, and Van Wee (2011); Kumar et al. (2016) found that time, price, and convenience were the main concerns of travelers in the mode choice process. Adverse weather conditions such as cold temperatures, heavy rain, high humidity, and stormy weather decreased bike-share activities, and more regionally specific comfortable temperatures (close to 90°F) increased bike-share trips (Godavarthy & Taleqani, 2017). Zhang, Yu, Desai, Lau, and Srivathsan (2016) also found that precipitation had a significant short-term impact on trip numbers: after heavy rainfall, bookings declined considerably below average and would take around three hours before rebounding to average trip rates again. But research by Heinen, van Wee, and Maat (2010); Miranda-Moreno and Nosal (2011); Nankervis (1999) suggested that weather does not typically deter regular cycle commuters unless conditions are particularly severe, i.e. temperatures below 4-5°C or above 35°C. Raviv and Kolka (2013) asserted that the primary factor that determines the success of a bike-sharing system is the ability to meet the demand, which can be pursued by providing a sufficient number of available bicycles and vacant lockers at each station. Inadequate cycling infrastructure decreased bike-sharing and private utility cycling (Goodman & Cheshire, 2014). As Heinen, et al. (2011); Stinson and Bhat (2003) found, travelers' mode choice is not only influenced by the external environment, but also by travelers' socio-demographic characteristics. In particular, car ownership has been shown to have the greatest impact on bicycle usage among all studied socio-demographic variables, accounting for significantly low use of a bicycle as a mode for commuting. The same applies to motorcycle owners. Koppelman and Bhat (2006) emphasize that it is important to identify factors whose values may be changed through proactive policy decisions. Passenger environmental awareness, attitude towards bad weather, and other psychological factors are not considered in this study, as these factors are more challenging to quantify and incorporate into this model. Thus, in this study, the four factors influencing mode choice include travel cost, travel time, accessibility level, and automobile ownership.

3. Material and method

3.1 Definition of the Simulation

This study simulates the impacts of bike-sharing under alternative transport policy initiatives by using agent-based modeling—a bottom-up approach that draws upon the spatial information. Bike-sharing embedded in transportation systems has been studied from a top-down viewpoint, either for system optimization (such as optimization of station locations) or for a deeper statistical understanding of their working mechanisms (such as logistics operations to identify and remedy zones with a surplus or shortage of bikes). Yet bottom-up approaches to studying bike-sharing that incorporate the behavior of users have not typically been applied so far (Shimizu, Akai, & Nishino, 2014). Agent-based modeling (ABM) is used for simulating the evolution of passenger mode choices as influenced by different transport policies (Lu & Hsu, 2017). An integrated transportation model is thus generated to simulate the interactions between passengers and transport modes. As distinguished from system dynamics, ABM can reflect the heterogeneity of travelers' characteristics and the complex interactions in a passenger transportation market. The behavior theories of random utility maximization and bounded rationality, which are widely used in travel behavior modeling and prediction, are applied to model passengers' mode choice behaviors. A geographic information system (GIS) is also employed to enhance the reality of the ABM model.

In the model, there are two types of agents: passengers and transport modes. The passengers commute during weekdays based on their different socio-economic status, which is generated from a representative distribution in the model (Guo, 2015). Each passenger has its preferential weights for choosing a mode for a commute. Six kinds of transport modes are included in the model. The first four modes are used for end-to-end trips, including bicycle, walk, motorcycle, and car. The other two modes are transit, i.e., bus and metro, which might need first/last mile connections to complete a trip. This study focuses on walk and bicycle serving as the first/last mile connect modes for the public transit modes. To show the mode choice processes based on the interactions between passenger and mode agents, the model excludes other irrelevant factors that may occur in reality.

To calibrate the agents' traveling behaviors, two kinds of data are collected. The first kind encompasses the attributes of passenger agents, which include income level, automobile ownership, time to travel, and origin and destination of the trip. The second kind consists of the variables of model agents, which include travel speed; travel cost; emission factors; spatial distribution of bike stations, metro stations and bus stops; and the corresponding routes. The spatial distribution data for bikes, metro, and the bus is especially important in accurate transportation map construction and highly related to the performances of transport modes. The model enables life-cycle impact assessments of these transport modes by using environmental performance data for the transport modes, including SOx, NOx, CO, and GHG emission factors.

As indicated previously, the key factors that influence passengers' mode choice are travel time, travel cost, accessibility level, and automobile ownership. Travel time in the model refers to the on-board time of the travel mode. The travel cost sums up all the explicit costs incurred during the commute trip. Accessibility level represents a locational characteristic that permits a station to be reached through the effort of those at other places using connected modes such as walking or bicycling. Automobile ownership means the ownership of a private car or motorcycle. For ease of comparison, the travel time and accessibility level are evaluated by how each agent values its time, defined as the value of time (VOT). Empirical studies have firmly established that travelers are much more sensitive to out-of-vehicle time than to in-vehicle time, meaning that a higher disutility is generated from a minute of out-of-vehicle time compared to a minute of in-vehicle time (Koppelman & Bhat, 2006). In this study, the VOT in vehicle and out of vehicle are evaluated as 60% and 100% of the passenger's hourly salary level. The four factors are defined in eq. (1) to eq. (4).

$$\mathrm{time} = \mathrm{d}_{travel}/v_{travel} \times s \times 60\% \tag{1}$$

$$cost = c_{travel} + c_{connect} \tag{2}$$

$$access = d_{connect}/v_{connect} \times s \times 100\% \tag{3}$$

$$\mathrm{own} = \begin{cases} 1\ (has\ the\ mode,\ \ e.g. car\ or\ motorcycle) \\ 0\ (otherwise) \end{cases} \tag{4}$$

Where d_{travel} and $d_{connect}$ represent the travel distance and connect distance, c_{travel} and $c_{connect}$ represent the cost of travel mode and cost of connect mode respectively, and s refers to the hourly salary of the passenger agent.

The four factors of the transport modes vary between time periods due to changes in the external environment. For example, the bike accessibility level could change due to the redistribution of bike stations. In addition to the four factors, actual traffic conditions affect travelers' choices. Faghih-Imani, Anowar, et al. (2017) found that individuals were unlikely to consider bike-sharing for long trips (>5 km or so). Thus, the bike mode is only deemed of utility if the one-way trip distance is under 5 km. Similarly, as stated by Boris and Zupan (1977), walking is considered of utility when the one-way trip distance is less than 1 km. Based on statistics of trip information (Department of Transportation, 2016), only when the end-to-end trip distance is longer than 500m will it be regarded as one trip. For example, if one traveler rides a bike to a nearby store and the cycling distance is less than 500m, the bike is not considered a transport mode in this study. In the first/last mile trips, the connect mode is also counted when the connect distance is longer than 500m. For example, in the case of one traveler taking a public bike from home to a metro station to connect to a metro trip, the bike is regarded as the connect mode when the cycling distance is longer than 500m. Hence, 500m is taken as the minimum trip distance for one specific mode.

3.2 Behavior theories

With the key factors influencing the passengers' mode choices defined, two behavior theories constructing the passengers' mode choice processes were implemented: random utility maximization (RUM) and bounded rationality (BR). RUM represented as perfect rationality (PR) has been widely applied in modeling travel behavior, assuming people assess and choose the best available mode of transport by considering all related factors such as cost, time, and the person's socioeconomic traits. However, this approach is not able to explain why individuals in similar situations and with similar socioeconomic traits make different mode choices. As opposed to RUM, BR takes into account the cognitive limitations of the decision-maker, limitations of both knowledge and computational capacity. When one person with bounded-rationality "satisfices," he seeks the alternatives that are satisfactory or "good enough" and not necessarily optimal. These two behavior theories were applied in the passengers' travel behavior simulation for comparison. And based on the historical data, the theory with the best fitness simulation results was selected for the subsequent scenario simulations.

Random utility maximization

Daniel Mcfadden parameterized and applied random utility maximization (RUM) into transportation demand in the early 1970s, work for which in part he later won the Nobel Prize in Economics. The utility maximization rule rests on two main concepts. The first is that the attribute vector characterizing each alternative can be reduced to a scalar utility value for each of those alternatives. The second concept is that the individual chooses the alternative with the highest utility value (Koppelman & Bhat, 2006). In a RUM model, the utility of one alternative mode is comprised of two parts: (1) the utility solely related to the attributes of alternatives, (2) the utility solely related to the characteristics of the decision maker, as shown in Eq. (5):

$$V_{i,j} = V\left(M_j\right) + V(P_i) \tag{5}$$

Where $V_{i,j}$ is the utility of mode j of the people i, $V(P_i)$ is the utility associated with the characteristics of people i, and $V\left(M_j\right)$ is the utility associated with the attributes of mode j. Based on the above four key factors, the mode utility is extended in Eq. (6):

$$V_{i,j} = \beta_1 \times cost_j + \beta_2 \times time_j + \beta_3 \times access_j + \beta_4 \times own_i \tag{6}$$

Where β_k is the weights of corresponding attributes; $cost_j, time_j$ and $access_j$ are the travel cost, travel time, and accessibility level of mode j respectively, which are normalized between zero and one; and own_i is a dummy variable for automobile ownership (automobile here refers to the car or motorcycle), one if the passenger has a car or motorcycle and zero otherwise.

Finally, the people choose the mode has the highest utility after comparing all the modes' utilities.

Bounded rationality

Bounded rationality (BR) was introduced by Herbert Simon in the 1950s. It has recently recaptured researchers' attention since it was first introduced in transportation research in the

1980s due to its ability to more realistically model and predict travel behavior. Through a comparative analysis of commuter departure time and route choice switch behavior between laboratory experiments and field surveys in Dallas and Austin, Texas, Mahmassani and Jou (2000) were able to demonstrate that boundedly rational route choice modeling generates valid representations of real commuter daily behavior. Three principle parameters were used in modeling the BR behavior in this study. They are aspiration level, stress threshold, and activation level. The aspiration level also called an indifference band, can change in the process of learning and interaction with the environment (Gifford & Checherita-Westphal, 2008). The deviation between the aspirations of an agent and the utility of a mode is defined as “stress” (Habib, Elgar, & Miller, 2006). If stress exceeds the stress threshold, the agent selects the choice with the maximum expected utility and its aspiration level falls. As long as the stress is within the stress threshold of the agent, the alternative will be selected and implemented again. Memory activation level is a habit indicator, as the mode with the maximum activation level in the choice set becomes the habitual option for that individual (Psarra, Arentze , & Timmermans, 2015). The updated activation level of agent *i* in time *t* is defined as follows:

$$AL_i^t = \log(AL_i^{t-1} + 1 + \beta), \tag{7}$$

if the mode has been selected at this time step

$$AL_i^t = \log(\alpha AL_i^{t-1} + 1), \text{ otherwise} \tag{8}$$

where $\beta > 1$ is the recency weight and $0 < \alpha < 1$ is the retention rate.

A logarithmic transformation is used because it is assumed that when the mode is newly selected, its activation level rapidly increases until it reaches a saturation point at which the activation level surge slows down. On the other hand, when the mode is no longer selected, its activation level dramatically falls (Psarra et al., 2015). Details about the procedure of bounded rationality behavior can be found in the Supplementary material.

3.3 Case study

The majority of people in Taiwan rely on cars, motorcycles, and scooters as the preferred mode of transport. Growing populations in cities have resulted in increased traffic congestion, air pollution, and car accidents. To address the negative impacts of motorized transport, the Taipei City Government has started promoting sustainable transport modes since 2008. The Public Bike System "YouBike" was officially launched in Taipei City in 2009. Taking advantage of Taipei Open Data, the spatial information of bike stations and bike lanes from 2009 to 2015 were collected. Other modes' stations and corresponding traffic lines were also incorporated into the model. The trips simulated are mainly based on the home-based work trip. The main transportation modes in Taipei include bike, walk, motorcycle, car, bus, and metro, which account for more than 95% of market share in the Taipei transportation system. The operating parameters such as the speed and cost of the studied modes were derived from Chang and Guo (2007); Huang (2016).

3.4 Model calibration and validation

The model was calibrated and validate through the comparison of two types of empirical data: a travel survey of respondents' daily used transport modes, and findings from previous Taipei transport system research literature. The travel surveys of daily used transport modes were collected from 2009 to 2015 in Taiwan, which include the mode shares of walk, bike, motorcycle, car, bus, and metro (Department of Transportation, 2010, 2011, 2012, 2013, 2014, 2015, 2016). In this survey, more than 30,000 people were interviewed by telephone every year. This data was used for model calibration. The calibration experiment was conducted by varying the combinations of four weights of the key factors. Exhaustive algorithms and heuristic algorithms were implemented to find the best parameter combination. The historical data of mode share in 2013 and 2015 were used as representative data to compare with the respective simulation results. The four key factors of the transport modes varied between 2013 and 2015.

For example, bike stations increased from 136 to 212. In addition, before April 2015, using YouBike was free for the first 30 min. Since April 1, 2015, the charge for the first and each subsequent 30-minute increment use was 5 NTD (New Taiwan Dollar) (roughly 1.66$). Thus, the travel cost, travel time, and accessibility level of bike and its connected transit changed accordingly. The ownership of motorcycles and cars also varied between these two years. Motorcycle ownership fell from 411 to 363 per 1,000 people from 2013 to 2015, while car ownership rose from 283 to 293 per 1,000 people. **Figure 2** compares the historical mode shares and their corresponding simulated mode shares of these two behavior theories with the best fitting parameter combination in 2013 and 2015.

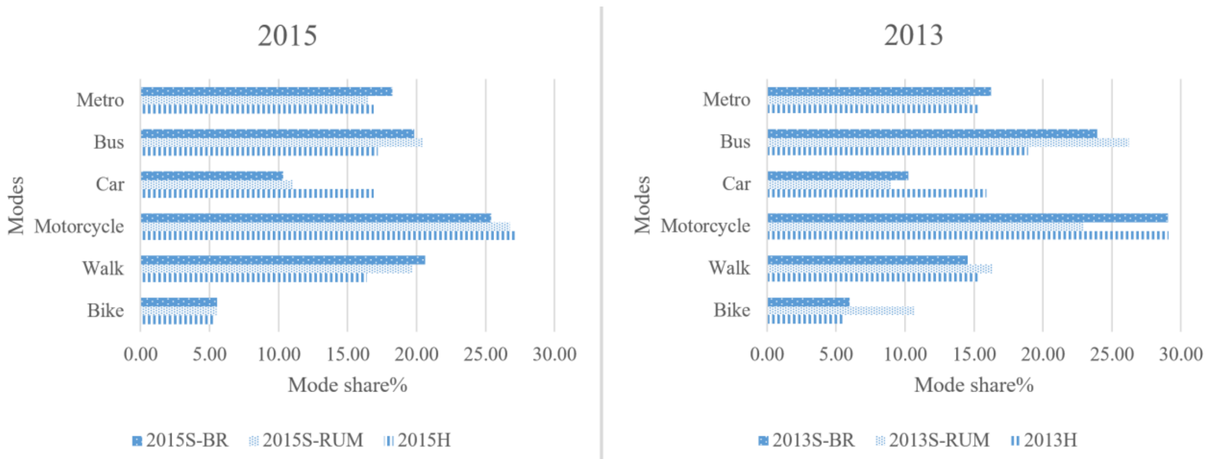

Figure 2. Calibration results of mode shares in 2013 and 2015

Note: 2015H/2013H means the historical date of the year 2015 and 2013. 2015S/2013S means the simulated results of the year 2015 and 2013.

As for the research findings from the literature review, in Taipei City, the average trip distances of bike, metro, motorcycle, and car are 2 km, 8.1 km, 9 km, and 12 km, respectively (Huang, 2016). The studies found that the cars and motorcycles in Taiwan are usually used for long-distance traveling given their faster speed and higher accessibility level. These travel patterns are used for model validation (see **Table.1**).

Table1. Validation results of average trip distance in 2015

Average trip distance (km)	Empirical study (Huang, 2016)	2015S-BR	2015S-RUM
Metro	8.10	7.29	7.19
Car	12.00	10.42	7.93
Motorcycle	9.00	7.64	10.92
Bike	2.00	1.72	2.31

The simulation results for BR demonstrated better fitness according to both of the calibration and validation procedures applied in this study. Thus the corresponding parameters and behavior theories of BR are applied to the following scenario simulation. The details about parameter configuration and statistical calibration and validation processes can be found in the supplementary material.

3.5 Scenarios

Based on the calibrated configuration of the model, two scenarios related to the key factors were simulated. The following scenarios are represented quantitatively in the simulation. **Table 2** summarizes the simulation results of the following scenarios.

Table 2. Simulation results of the two scenarios

Mode	2015 BAU	Scenario1	Scenario2	
		Infrastructure extensions	Free for transit connection	2 NTD coupon
Bike%	5.40	5.79	6.30	5.60
Walk%	16.40	15.70	20.47	20.00
Motor%	27.30	31.40	24.41	33.60
Car%	16.90	12.40	10.24	12.80
Bus%	17.20	21.49	19.69	14.40
Metro%	16.90	13.22	18.90	13.60

Notes: BAU represents business as usual, and NTD refers to the New Taiwan Dollar.

3.5.1 Bike infrastructure extensions

High bicycle modal share can be achieved through maintaining and continually improving safe and extensive bicycling infrastructure. Castillo-Manzano and Sánchez-Braza (2013) described Seville's high bicycling modal share as the result of the implementation of extensive new bicycling infrastructure. Public bicycle stations are usually located on a sidewalk near a transit station (Liu et al., 2012). In Taipei, most of the bike-sharing stations are located at nearby metro stations, with a few also located at bus stations. Such integration of bicycling infrastructure with other modes of public transit could enable stakeholders economic and other benefits (Chow & Sayarshad, 2014; Pucher & Buehler, 2009). Thus, 369 new bike-sharing stations were added close to the bus stations except for the remote mountainous areas in the north of Taipei. With the spatial data-driven model, travelers (agents) can measure the distance between home/workplace and stations based on the real road network, which relates to one of the key factors—the accessibility level of the mode. Lin, Yang, and Chang (2013) showed that bicycle stations should not be located more than 300–500m from important origins and destinations of traffic. The average distance between the bike-sharing stations and users' home/workplace in 2015 was calculated to be approximately 818 meters. After the extension of bike-sharing stations, the average distance between bike-sharing stations and users' home/workplace decreased to 604 meters. The travel cost, travel time, and accessibility level of bikes and their connected transits changed accordingly. Compared to the BAU scenario in 2015, the bike mode share increased from 5.40% to 5.79%, and bus mode share increased from 17.20% to 21.49%. As an alternative mode to bus, metro market competitiveness thus weakened.

bike-sharing can extend the catchment area of public transit (Shaheen et al., 2013). Huang (2016) found that 48% of YouBike trips started or ended at a metro station in Taipei, which can be speculated that almost half of YouBike services were used in the first/last mile service of transit. In this scenario, with the extension of bike-sharing stations, 63% bike is used to connect the first/last mile of the transit. But it should be noted 85% connecting bike is used for the first/last mile service of metro although the strategy is focused on building more bike sharing stations around the bus stations. This phenomenon can be explained by the spatial function of the model. It can be found the average distance between bus stations and users' home/workplace in Taipei is 203m, which is less than 1,000m and can be connected by walk. While the average distance between home/place and metro is much longer, 1,373 meters, even longer than the maximum walking distance 1,000 meters, that's why most connecting trips occur around the metro stations.

3.5.2 Bike-sharing incentives

Huang (2016) found that average bike-sharing trips declined by 26%, and trip distances—around 1-2 km—did not significantly change, after the cancellation of the "free use in the first 30 min" policy in April 2015. With consideration of this finding, some incentive strategies to encourage people using bike-sharing could consist of the free use of YouBike when used to connect the transit with the smart travel card, or a 2NTD (roughly 0.66$) coupon for every completed trip that can be used on subsequent trips. With one or the other incentive strategies simulated in the present study, the travel costs of the bike and its connected transit changed accordingly.

Compared to the BAU scenario in 2015, the simulation results show that the bike mode share increases from 5.40% to 6.30% with the first incentive strategy, and the shares of bus and metro also increase by 2.49% and 2.00%. Correspondingly, the motorcycle mode share decreases by 2.89% with the first incentive strategies. The bike mode share increases from 5.40% to 5.60% with the second incentive strategy. With the first bike-sharing incentive strategy, 75% bike is used to connect the first/last mile trips of the transit, but the connecting percentage in the second bike sharing incentive strategy is only 45%, which has little change compared with the BAU scenario. This is because bike-sharing and transit become complementary modes in the first incentive scenario, which can encourage more people to use bike and transit compared to implementing an incentive strategy that only targets cycling.

In Taiwan, motorcycles are the primary transport mode and known to be the biggest single source of vehicular pollution. Despite the introduction of bike-sharing through YouBike in 2009, bike-sharing exhibits limited influence on motorcycle use based on the simulation results for the above two scenarios. As for the motorcycle and car, there are no first/last mile problems. The travel speeds of motorcycle and car are even faster than bus. However, it should be noted that the transit mode shares increased by 2%-4% with the strategies encouraging the use of bike-sharing to connect to transit.

4. Results and Discussion

4.1 Results analysis

The environmental impacts of these three scenarios were analyzed, with the associated SOx, NOx, CO, and GHG emissions estimated. **Table 3** shows the emission factors with the unit of per passenger-kilometer traveled (PKT) (Chester, Horvath, & Madanat, 2010; Lin, Su, Chang, Chang, & Huang, 2011), and **Table 4** shows the damage cost of the respective pollutant measured in NTD (Lin et al., 2011). Thus, the corresponding environmental impacts are transferred to the total damage cost for comparison (see Eq. (9)). The minimized total damage cost is achieved in the scenario of free use of bike sharing to connect transit. The total damage cost can be reduced by 16%, equal to 1.5 million US dollars reduction in transportation damage cost per year compared to the 2015 BAU scenario. Thus, free use of bike sharing to connect transit could be more environmental-friendly than other traffic policies that only target bike-sharing.

Table 3. Emission factors of respective modes

Modes	Bike	Walk	Motorcycle	Car	Bus	Metro
NOx (g/PKT)	0.00	0.00	0.34	0.64	0.60	0.09
SOx (g/PKT)	0.00	0.00	0.00	0.01	0.00	0.14
CO (g/PKT)	0.00	0.00	6.12	7.96	0.14	0.02
GHG (CO2eg/PKT)	0.00	0.00	138.51	231.28	78.24	77.48

Table 4. Damage cost of the respective pollutant

Damage cost (2009NTD/g)	
NOx	0.101342
SOx	0.252785
CO	0.001198
GHG	0.000590

$$\mathrm{TDC} = \sum EF_i \times DC_i \times Td_j \tag{9}$$

Note: Here *TDC*, EF_i, and DC_i represent total damage cost, emission factor of the pollutant *i*, and damage cost of the pollutant *i*. $Td_{travelj}$ means the total travel distance of the mode *j*.

The benefits of physical activity including cycling and walking were compared between the minimized environmental impacts scenario (free use of bike sharing to connect transit) and the BAU scenario. The World Health Organization's Health Economic Assessment Tool (HEAT) was used to estimate avoided premature deaths due to physical activity from walking or cycling (World Health Organization, 2017). With this tool, the economic values of the health benefits that occur as a result of the reduction in mortality due to their physical activity are explored. In the minimized environmental impacts scenario, the average daily cycling and walking time for regular commuters are 16 and 36 minutes, respectively. Thus, the relative risk for cycling is 0.89 for regular commuter cycling for 16 minutes per week, that is, a population of regular cyclists is 11% less likely to die from all causes combined than a population of non-cyclists. In the same way, the relative risk for walking is 0.90 for regular walking of 180 minutes per week.

Compared with the BAU scenario, 7,488 and 33,862 people shift to cycling and walking in the minimized environmental impacts scenario. As a result, in the minimized environmental impacts scenario, 22 premature deaths can be further prevented per year compared with the BAU scenario. The detailed premature death calculation processes can be found in the Supplementary material. The human health impacts taking into consideration both physical activity and ambient air pollution were also analyzed (see Supplementary material).

4.2 Future directions

To resolve current methodological limitations, future model development could first incorporate weather effects. Individuals hesitate to ride a bike when facing adverse weather (Faghih-Imani, Anowar, et al., 2017). When there is favorable weather, the number of trips and travel time have both been shown to be greater (Caulfield, et al., 2017). Several weather conditions (such as precipitation) should be simulated based on comprehensive historical weather data. Second, in addition to the commute activities modeled in this study, leisure travel also contributes to the usage of bike-sharing. People using bike-sharing for tourism also have different values for travel time, travel cost, and so on, often being less sensitive to travel time compared to commuting citizens. Tourists’ travel patterns can be modeled further in the course of bike-sharing system development. Third, some studies have revealed that psychological factors (such as comfort and perceptions of safety) have a significant influence on bicycling behavior and should be given further attention (Heinen et al., 2011). In future research, agent decision-making should also incorporate these psychological factors.

5. Conclusion

In this study, a multidisciplinary approach to spatial multi-agent simulation for improving the sustainability of an integrated transportation system with bike-sharing was developed using real spatial information, and modeling disaggregated passenger behaviors. An ABM type model was developed to examine the usage of bike-sharing in a city's integrated transportation system by simulating the interactions between passengers and transport modes. The model can dynamically display how passengers' mode choices evolve under the influences of different transport policy strategies. In this model, all the modes operate in their traffic lines based on real road network data, and all the potential passengers commute by starting their trips from home and finishing at the workplace. The inclusion of these spatial behaviors enables the model to more accurately reflect the real transportation system.

Comparative analysis of the simulation results for two scenarios provide insights into the application of three traffic system measures, namely building more dockings near bus stations, free use of bike sharing to connect transit, and a 2NTD coupon for every completed trip. The results indicate that the second strategy is the most sustainable one, with the corresponding total damage cost of commute pollution reduced by 1.5 million US dollars per year compared to the 2015 BAU scenario, and 22 premature deaths further prevented per year due to the mode shift to cycling and walking. However, bike-sharing has limited influence on the use of private modes in Taipei, especially for motorcycle owners. Discouraging motorcycle use may produce the most immediate positive effects from an environmental perspective. This study provides an advanced tool to simulate bike-sharing decision making and understand environmental consequences under various policy scenarios. The model can be applied to other cities to aid in improving the sustainability of integrated transportation systems with bike-sharing.

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