LONG-TERM EFFECTS OF INFORMATION SHARING ON THE USAGE OF DYNAMIC RIDESHARING SYSTEM

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Ridesharing is a traffic congestion mitigation alternative to make a door-to-door trip by sharing a ride to other travelers who have similar travel itineraries. Dynamic ridesharing system (DRS) is a real-time system in which travelers can find partner(s) to share a ride for their upcoming trip. As a real-time system, travelers may not have certain information about other travelers beforehand (e.g., who will be their ridesharing partner(s)); a decision on the use of DRS is expected to be based on what travelers have learned and perceived so far. Considering an existence of social network, it is unavoidable that travelers will share their information among their friends which is expected to influence on individual behavior and decisions.

In this study, we aim to investigate how information sharing on social network can influence on the use of DRS in long term. To do so, we proposed a behavior-based DRS model incorporating with process of travelers learning information collected from friends on social network. The results from the numerical experiments showed that information sharing on social network could induce more travelers to continue ridesharing.

Key Words : *Dynamic ridesharing systems, social network, information propagation, behavior-based model, day-to-day learning process*

1. INTRODUCTION

Ridesharing, a sharing of a ride between travelers who have similar travel itineraries (e.g., origin, destination), has been introduced as an alternative travel mode for a personal door-to-door trip. By ridesharing, the number of vehicles can be reduced which consequently results in reduction of traffic congestion, resource consumption, and air pollution. On the other hand, from traveler's point of view, ridesharing can reduce individual travel cost as the cost can be shared with ridesharing partner(s), however, it may requires some tradeoffs, e.g., longer travel time caused by necessary detour. Dynamic ridesharing system (DRS) is a real time system that travelers can use for finding potential ridesharing partner(s) to share a ride for their upcoming trip. Many studies have developed various models to effectively and/or efficiently assign the matching among travelers (Agatz et al., 2012; Kleiner et al., 2011; Levin et al., 2016).

The development of information and communication technologies (ICT) has eased information sharing on social network. The information sharing has been revealed to influence on people behavior. For example, travel decisions (e.g., route choice, locational decision) were investigated to be influenced by the information on social network (Páez and Scott

2007). Therefore, for ridesharing, the related-decisions (e.g., decisions on the use of DRS, ridesharing partner) are also expected to have such influence.

The aim of this research is to study how the existence of social network influences on the DRS. Social network is defined as a network connecting people by social relationships (e.g., friendship) in which people can communicate and share information through some interactions (Kempe et al., 2003). Specifically, one of the objectives is to examine the effects of information sharing among friends on social network on the evolution of the use of DRS. Another objective is to investigate whether the spatially similar information collected from network has different influence on the use of DRS. This is considered because nowadays, one may have numerous number of friends, especially on online social network; in order to obtain the meaningful information for travel-related decisions, one may collect information from some friends who have similar origin and destination. Such collected information is referred as spatially similar information in this study.

In order to achive these objectives, we propose the day-to-day dynamics model for DRS incorporating the traveler's learning behavior of collecting information from friends on social network (Section 3). The day-to-day dynamics and existing day-to-day DRS models are reviewed in Section 2. The effects of information sharing on social network are investigated by the simulation approach based on the proposed model in Section 4. We conclude our study and findings in Section 5.

2. DAY-TO-DAY DYNAMICS MODELS

The day-to-day dynamics have been used to describe the evolution of the system which is a consequence of the user's behavior changing. In transport studies, the day-to-day dynamics models have been developed to explain how travelers adjust their travel decisions (e.g., mode choice, route choice) over days based on their learning process from individual experience and/or perceived information, and to investigate the evolved state of the transport system (e.g., long-term travel mode share) (Smith 1984; Watling 2003).

In ridesharing-related studies, Djavadian and Chow (2016) developed an agent-based day-to-day dynamics model for transport services without fixed route and/or schedule (including ridesharing) where travelers can change their behavior on travel mode and departure time. Their aim was to examine the effects of vehicle operational policy on travel demand and social welfare. On the other hand, Thaithatkul et al. (2017) developed the model specifically for ridesharing where travelers can change their travel mode and ridesharing partner choices over day in order to investigate the day-to-day dynamics characteristics of DRS. The learning models for both studies were developed similarly in which travelers perceive the average information from other travelers who use the same travel mode. However, the aspect of information sharing on social network has not yet been incorportated and investigated in these studies.

3. MODEL DEVELOPMENT

DRS in the proposed model is defined as a real-time service that gathers potential users, which are travelers who may have willingness to use DRS for finding ridesharing partner for their upcoming trip, and facilitates the matching process in the similar way as Thaithatkul et al. (2017). This means that user's behavior is not controlled by the DRS. The considered user's decisions are choices of using DRS, and ridesharing partner. As a real-time system, user can also decide whether to stop using DRS at anytime; this decision is represented by repeating a decision on the use of DRS.

To develop the model for the above explained framework, the key assumptions are firstly explained, and followed by the model formulation consisting of utility function, within-day decisions, day-to-day learning process. The overview of the model development is shown in Fig.1. The variables and parameters used in model formulation are listed in Table 1.

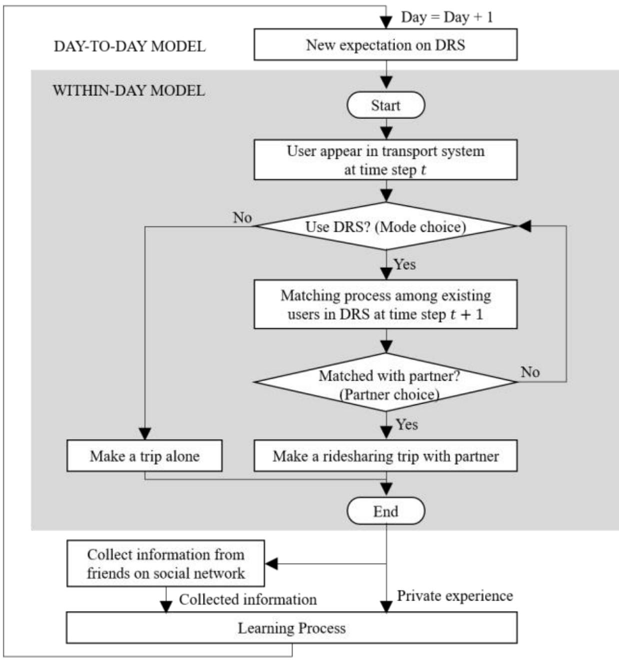


Fig.1 Overview of model development.

Table 1 Description of variables and parameters used in model formulation

Variables	Description
k	day k
$\boldsymbol{S}_k$	users' arrival sequence on day k
i, j	users in sequence $\boldsymbol{S}_k$, $i, j \in \boldsymbol{S}_k$
$m_{i,k}^r$	user i's matching partner in the stable matching solution of matching round r on day k
$m_{i,k}^e$	user i's actual ridesharing partner on day k
t	time t
$t_{i,k}^e$	time that user i exits the DRS and makes a trip on day k
$\tau_{i,k}(t)$	period of time since user i appears in the DRS until time t on day k, $\tau_{i,k}(t) = t - t_{i,k}^a$
$\tau_{i,k}^e$	period of time since user i appears in the DRS until time $t_{i,k}^e$ on day k, $\tau_{i,k}^e = \tau_{i,k}(t_{i,k}^e)$ (i.e. waiting time to be matched with ridesharing partner)
TT_i^*	acceptable travel time of user i
$v_{i,k}(j,t)$	utility if user i rideshares with user j at time t on day k which is evaluated by monetary terms
$g_i(j)$	cost of in-vehicle travel time of a trip that user i rideshares with user j
$f_i(j)$	travel fare of a trip that user i rideshares with user j
$x_i(j)$	period of time that user i spends after matching with user j until reaching her/his destination
$d_i(\cdot)$	penalty for excessive travel time of user i, which is a function of $\tau_{i,k}(t) + x_i(j) - TT_i^*$
$EV_{i,k}^A(t)$	user i's expectation-of-utility for traveling alone at time t on day k, which is given equal to $v_{i,k}(i,t)$
$EV_{i,k}(t)$	user i's expectation-of-utility for ridesharing at time t on day k, which is the utility that user i expects from using DRS at time t on day k based on individual day-to-day learning process
$EG_{i,k}$	user i's expectation-of-cost-of-in-vehicle-travel-time for ridesharing on day k
$EF_{i,k}$	user i's expectation-of-fare for ridesharing on day k
$EX_{i,k}$	user i's expectation-of-in-vehicle-travel-time for ridesharing on day k
$ET_{i,k}$	user i's expectation-of-time spent in DRS for finding a ridesharing partner on day k
$\bar{\alpha}_{i,k}^g$	user i's collected information of average ratio of expectation-of-cost-of-in-vehicle-travel-time for ridesharing trip comparing with riding alone trip on day k
$\bar{\alpha}_{i,k}^f$	user i's collected information of average ratio of expectation-of-fare for ridesharing trip comparing with riding alone trip on day k
$\bar{\alpha}_{i,k}^x$	user i's collected information of average ratio of expectation-of-in-vehicle-travel-time for ridesharing trip comparing with riding alone trip on day k
$\bar{\tau}_{i,k}$	user i's collected information of average expectation-of-time spent in DRS for finding a ridesharing partner on day k
$\boldsymbol{H}_i^*$	a set of friends on social network whom user i collects information from
$\phi_{i,k}(t)$	user i's travel mode choice decision at time t on day k, which equals to one if s/he decides to use the DRS and zero otherwise
$\phi_{i.k}^e$	user i's actual travel mode choice on day k
β_i	user i's update rate of her/his memory by the new information
$\beta_{i,k}$	user i's update rate of her/his memory by the new information on day k which is equal to β_i if there is new information on day k
γ_i	user i's weight of learning between private experience and collected information
$\gamma_{i,k}$	user i's weight of learning between private experience and collected information on day k which is equal to γ_i if there are both information on day k
r	matching round r
Δt	time interval of matching process in ridesharing service

(1) Key assumptions

(i) A means of transport is a for-hire vehicle (e.g., taxi, shared autonomous vehicle) with two passenger seats.

(ii) Vehicles are always sufficient and effectively operated.

(iii) Travel demand is homogeneous over days. In each day, users intermittently and randomly appear in the transport system in some sequence.

(iv) Considering rational users, individual decision strategy is to maximize expectation-of-utility.

(v) Utility is evaluated by following monetary-based factors: cost of in-vehicle travel time, travel fare, and penalty of excessive travel time.

(vi) Penalty of excessive travel time is a cost that occurs if user arrives at the destination later than acceptable arrival time, which is a monotonical increasing function of excessive travel time.

(vii) Expectation-of-utility is updated over days by new information using exponential moving average through day-to-day learning process. The new information is a weighted sum of two information sources if they are available which are: information sharing with some friends on social network, and private ridesharing experience.

The first four assumptions are in the same way as Thaithatkul et al. (2017). Assumptions (i) and (ii) are set to simplify the model where travel mode choice is only between ridesharing and riding alone; the matching is only considered among passengers; there is no traffic congestion; and waiting time for vehicle including vehicle dispatching time can be neglected. Assumption (iii) means that, during a certain period of time (e.g., peak hours), user has incomplete information of other users because of random arrival, so rational user will make decisions by maximizing *expectation*-of-utility, a utility that user expects to get at a certain time of a day which can be realized through day-to-day learning process, as in assumption (iv). Utility in assumption (v) is evaluated by the factors that are affected by ridesharing. Cost of in-vehicle travel time can be higher when user rideshare as ridesharing may cause inconvenience and discomfort to user and ridesharing partner. Travel fare can be reduced when user rideshares as it can be shared with partner. Finding a ridesharing partner together with the necessary detour for ridesharing with that partner may cause the longer travel time; the excessive travel time that occurs will cost as explained in assumption (vi), similar to the late arrival cost.

Assumption (vii) is for incorporating the user's learning behavior of the information sharing from the social network into the DRS. Social network in the proposed model is a set of users connecting to each other by social relationship. Friends of a user on social network refer to persons who are directly connected with that user on social network. The information sharing is represented by the process in which all users collect information from some number of their friends who have similar origin and destination. The information sharing can be done by any communication method such as face-to-face interaction, using online social network services.

(2) Utility function

According to assumption (v), the utility function of user i ridesharing with user j at time t on day k is defined as

$$v_{i,k}(j,t) = -g_i(j) - f_i(j) - d_i(\tau_{i,k}(t) + x_i(j) - TT_i^*), \qquad (1)$$

for all i and j who are member of arrival sequence $\boldsymbol{S}_k$. The cost of in-vehicle travel time $g_i(j)$ and travel fare $f_i(j)$ are dependent on user j's origin and destination, while penalty of excessive travel time $d_i(\cdot)$ is dependent on excessive travel time, which is a time that user additionally spends in total travel time more than an acceptable travel time TT_i^*. The total travel time consists of a period of time that user spends in DRS for finding a partner $\tau_{i,k}(t)$ and in-vehicle travel time $x_i(j)$. A utility of user i traveling alone at time t on day k is denoted as $v_{i,k}(i,t)$.

Notice that functions $g_i(j)$, $f_i(j)$, $x_i(j)$, and $d_i(\cdot)$ must be somehow specified (see Section 3 for examples of functions specification used in numerical experiments in this study).

(3) Within-day decisions

The expectation-of-utility for ridesharing at time t on day k —that is used for within-day decision making—is denoted by $EV_{i,k}(t)$ and formulated as

$$EV_{i,k}(t) = -EG_{i,k} - EF_{i,k} - d_i(ET_{i,k} + EX_{i,k} + \tau_{i,k}(t) - TT_i^*) \qquad (2)$$

for all i in $\boldsymbol{S}_k$ where $EG_{i,k}$, $EF_{i,k}$, $ET_{i,k}$, and $EX_{i,k}$ denote the expectations for ridesharing on cost of in-vehicle travel time, travel fare, time spent for finding partner in DRS, and in-vehicle travel time, respectively. These four expectation varialables are constant on each day and updated over days by the day-to-day learning process (explained in following section), while the expectation-of-utility for ridesharing $EV_{i,k}(t)$ can be decreased over time on a day depending on the time that user has spent in DRS, $\tau_{i,k}(t)$. The expectation-of-utility for traveling alone is denoted as $EV_{i,k}^A(t)$ which is assumed to be known equal to $v_{i,k}(i,t)$ as a conventional travel mode.

User i's decision on the use of DRS (i.e., mode choice) at time t on day k, $\phi_{i,k}(t)$, is defined as

$$\phi_{i,k}(t) = \begin{cases} 1 & \text{if } EV_{i,k}(t+\Delta t) > EV_{i,k}^A(t), \\ 0 & \text{otherwise,} \end{cases} \qquad (3)$$

for all i in $\boldsymbol{S}_k$. Let the matching process be executed at every Δt time interval to involve newly arrived users in the DRS. Under the expectation-of-utility maximization concept, user i will use DRS (i.e., $\phi_{i,k}(t) = 1$) only if mathcing with some partner in the upcoming matching process $EV_{i,k}(t+\Delta t)$ is expected to be better than immediately traveling alone $EV_{i,k}^A(t)$. Those users who decide to use DRS will be involved in the matching process for a partner choice decision explained later in this section. On the other hand, if the above mentioned condition is not satisfied, user i will travel alone at time t such that $\phi_{i,k}(t) = 0$. The following actual information for his trip is then denoted as follows: time he has spent in DRS is $\tau_{i,k}^e$, time that he exits DRS for making a trip is $t_{i,k}^e$, travel mode of his trip is $\phi_{i,k}^e$, and utility of his trip is $v_{i,k}(i, t_{i,k}^e)$.

For users who decide to use DRS, they will be involved in the matching process. Let the matching at every Δt be called matching round r, users who are involved in matching round r will have information of all other users in round r who are also currently looking for their preferable ridesharing partner. To maximize individual utility, all current users in round r are trying to be matched with the one who maximizes their utility. The spontaneous matching results from this behavior may reach so-called stable matching (Gale and Shapley, 1962), which is a set of matching pairs where no one can be better off by solely changing his paired partner, if it exists. Additionally, since user also has choices of traveling alone and waiting for the next matching round, the utility of matching with that partner must not be worse than those two choices. In other words, to match with partner j, the following condition must be satisfied for user i : $v_{i,k}(j,t) \geq \max\{EV^A_{i,k}(t+\Delta t), EV_{i,k}(t+2\Delta t)\}$, and vice versa. The above described matching process for each round r can be represented by employing the one-to-one passenger matching model proposed by Thaithatkul et al. (2015), which is a modification of stable roommate problem (Knuth, 1997).

The matched partner of user i from the stable matching of round r is denoted by $m^r_{i,k}$. For $m^r_{i,k} = j$ where $i \neq j$, it represents the successful ridesharing pair where both of them maximize each other utility. User i then exits DRS and makes a trip with user j; this actual partner is denoted as $m^e_{i,k}$. The users who successfully match with partner and eventually rideshare are called *ridesharing users*. On the other hand, if $m^r_{i,k} = i$, it means that user i cannot find any one who maximizes his utility or he cannot be stably matched with anyone in round r. In this case, user i will again make a decision on the use of DRS to decide whether to continue using DRS or to stop and travel alone instead.

(4) Day-to-day learning model

The expectation variables $EG_{i,k}$, $EF_{i,k}$, $ET_{i,k}$, and $EX_{i,k}$, which are used for within-day decision making, are updated through following day-to-day learning process.

$$EG_{i,k} = \beta_{i,k}\begin{bmatrix}\gamma_{i,k} g_i\left(m^e_{i,k-1}\right) + \\ \left(1-\gamma_{i,k}\right)\bar{\alpha}^g_{i,k-1} g_i(i)\end{bmatrix} + \left(1-\beta_{i,k}\right)EG_{i,k-1}, \tag{4}$$

$$EF_{i,k} = \beta_{i,k}\begin{bmatrix}\gamma_{i,k} f_i\left(m^e_{i,k-1}\right) \\ +\left(1-\gamma_{i,k}\right)\bar{\alpha}^f_{i,k-1} f_i(i)\end{bmatrix} + \left(1-\beta_{i,k}\right)EF_{i,k-1}, \tag{5}$$

$$ET_{i,k} = \beta_{i,k}\left[\gamma_{i,k}\tau^e_{i,k-1} + \left(1-\gamma_{i,k}\right)\bar{\tau}_{i,k-1}\right] + \left(1-\beta_{i,k}\right)ET_{i,k-1}, \tag{6}$$

$$EX_{i,k} = \beta_{i,k}\begin{bmatrix}\gamma_{i,k} x_i\left(m^e_{i,k-1}\right) \\ +\left(1-\gamma_{i,k}\right)\bar{\alpha}^x_{i,k-1} f_i(i)\end{bmatrix} + \left(1-\beta_{i,k}\right)EX_{i,k-1}, \tag{7}$$

where

$$\beta_{i,k} = \begin{cases}\beta_i & \text{if } \phi^e_{i,k-1} = 1 \text{ or } |\boldsymbol{H}^*_i| > 0, \\ 0 & \text{otherwise,}\end{cases} \tag{8}$$

$$\gamma_{i,k} = \begin{cases}\gamma_i & \text{if } \phi^e_{i,k-1} = 1 \text{ and } |\boldsymbol{H}^*_i| > 0, \\ 1 & \text{if } \phi^e_{i,k-1} = 1 \text{ and } |\boldsymbol{H}^*_i| = 0, \\ 0 & \text{otherwise,}\end{cases} \tag{9}$$

for all i in $\boldsymbol{S_k}$. The new expectations of day k are obtained by updating expectations of previous day $k-1$ with new information using exponential moving average at rate β_i if the new information exists. The new information is an weighted sum of private ridesharing experience and information collected from some friends on social network on previous day $k-1$ with weight γ_i. Note that if only one of two information exists, user will fully learn from that information. Regarding the information collected from social network, a set of friends whom user collects information from $\boldsymbol{H}^*_i$ is a set of some number of friends who have similar origin and destination (see an example of definition of $\boldsymbol{H}^*_i$ used in numerical experiment in Section 4). The information that user collects is represented as the information of expectations in order to consider the information propagation through social network. In other words, user will also implicitly perceives the information from friends-of-friends. User learns the collected information by averaging the information as follows

$$\bar{\alpha}^g_{i,k} = \frac{\sum_{j\in\boldsymbol{H}^*_i} EG_{j,k}/g_j(j)}{|\boldsymbol{H}^*_i|}, \tag{10}$$

$$\bar{\alpha}^f_{i,k} = \frac{\sum_{j\in\boldsymbol{H}^*_i} EF_{j,k}/f_j(j)}{|\boldsymbol{H}^*_i|}, \tag{11}$$

$$\bar{\tau}_{i,k} = \frac{\sum_{j\in\boldsymbol{H}^*_i} ET_{j,k}}{|\boldsymbol{H}^*_i|}, \tag{12}$$

$$\bar{\alpha}^x_{i,k} = \frac{\sum_{j\in\boldsymbol{H}^*_i} EX_{j,k}/x_j(j)}{|\boldsymbol{H}^*_i|}, \tag{13}$$

for all i in $\boldsymbol{S_k}$. The information of cost of in-vehicle travel time $\bar{\alpha}^g_{i,k}$, travel fare $\bar{\alpha}^f_{i,k}$, and in-vehicle travel time $\bar{\alpha}^x_{i,k}$ is averaged from the relative values by comparing the expectations on ridesharing with those of riding alone to normalize the absolute difference of friends' travel itineraries.

With this learning process, users may change their decisions over day. As a consequence, the number of ridesharing user will also change over day, and may evolve to some state. Note that the initial information about DRS must be given to users for their decision making on the first day.

4. NUMERICAL EXPERIMENT

The numerical experiment is conducted to examine the long-term effects of information sharing among friends in social network on the usage of DRS, and to investigate the influence of spatial similarity of information collected from friends who have similar origin and destination. To do so, the results of the evolution of number of ridesharing users are compared among scenarios with different average number of friends on social network of all users and different level of spatial similarity of information that users collect. The details of considered scenarios are explained in Section 4.2. The model specification used in this numerical experiment and experiment design are explained in Sections 4.1 and 4.3, respectively. The results are presented in Section 4.4, and discussed in Section 4.5.

(1) Model specification

Functions $x_i(j)$, $g_i(j)$, $f_i(j)$, $d_i(\cdot)$ in Eq. (1), definition of $\boldsymbol{H}_i^*$, and parameter Δt are specified as follows.

Given that a travel route for ridesharing be the shortest path that picks up user and his partner from their origin and drops them of at their destination, and in-vehicle travel time be proportional to Euclidian distance. For a ridesharing trip, it may consist of a period of time that user rides on a vehile alone for picking up and/or dropping off his partner, and a period of time that user and his partner ride on a vehicle together; travel time for these two periods are denoted by $a_i(j)$ and $b_i(j)$, respectively. The total in-vehicle travel time $x_i(j)$ is expressed as

$$x_i(j) = a_i(j) + b_i(j). \tag{14}$$

Note that vehicle dispatching time and traffic congestion are neglected as mentioned in assumption (ii).

The cost of in-vehicle travel time $g_i(j)$ is defined as

$$g_i(j) = \mu_1 a_i(j) + \mu_2 b_i(j), \tag{15}$$

where μ_1 and μ_2 denote costs of traveling in a vehile for one unit of time for traveling alone and ridesharing, respectively. Considering that ridesharing costs higher than riding alone as user may feel inconvenient and discomfortable when he rideshares, so that μ_2 is normally larger than μ_1. In this numerical experiment, μ_1 is given at 0.1 unit of money/unit of time, and μ_2 is given to be 50% more than μ_1 similar to the investigation in Hunt and McMillan (1997).

Regarding travel fare, the fare system where user can equally share the fare with his partner while they rideshare together is considered. Travel fare for ridesharing trip is then expressed as

$$f_i(j) = \alpha a_i(j) + (\alpha/2) b_i(j), \tag{16}$$

where α denotes a fare of traveling one unit of time. α is given to be 10 times larger than the cost of in-vehicle travel time for traveling alone, i.e., $\alpha = 1$.

The penalty for excessive travel time is defined similar to Arnott et al. (1999) as

$$d_i\left(\tau_{i,k}(t) + x_i(j) - TT_i^*\right) = \begin{cases} 0 & \text{if } \tau_{i,k}(t) + x_i(j) - TT_i^* \leq 0, \\ \mu_1(\tau_{i,k}(t) + x_i(j) - TT_i^*)^2 & \text{otherwise,} \end{cases} \tag{17}$$

where acceptable travel time TT_i^* is given to be 10% larger than regular travel time when user travels alone.

Considering that user may have limited time and memory to collect information, a set of friends whom user collects information is defined as a set with maximum number of n friends (i.e., $|\boldsymbol{H}_i^*| \leq n$) who have origin and destination closest to user within Euclidian distance d. A social network is represented as a well-known scale-free network, where the links connecting user and his friends are generated by the Barabasi-Albert algorithm. With this algorithm, user is connected to at least l friends; and the distribution of number of friends for all users follows a power law. The parameters n, d, and l are given differently among input scenarios explained later in the following section

Lastly, the matching process is assumed to be executed at every one unit of time, i.e., $\Delta t = 1$.

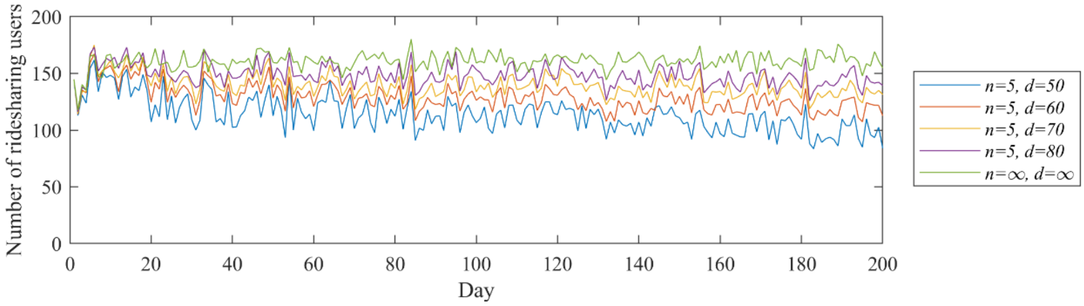
(2) Input scenarios

Given a total users of 500 users, their origins and destination are randomly, uniformly, and independently sampled within the same 200x200 unit of distance area. All users are assumed to arrive at the transport system with completely random distribution (Poisoon arrival) with the average arrival rate of five users/unit of time.

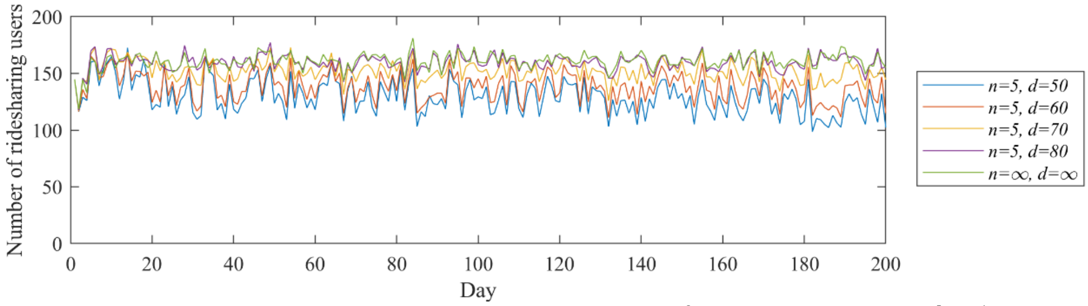
Scenarios with the different combination of parameters n, d, and l are considered where

- $n = 5, \infty$,
- $d = 50, 60, 70, 80, \infty$,
- $l = 20, 50, 100$.

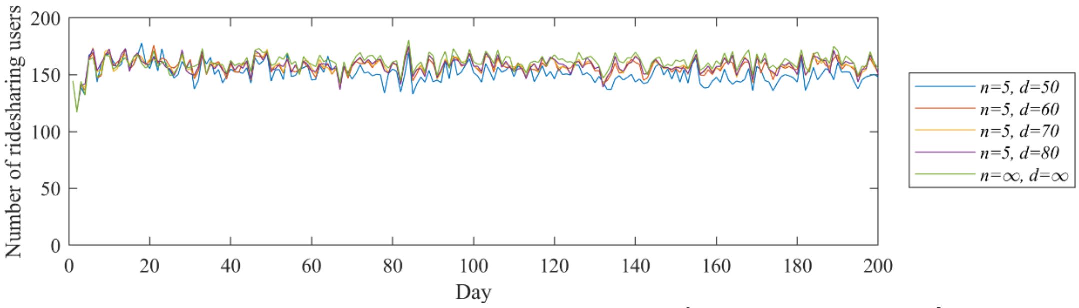
Maximum number of friends that user collects information from is given at five and infinity to represent the different situations when user's memory and time for collecting information are limited and unlimited, respectively. Note that the increasing of n was tested to have insiginificant effects on the long-term DRS adoption). Distance d for defining friends who are



(a) Scenarios where users are connected to at least 20 friends in social network ($l = 20$)



(b) Scenarios where users are connected to at least 50 friends in social network ($l = 50$)



(c) Scenarios where users are connected to at least 100 friends in social network ($l = 100$)

Fig. 2. Evolution of number of ridesharing users compared among scenarios with spatially different information collected from friends.

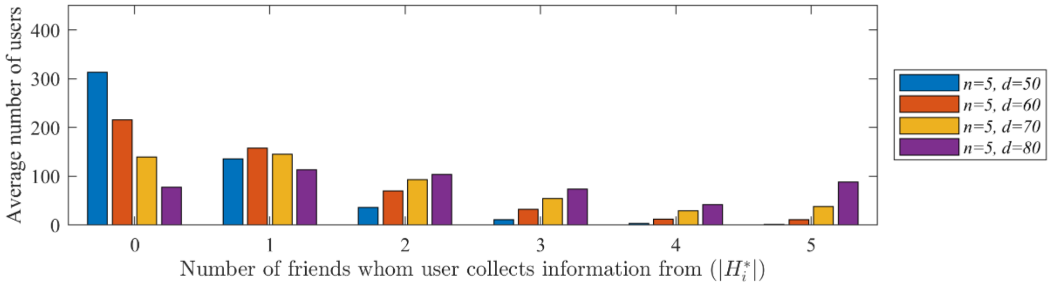
close in physical space is varied to investigate the effects of spatial similarity of information. The parameter l of scale-free network is varied to consider both offline (small l) and online (large l) social networks. The average number of friends for scenarios with l at 20, 50, and 100 are 38, 90, and 160 friends, respectively.

(3) Numerical experiment design

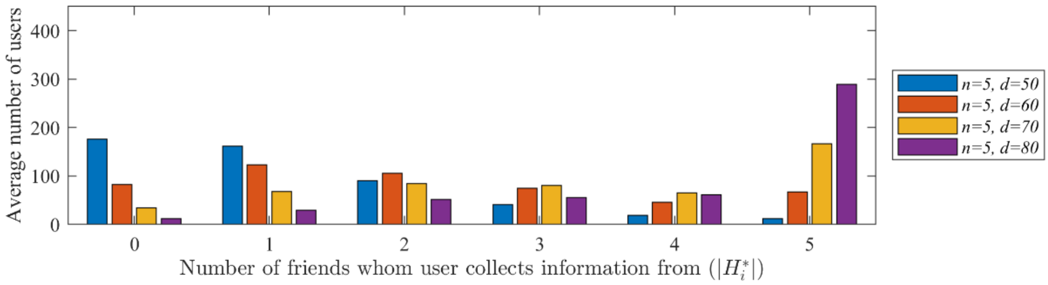
Each scenario is conducted for ten replications with different sampling of users' origins and destinations to obtain the average results. For each replication, 500 users repeatedly travel with the same origin and destination but different arrival time for 200 consecutive days. Each day has a finite time length which is from time that first user arrives at the transport system to the time that last user arrives. The results are evaluated as an average number of ridesharing users of each day from all ten replications. For the first day, all users are assumed to perceive the same information of DRS's best performance that is user can immediately find a ridesharing partner who can share his entire trip without any detour; in other words, $\bar{\alpha}^g_{i,0} = 1.5$, $\bar{\alpha}^f_{i,0} = 0.5$, $\bar{\tau}_{i,0} = 0$ and $\bar{\alpha}^x_{i,0} = 1$.

(4) Results

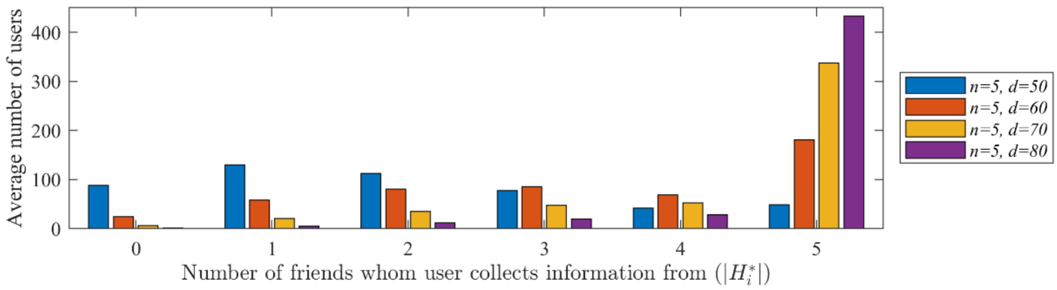
To investigate the effects of spatially similar information, the evolutions of average number of ridesharing users for scenarios with different d are compared in Fig.2. The results of scenarios with l at 100 (Fig.2(c)) show that the average number of ridsharing users tends to evolve to similar state for any d. This can imply that the spatial similarity of information may not have substantial effects on the long-term DRS adoption. However, this does not appear for scenarios with l at 20 (Fig.2(a)) and 50 (Fig.2(b)) which can be caused by the insufficient number of collected information as users in scenarios with l at 20 and 50 have lower average number of friends comparing to sceanrios with l at 100. Fig.3 shows the number of users who collect information from 0 – 5 friends for scenarios with n at 5. Comparing among three scenarios of l at 20, 50, and 100 with the same d at 50 and n at 5, the scenario with $l = 20$—where more than half of users have no friend who are close in physical space to collect information—tends to



(a) Scenarios where users are connected to at least 20 friends in social network ($l = 20$)



(b) Scenarios where users are connected to at least 50 friends in social network ($l = 50$)



(c) Scenarios where users are connected to at least 100 friends in social network ($l = 100$)

Fig. 3. Average number of users categorized by number of friends whom user collects information from.

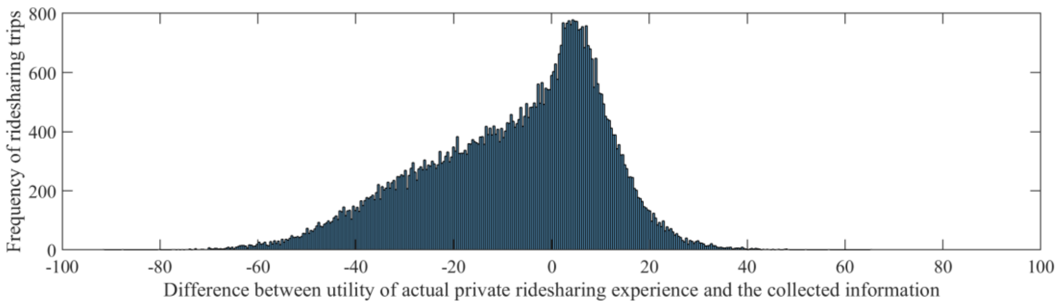
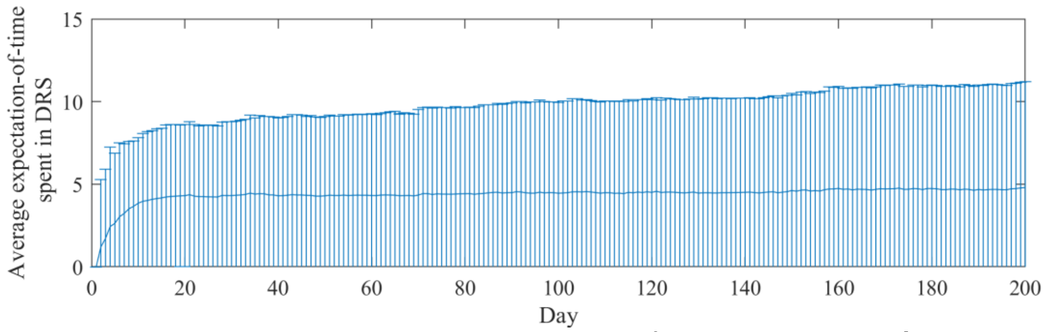


Fig. 4. Distribution of frequency of ridesharing trips according to the difference between utility of actual ridesharing experience and collected information during last 50 days for all replications of scenario where $l = 20$, $d = 80$, and $n = 5$.

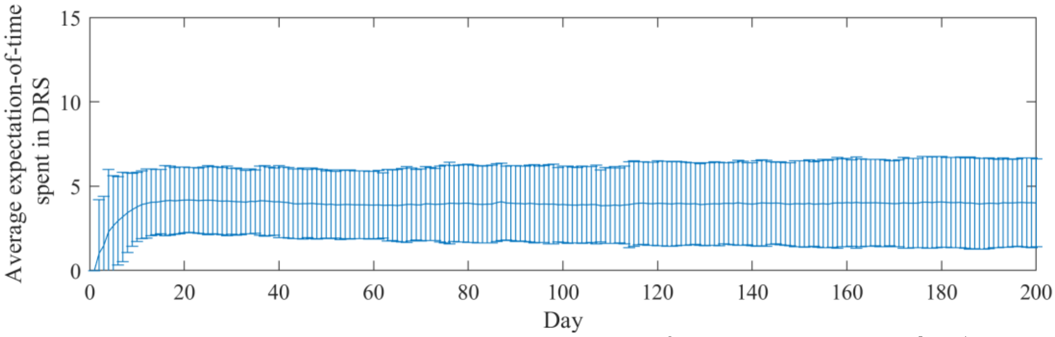
evolve to the state with lower adoption than the other two scenarios where users can collect information from more friends. But if users have sufficient collected information, adoption of DRS tends to evolve to the similar state. This can be seen by comparing scenario with l at 50 and d at 80 and scenarios with l at 100 and d at 60, 70, and 80.

The distribution in Fig.4 shows the frequency of ridesharing trip according to the defference between their private ridesharing experience and their collected information during last 50 days for all replications of scenario with l at 20 and d at 80. This result shows the importance of sufficient collected information as it shows that there are 58% of 64,520 ridesharing trips that users continue ridesharing even though they have worse private ridesharing experience than the information collected from friends. This cam imply that the good information perceived from friends convinces users to continue ridesharing.

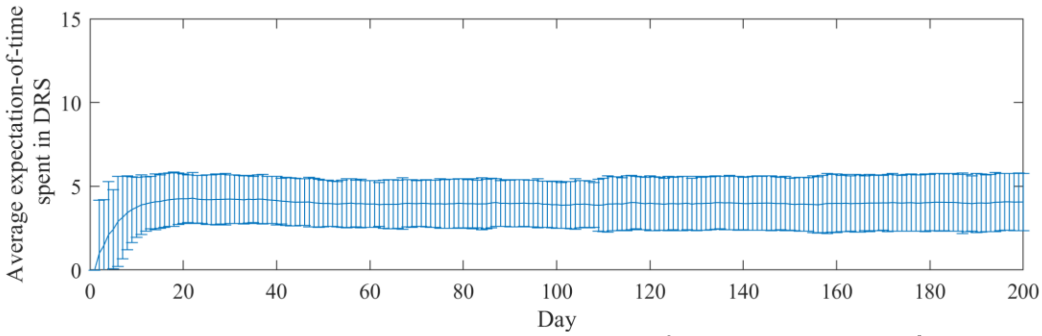
Moreover, to investigate more about the effects



1) Scenarios where users are connected to at least 20 friends in social network ($l = 20$)



2) Scenarios where users are connected to at least 50 friends in social network ($l = 50$)



3) Scenarios where users are connected to at least 100 friends in social network ($l = 100$)

Fig. 5. Average expectation-of-time spent in DRS ($ET_{i,k}$) and its standard deviation for scenarios with $l = 20, 50,$ and 100 where $d = 80$

of social network, the average normalized expectations on DRS (i.e., $EG_{i,k}/g_i(i)$, $EF_{i,k}/f_i(i)$, $EX_{i,k}/x_i(i)$, and $ET_{i,k}$) with their standard deviation is compared among scenarios with l at 20, 50 and 100. The results show that the more friends users have, the less diversity of expectations (less standard deviation) as shown in Fig.5 for the results of comparing $ET_{i,k}$ of scenarios with d at 80. This leads to the less fluctuation of the DRS evolution as shown in Fig.2. On the other hand, a low number of friends may cause the increasing of diversity of expectations over days.

(5) Discussion

The spatial similarity of information that users collect from friends who have similar origin and destination was revealed to have insubstantial influence on the evolution of number of ridesharing users when DRS is operated in the area with uniform distribution of origin and destination. This is expected to be caused by the influence of propagation of information on social network which diminishes the effects of distance difference in physical space. On the other hand, the number of collected information, which depends on how many friends on social network users have, was revealed to influence the number of ridesharing users in long term where the more friends users have, the more number of ridesharing users. This is because users who may have bad experience on the use of DRS are convinced to continue using DRS by the good information propagated through social network. However, it should be noted that this investigated phenomenon may be caused by the following limitation of developed model and numerical experiments: a user equally learns the information collected from friends even though their closeness in physical space is different; user only learns DRS from his private experienc of successful ridesharing trip; the numerical experiments were conducted for the area with uniform distribution of origin and destination. Therefore, in order to confirm whether this phenomenon always holds true, model extensions and additional numerical experiments are necessary.

4. CONCLUSION

In this paper, we investigated the influence of information sharing behavior on social network on the use of DRS in long term. Specifically, we developed the model by incorporating the traveler’s behavior of collecting information from friends on social network into the day-to-day learning process of behavior-based DRS model such that traveler can change ridesharing-related deicisons (i.e., travel mode, ridesharing pratner) over days based on information collected from social network. The investigation was conducted by numerical experiments. The results highlighted the influence of social network, namely, there are more travelers who eventually rideshare if travelers have more friends to collect information from. This is becuase the good information sharing among friends can convince travelers who personally experience bad ridesharing trip to continue ridesharing. On ther other hand, the spatial similarity of information collected from friends who have similar origin and destination resulted to have insubstantial influence on traveler’s behavior of travel mode choice. This is expected to be caused by the propagation of information on social network that may decrease the effects of distance difference in physical space.

The possible future studies are to extend the learning process of the developed model to consider the behavior when traveler unevenly learn information collected from friends according to closeness in physical space and/or in social network, and to cover the sharing of information of unsuccessful ridesharing trips. Moreover, the numerical experiments can also be extended to the distribution of origin and destination of real-world scenarios.

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