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An examination of the accuracy of an activity-based travel simulation against smartcard and navigation device data

ABSTRACT
Activity-based travel simulators have been experiencing difficulty obtaining high quality activity-travel data and network information, which limits the applicability of the simulator to real world problems. For example, accurate information regarding travel time, link traffic volume and trip distribution is essential for sensitivity analysis using an activity-based travel simulator. Survey data, which relies on respondents' memories, is typically inaccurate. The recent development of big data engineering has enabled us to use passively collected big data such as from smartcards and navigation devices; their travel time and spatial information is highly accurate. Activity-based travel simulation based on the household travel survey (HTS) can therefore identify inaccuracies in simulated travels by comparing smartcard and navigation device data. This paper aims to examine the accuracy of journeys simulated by an activity-based travel simulator, FEATHERS Seoul (FS), against smartcard and car navigation device data collected in Seoul. The analysis found that the activity-based simulator performs well and reproduces individual travel decisions, as reflected by the overall trip frequency and distance, but it partly fails to correctly reproduce geographical distributions in flexible, non-work trip destinations. The results imply that an activity-based travel simulator needs to improve its incorporation of geographical characteristics using big data engineering to enhance the simulated travel accuracy.

Keywords: FEATHERS Seoul (FS), Household travel survey (HTS) data, Simulated travel, Smartcard data, Navigation device data

Introduction

Several practical problems of activity-based travel simulators limit their real-world applicability, despite their potential to better evaluate transportation policy measures (Pendyala and Bhat, 2008). One of their major problems is data accuracy; several review articles (McNally et al., 2000; Rasouli and Timmermans, 2014) dictate the limitations of the traditional four-step model (FSM) in its assessment of contemporary policy measures that focus on transportation demand management and emphasize the potential strengths of the activity-based model (ABM). However, the strength of ABM can only be achieved by securing data accuracy, because of the model's complex and synthetic nature that combines activity engagement, trips, network environments, and individual socio-spatial characteristics.

The only available large-scale data set that can currently be used to estimate the activity-based simulation of individual travel behavior is the household travel survey (HTS), which often has accuracy problems. A wide variety of socio-economic scenario-based policy evaluations are available through activity-based travel simulators that utilize information about individual socio-economic and geographical characteristics and implement individual travel decision models. The simulator typically uses a set of data that includes the census data of population characteristics, networks, and location data regarding transportation environment characteristics and the travel survey data of individual travel record details. Among these, the travel survey data particularly suffers the accuracy problem.

HTS data provides information such as trip start and end times and locations, which are unfortunately generally inaccurate. Travel surveys solely rely on respondents' memories. No one can precisely remember trip start and end times that were conducted in previous days. Furthermore, respondents may omit some trip records due to memory limitations or, in some cases, privacy reasons. These are the major sources of information inaccuracies for variables such as travel time, trip distribution, and link traffic volume, which are crucial for activity-based model estimations (Cho et al., 2014; Lee et al., 2014).

The inherently problematic nature of travel surveys has prompted use of alternative data sources such as GPS logs and smartcard data. Several research studies have observed improved accuracy for trip frequency, trip duration, and trip distance when employing passive data collection rather than diary design (Park et al., 2003; Roorda et al., 2007; Bellemans et al., 2008). Digital technology–based unobtrusive data collection methods by definition outperform their more traditional counterparts in terms of time–space measurement. Therefore, passively collected data is better suited for the particular purpose of transportation planning.

However, activity-based travel simulators have yet to rely on HTS data for estimation, because passively collected data does not provide information about the individual characteristics that are absolutely necessary for simulating travel-related decisions in response to policy scenarios. Thus, the role of very accurate, passively collected data about travel behavior supports activity-based travel simulator's policy scenario evaluation. One way it does this is that passively collected data examines whether the activity-based simulator estimation in a travel diary correctly simulates a journey. That is, the passively collected data does not replace the existing travel diary but provides information about whether the simulated travel behavior represents a real world instance of transportation.

Two types of passively collected data are used to examine the accuracy of an activity-based travel simulator. The first is a transaction-based scanner, and the second is a GPS-based travel detector. The first examines travel using public transportation, while the second examines car travel. The travel scanner and travel detector have different properties, and hence one may expect the results of examining diary-based simulated travel to have different details. Smartcard and navigation device data are respectively representative examples of a travel scanner and travel detector. Several research studies have analyzed the accuracy of bolstering diary-based simulators using either smartcard or navigation device data (Cheon et al., 2013; Devillaine et al., 2012; Bouman et al., 2012; Pelletier et al., 2011; Cho et al., 2015). Those studies found that analyzing smartcard and navigation device data can reveal individuals' travel behavior and presents the possibility of analyzing the travel simulator's accuracy (Cheon et al., 2013; Devillaine et al., 2012; Bouman et al., 2012; Pelletier et al., 2011). In addition, research to validate the travel simulator has been carried out on the verification of the use of passenger measurement in specific areas and verification using GPS (Park et al., 2003; Roorda et al., 2008) (Cho et al., 2015). This study proposes a method of evaluating and verifying the accuracy of a travel simulator using big data about travel obtained from various sources.

This paper aims to develop a method to examine the accuracy of the simulated travel behavior by comparing with smartcard data for public mode use and navigation device data for private car use to identify which aspects of diary data should be improved. The main purpose of this study is to evaluate how realistic simulations can reflect and simulate the reality of travel behavior using precise transport big data that reflects reality. Thus, this paper is organized as follows. Section 2 briefly reports the characteristics of travel behavior in Seoul, Section 3 suggests the paper's research concepts, and Section 4 summarizes the analysis results. The paper ends with a summary of the analysis and future research suggestions in Section 5.

Study area

Seoul is illustrated in Fig 1; it has a population of 10 million spread over 605 km^2. This is approximately 20% of the country's entire population and 0.5% of its total size. The country's population density is 517 persons per km^2, whereas that in Seoul is 16,542. In other words, the city is highly concentrated as the capital city and densely populated. The area's transportation infrastructure is also highly concentrated. The average number of household members is 2.64. The city has 424 administrative units, called "*dong*," which are also used as transportation analysis zones (TAZs).

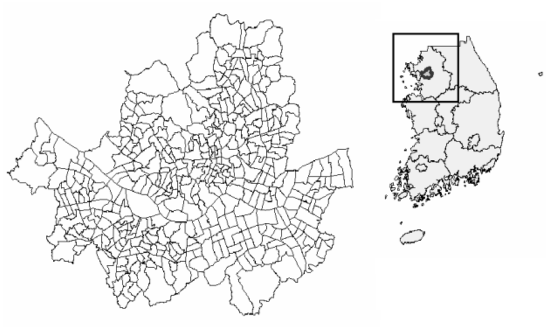


Fig. 1. Seoul, the study area.

The area's public transportation system includes nine subway lines with 311 subway stations, and 411 bus lines with approximately 38,000 bus stops. In total, 11 million trips use public transportation modes each day. There are approximately 3 million registered cars, and 2.4 million people report daily car use. The average car travel time for free floating is approx. 50 min for zone-to-zone, and is weighted 190% in peak hours (7–9 am and 5–7 pm).

Some important characteristics of travel behavior in Seoul that can be summarized by the above-mentioned data are provided as follows. First, travel conducted in Seoul has age and gender distributions as in Table 1, reported by HTS. Approximately 49.4% of the population is male. There are slightly more males than females under 19 years old, whereas there are more females than males over all age classes over 20 years old, as expected.

Table 1
Age/gender distributions of Seoul.

age	male	%	female	%
-19	81248	30.3%	74351	27.1%
20-24	10087	3.8%	15829	5.8%
25-29	16879	6.3%	19197	7.0%
30-34	17166	6.4%	17899	6.5%
35-39	22803	8.5%	26705	9.7%
40-44	25176	9.4%	28753	10.5%
45-49	23971	8.9%	24986	9.1%
50-54	22537	8.4%	23454	8.5%
55-59	17252	6.4%	17048	6.2%
60-64	13666	5.1%	12214	4.4%
65-69	9603	3.6%	7554	2.7%
70-74	4943	1.8%	3970	1.4%
75-79	1843	0.7%	1762	0.6%
80+	746	0.3%	1017	0.4%
total	267,920	100%	274,739	100%

Fig 2 reports the mode share of Seoul, as summarized by HTS. Approximately 40% of trips use public transportation including metro/train and bus, while private car driving and car passengers account for 23% of trips. Approximately 40% of conducted trips were walking or bike/motorcycle riding.

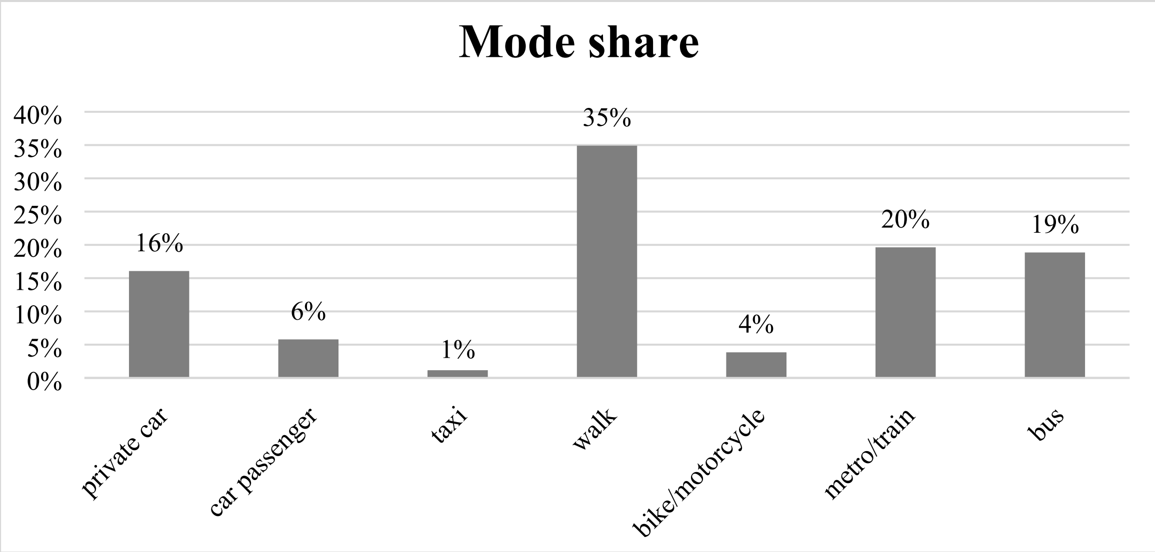


Fig. 2. Mode share of Seoul.

Fig 3 shows the distribution of trip purposes for Seoul summarized by HTS. While "home" is the highest proportion of trip purposes, "work-related (work, business, back to work)" represents 22% of trips. Non-work, flexible trips including to private educational institutes, shopping, leisure/recreation, bring/fetching, and other trips account for 20% of trips.

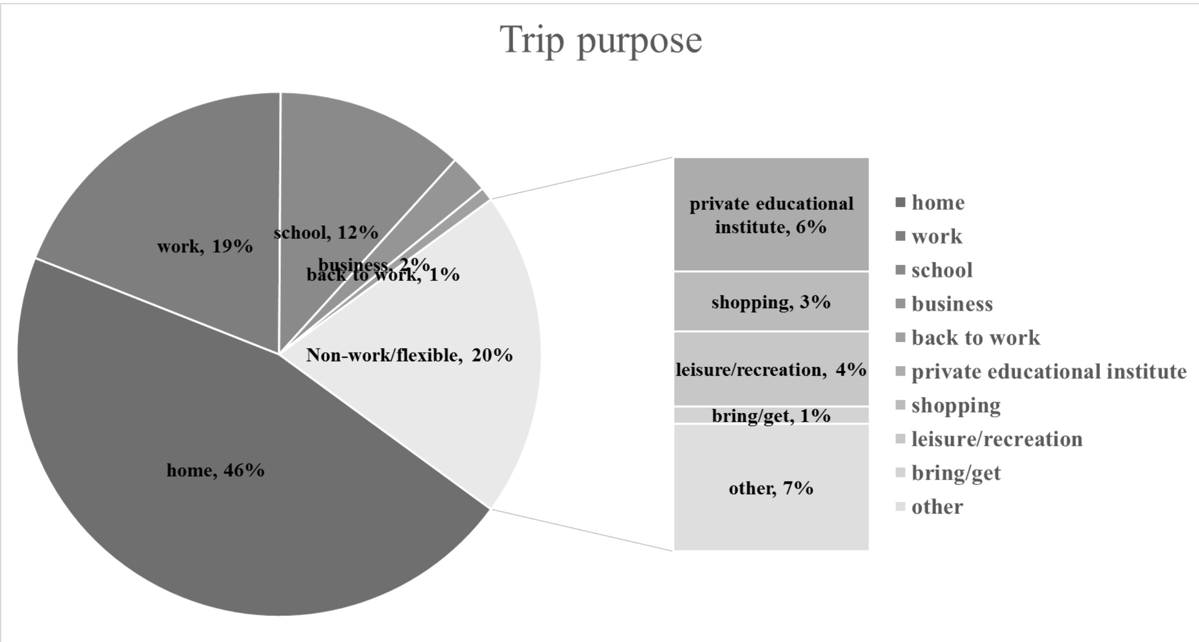


Fig. 3. Distribution of trip purposes for Seoul.

Fig 4 represents the distribution of trip start times for Seoul. All three datasets for HTS, smartcard, and navigation devices report that the morning peak is 7–9 am, and the afternoon peak is 5–7 pm. In the morning peak hours, HTS shows the highest proportion, whereas navigation device data reports the lowest proportion. In the afternoon peak hours, navigation device data shows a lower proportion, while HTS and smartcard data show higher proportions.

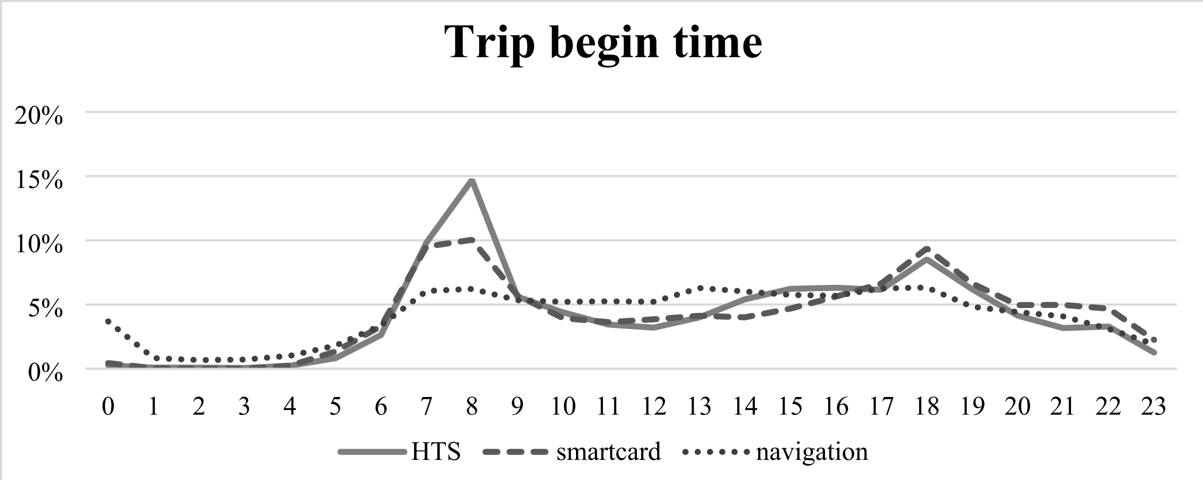


Fig. 4. Distribution of trip start times for Seoul as reported by different data sources.

Research concept

We first describe the travel simulator used to simulate travel behavior and the three different data sources, HTS, smartcard, and navigation device data that were used in the analysis in this section. The HTS diary data was used to simulate travel behavior, and smartcard and navigation device data were used to validate simulation results by comparing simulated and observed travel behaviors that used public and private modes. The suggested validation method then identified typical mismatches between simulated trips and those observed using public and private transportation modes.

Activity-based travel simulator

The analysis of the paper employs FEATHERS Seoul (FS), which is an activity-based travel simulator, to simulate travel behavior. Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS (FEATHERS) is an activity-based travel demand forecast system, and was originally developed to evaluate transportation policy measures in Flanders, Belgium. The system generates individual activity behaviors and travel for a given period of time and forecasts travel demand by transport mode that occurs in the actual transportation network (Bellemans et al., 2010). The model can reproduce activity and travel schedules based on heuristic rules that reflect individuals' travel decisions under specific transportation environments. FEATHERS uses 26 decision trees to classify individuals' activity/travel behaviors and makes heuristic rules regarding socio-demographic, environment, and network information. FS is an extension of the original FEATHERS that can be applied to the analysis of travel behavior in the context of the Seoul Metropolitan Area (SMA: Lee et al., 2012; Cho et al., 2014).

The first step in FS estimating activity and travel demand is segmenting observations. Classification of observation data is made by setting the interval using statistical methods so that continuous data can be categorized as discrete data. From the observation data, FS uses the decision tree method to derive activities and travel decision rules for 26 steps. In this process, 75% of observations are used as training data to create decision rules and the remaining 25% is used to verify the decision rules. According to the created rules, the synthesized population is entered into the forecasting step to predict activity and travel, and generate individual and household activities and travel schedules. Work-related fixed activities are assigned first based on the socio-economic characteristics of individuals and households, followed by non-work-related flexible activities and travel, which are assigned to available time slots. The schedule data generated through this process reflects the characteristics of the individuals and households of the synthesized population, and daily schedules are created based on the decision-making rules.

FS, like other activity-based simulators, uses input data including travel diaries, population, and environmental data for the simulation. The paper's travel diary data is obtained from a HTS conducted in 2010 in SMA. Population data includes the characteristics of individuals and households as surveyed in the 2010 census. Environmental data consists of land use information and transportation system characteristics such as transport modes, travel times, and travel costs. Currently, FS products have been validated in such a way that the data collected from HTS is first partitioned into training and holdout sets, and the travel behavior simulated using the trained FS is then compared with the travel behavior of the holdout data with regard to variables such as the average travel time, travel distance, and modal splits.

This validation method has potential accuracy problems, as people often over-estimate travel times. This is reflected in the HTS data; partitioning the HTS data into training and holdout sets and validating the travel behavior simulation based on the comparing the training data with the holdout data would therefore not solve this fundamental problem. The paper first simulates travel behavior using FS based on HTS data and then compares the results with the transportation big data of smartcards and car navigation devices. Approximately 10% of the synthesized population was sampled, and their travel behavior was simulated for testing. The FS output structure consisted of personal characteristic attributes including age, gender, work status, and household characteristic attributes such as household composition, income, number of household members, etc. It also included information about behavioral attributes such as activity and travel information.

One may argue that the validation should find a simpler method that first validates the simulated travel behavior using only the HTS data, and then simply adjust the simulated travel behavior in proportion to the over-/under-estimated relationship between the HTS data and other big data such as that of smartcards and navigation devices. However, such calibration-type adjustment methods do not fit the activity-based travel simulation scheme. For example if the travel time for an activity is reduced via such adjustment, the newly available time slot may change the originally planned trip destination, which in turn changes the rest of the schedule and travel behavior in the simulation. In short, a simple calibration-type adjustment of a part of travel behavior does not capture the interplay of activities and trips in the schedule and fails to realize the strength of the activity-based simulator. The analysis of the present paper therefore illustrates any systematic difference between travel behavior simulated from the HTS data and travel behavior of the smartcard and navigation device data.

Travel data

The HTS data that the paper uses were collected in 2010 in SMA by the Ministry of Land, Infrastructure, and Transportation of Korea. The data include individual and household information and their trip details, including begin and end times and places, transport mode, accompanying persons, and trip purpose. The traditional paper-and-pencil method was used. The data is intensively used by FS to simulate travel behavior and validate the model system. The data includes 1,390,179 trips of 661,689 individuals from 226,563 households.

No single data set covers the complete details of the transportation uses in Seoul. The major sources of transportation data in Seoul include HTS conducted every 5 years, smartcard data for everyday public mode use, and navigation data for everyday car use. HTS has a complete set of travel-related variables including household and individual characteristics and the details of trips. Because of this property, HTS is the main source of estimating the activity-based travel simulator for policy scenario assessment. The unfortunate characteristics of the HTS are the inaccuracy of some crucial travel information and the sample size (around 2.5% of the population), which are often not insufficient to represent certain sub-populations or trips. Smartcard and navigation device data provide highly accurate travel information; in particular smartcard data represent nearly the whole population using public modes. However, these two forms of data do not provide personal information and can therefore only complement diary data of the travel survey for the activity-based simulator.

The smartcard data that the paper uses were collected in 2013 in Seoul. The data were originally collected for the purpose of fee collection by the Seoul Metro Authority and were provided to Korea Transport Institute (KOTI), which disseminates the data for limited purposes including academic research. The information of individual public mode use is passively, automatically detected when the user touches the card reader terminal at the subway station and in busses at embarkation and debarkation. The size of the data is more than 10 million trips of more than 4 million individuals every day. Each data item provides the information of the randomized user ID, transport mode used and the exact time and location of departure and arrival. It also includes the information of transfer, the number of accompanying passengers, transit fare, travel distance, and the type of the smartcard user (adult, youth, child, and senior).

The car navigation device data of the paper were collected in 2013 in Korea. The data were archived by navigation service companies. Like the smartcard data, the navigation device data were also provided to KOTI. On average, the frequency of vehicle trips of the navigation device data covers approx. 0.4% of the total vehicle trip frequency observed by the national OD flow of vehicles. Car driving trajectories from origin to destination are automatically archived in log files when the navigation terminal attached to the vehicle is given the destination information by the user. The data also include the information of navigation ID, trip order, departure–arrival links, departure and arrival times, and speed and time or journeys. For an individual on a day with a fixed time interval (e.g., every 2 to 3 minutes), the navigation device data identify a set of trajectories, each of which is an ordered set of links connecting a begin node and an end node of the link. However, for the purpose of simplification of the trajectory information that is to be explained below, the paper converted each trajectory to a trip of the first departure and last arrival times and locations (nodes). For example, if an individual (that is, a vehicle) conducted three trajectories ([1-2-3-4-5], [1-2-3-4], [1-2-3-4-5-6-7]), the navigation device data identify three trips ([1-5], [1-4], [1-7]). Trajectories were distinguished by on and off operations of the navigation device. The navigation device data of the paper include 466,865 trips of 157,043 vehicles.

Several pre-processing works were taken to handle the three different data sets together. First, the navigation device data are mostly from adults. Therefore, the analysis had to include only the adults' travel behavior records from the HTS and smartcard data. Secondly, as the analysis of the paper required unified geographical units for all three data sets, the geographical unit of the data was tuned to the administrative unit for all three. The HTS data were collected on administration units, whereas the smartcard data were collected at each bus stop and subway station. The navigation device data were collected by links and nodes of road networks. Thirdly, complex trips were all converted to simple trips without transfers for all three data sets because FS, the travel simulator of the paper, does not have the functionality to recognize transfers and produce complex trips. The complex trips, including transfer(s) of the smartcard data, were, therefore, converted to simple trips. The navigation device data also used the information of only the first departure and the last arrival for each trip trajectory. Smartcard and navigation device data simplified trips by connecting the origin–destination of individual routes of data.

Both the smartcard and navigation device data have series of travel trajectories, whereas the simulated travel data do not have any specific trajectories other than origin to destination. Therefore, in the case of smartcard data, transactions with transfer trips were merged into single trips. In the case of navigation device data, trajectories were simplified as simple trips. Complex travel trajectories were expressed as simple straight lines. Those simple straight lines were then merged into each individual's trip diary in order. As a result, the analysis unit was set to the TAZ unit. All data (HTS, smartcard, and navigation device) were collected on Wednesday, an ordinary weekday.

Finally, and perhaps most delicately, the analysis includes only the trips for flexible, non-work activities from all three data sets. Although the commuting trip type covers a majority of the trips; the navigation functionality is mostly switched off when one drives to work along everyday routes. School trips were not included either in the analysis of the paper because of the navigation device data that are mostly reported by the adults, not the youth. The paper therefore analyzes only the trips for non-work and flexible activities including shopping, personal business, and leisure, recreation, and visiting relatives. These trips tend to be determined and implemented in-between or after the fixed, mandatory activities that affect the choice of flexible activities (Ramli et al., 2011). The rapid increase of single-person households also affects the choice of leisure and shopping trips as well as trip frequency and transport modes (Fan et al., 2010). Therefore, in the current paper, the HTS data used only the trips for flexible, non-work purposes. The navigation device data was fully used because all data items were assumed to be the trips for flexible, non-work purposes only. A difficulty occurred with the smartcard data, which has no direct clue to identify the trip purposes. The paper therefore assumes that a trip is of fixed, work purpose if begin time of the trip falls between 07:30 to 09:30, activity duration after the arrival is more than 600 minutes, and the administrative units of the departure of the first trip and the arrival of the last trip are the same (Lee et al., 2015).

Analysis scheme

Fig 5 depicts the overall flow of the analysis scheme of the paper. The analysis investigates the difference in global statistics of flexible, non-work trips' frequency, distance, and duration between travel behavior simulated from the HTS data and that of the smart card/navigation device data. The analysis then examines the difference in local statistics of flexible, non-work trips' destination distribution between simulated behavior and big data.

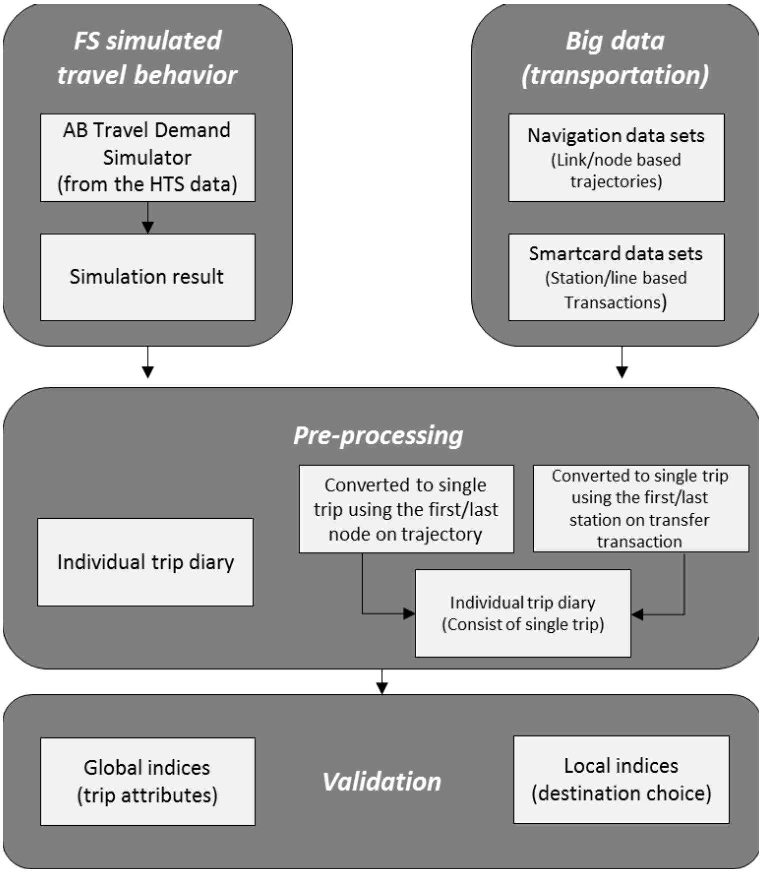


Fig. 5. Analysis flow.

Validation of simulation results of the activity-based travel simulator was typically conducted either with training and holdout sets of the same diary data or by comparing with the actual data representing only part of the study area, peak hours, or particular transport mode. Thus, validation of this kind has several limitations regarding fundamental accuracy or representativeness. Using the big data of smartcard and navigation devices for the validation of activity-based simulator estimated on a diary data therefore suggests the potential to overcome the accuracy problem as well as the representativeness problem.

Furthermore, validation in this way also suggests a method to identify which aspects of the diary data should be improved for better simulation of the trips. To this end, validation is first conducted for global correspondence between simulated and observed trips regarding aggregate individual decisions on trip frequency, trip distance, and trip duration. Validation is then conducted for local correspondence between simulated and observed trips regarding destination choices, which will examine how accurately simulated trip destinations are predicted by the observed big data and show and explain geographical difference in the prediction.

The major sources of problems concerned with global correspondence would be the inaccuracy of the travel information due to the limitation of respondents' memory on activities and travels conducted on the day before the survey day. The major sources of problems concerned with local correspondence would be geographical characteristics of TAZs and the degree of the representativeness of diary data, which likely differs between TAZs.

Analysis results

Global indices

Table 2 reports the global statistics of flexible, non-work trips' average frequency, duration, and distance. The public mode use simulated by FS was compared with the smartcard data, whereas the private vehicle use simulated by FS was compared with the navigation device data. The major difference was found in the trip duration between FS and smartcard. When the access and egress times to the public mode use were included in the total duration, this difference decreased. The difference between FS and smartcard in public trip duration is mainly caused by access time and egress time. For FS, the total travel time including access/egress time was estimated, but for smartcard, only the in-vehicle travel time (excluding access/egress time) was included. If the travel time includes an average access/egress time in in-vehicle travel time, the difference in average travel time is reduced from 32 minutes to 14 minutes. Overall, the trip duration has more difference between the simulated and observed travel behavior than other variables (frequency and distance). Assuming that the HTS data used by FS reflects personal interpretation of the trip duration, it can be said that individuals over-estimate the trip duration when public modes are used, while under-estimating the trip duration when private cars are used. Diary data relying on individual memory are relatively accurate in retrieving the information whether the individual made trips and about the trip departure and arrival locations, but are highly inaccurate in retrieving travel departure and arrival times. Individuals tend to round off the clock time heavily when reporting begin and end times of trips.

Table 2
Global indices of flexible, non-work trips.

Index	FS-Public(s.t.d)	Smart card(s.t.d)	FS-Car (s.t.d)	Navigation (s.t.d)
Average trip frequency	2.22 (0.61)	1.88 (0.89)	2.24 (0.67)	2.07 (1.24)
Average trip duration (minute)	84.79 (11.44)	52.39 (41.34)*	73.56 (12.11)	85.22 (107.22)
Average trip distance (km)	17.41 (48.79)	15.15 (12.24)	17.18 (49.12)	16.11 (14.02)

Note: The figure with * becomes 70.77 (41.34) when including average access and egress times.
Note: The s.t.d denotes standard deviation.

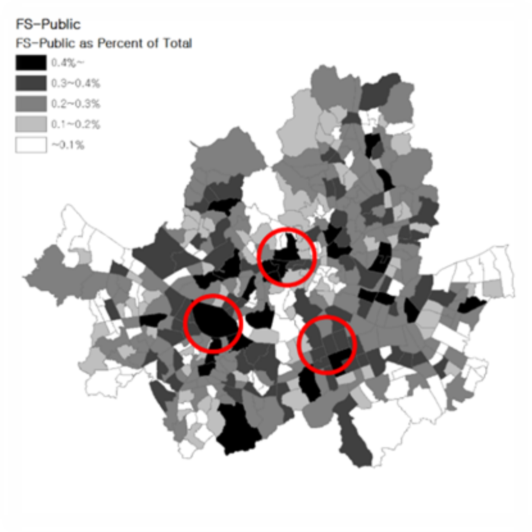
Local indices

Fig 6 shows local statistics of the flexible, non-work trips' destination distribution. The choropleth map shows the percentage of trip destination choices for each TAZ against all trips. Overall distributions of destination choices in Seoul by HTS-based FS and the navigation device/smartcard data are all similar. The differences found are that FS simulation gives more widely spread distribution than smartcard data and navigation observations. However, they all show the concentration of the trip destinations in the city's downtown areas in circles.

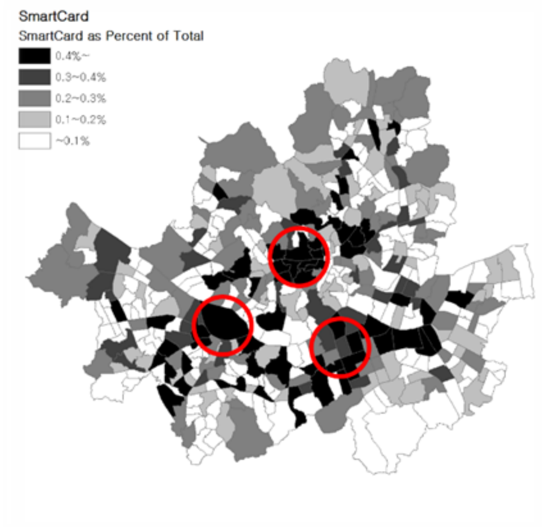
The paper further analyzed the degree to which the destination distribution simulated by FS using the HTS data was correctly explained by the big data. The simplest method to do this is to overlay the two maps (Fig. 6 (a) vs. (b), and Fig. 6 (c) vs. (d)) and see the difference. This may give an overall picture of the difference, but a spatial regression would statistically show how much the distribution of simulated trip destinations are explained by its observed counterparts. Any geographical distribution has the impact of geographical autocorrelation. The statistical correspondence of a particular TAZ between the simulated and observed trips is likely affected by surrounding TAZs' correspondences. Geographically Weighted Regression (GWR) was therefore employed to test the correspondence of the simulated trip destinations against the observed ones. This can be expressed as:

$$y_i = \beta_i \boldsymbol{W} + \beta_i \boldsymbol{W} x_i, \quad (1)$$

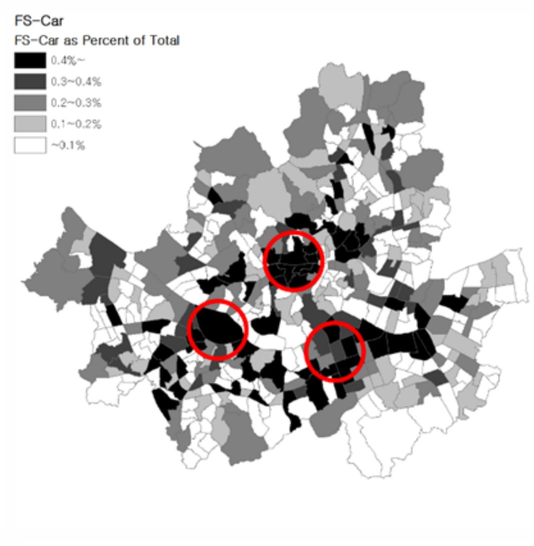
where y_i is frequency of the simulated trips whose destinations are TAZ i, x_i is frequency of the observed trips whose destinations are TAZ i, β is the parameter, and $\boldsymbol{W}$ is the spatially weighted matrix computed on TAZs surrounding TAZ i (Charlton and Fotheringham, 2009). This allows exploration of geographical variation in the relationship between the simulated (FS data) and observed trips (smartcard and navigation device data).



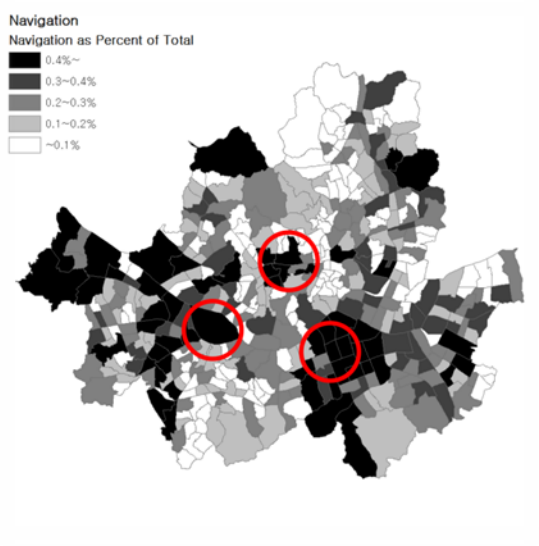
(a) Public mode trips simulated by FS data



(b) Public mode trips observed by smart card



(c) Car trips simulated by FS

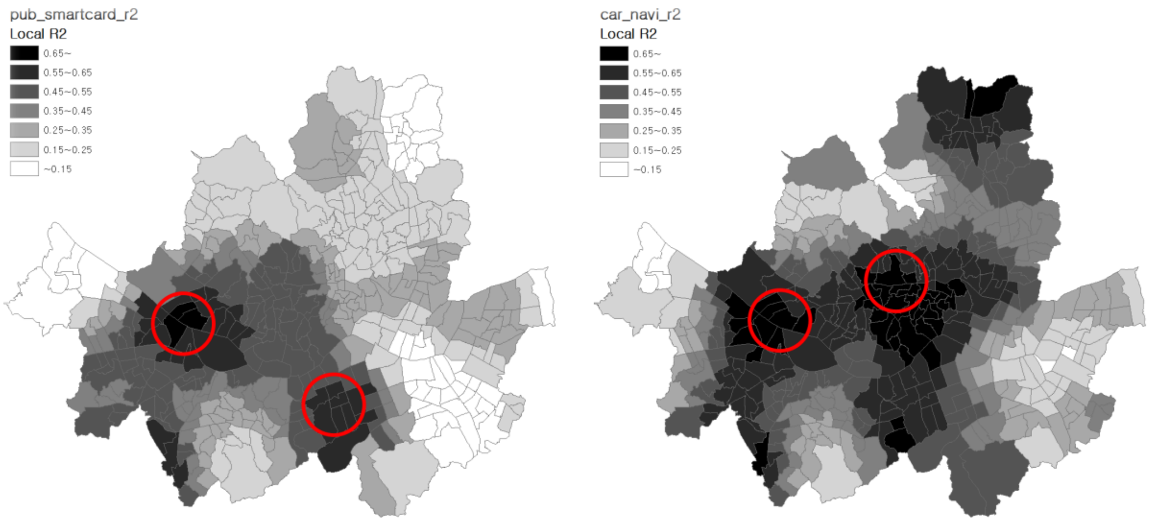


(d) Car trips observed by navigation device data

Fig. 6. Flexible, non-work trip destinations.

Fig 7 shows the explanatory power, R^2, of GWR of equation (1) that each administrative unit has. The darker the color is, the higher the R^2 of the geographical unit is. The R^2 here denotes the degree of the difference in travel behavior between the simulated data of FS and the observed data of smartcard and navigation device. The figure clearly shows that the geographical distribution of R^2 is uneven across TAZs, and the reason for this can be inferred by the information of land use types and network provision of the area. Both Fig 8(a) and 8(b) illustrate the higher R^2 in the TAZs near the center of the city and the lower R^2 in the peripheral TAZs. The transportation network provided the TAZs near the center of the city is better than that to the peripheral TAZs because the central TAZs have in general more people visiting and are located in the middle of the city. The activity-based travel simulator reflects land use and network characteristics when it simulates travel behavior. In the areas of higher supply of transportation infrastructure, the simulated trips and observed ones tend to move together, and R^2 increases mostly in the central part of the city. On the other hand, in the case of lower supply of transportation network, the simulator tends to under-estimate trip frequency compared with the actual frequency, which reduces R^2 mostly in the peripheral part of the city. Similar occurs when the land use characteristics are concerned. TAZs with land use inviting trips of higher frequency induces the travel simulator to generate trips similar to observed ones, which leads to bigger R^2. TAZs with land use attracting fewer trips results in smaller R^2 as the activity-based travel simulator then simulates trip frequencies bigger or smaller than the observed ones.

The relationships between R^2 and characteristics of land use and network are stronger with the public transport mode use of smartcard data than with the private car use of navigation device data. This is because the travel simulator over-reduces public mode trips to the TAZs of lower network provision and less attractive land use than actual trips. The simulator reduces car trips less than public mode trips, assuming that car travel is less restricted by network provision and land use because car use is relatively independent from the network provision and land use characteristics compared with public mode use.



(a) FS public-mode trips explained by smartcard data (b) FS car trips explained by navigation device data

Fig. 7. Explanatory power R^2 of GWR of each administrative unit.

Conclusion and discussion

The paper aimed at developing a method to evaluate simulated travel behavior against observed behavior by comparing simulated trips with the trips observed by big data. Simulation was conducted by an activity-based travel simulator, FEATHERS Seoul (FS), using the HTS data collected in 2010 in SMA. The simulator was estimated using the HTS data, which tends to over-/under-estimate travel behavior because of the accuracy problem of the travel survey relying on respondents' memory. Accuracy of the simulated journeys using public modes and private cars was therefore examined by using different big data sources of smartcard and navigation devices, respectively.

The sources of the data are different, and some pre-processing process of data was done so that travels could be compared between the data. First, only the records of adult users were included in the analysis because of the navigation device data that were reported by adults only. Secondly, complex trips having multiple intermediate stops were converted to simple trips because of the HTS data (which included only simple trips). Thirdly, only the flexible, non-work trip purposes were analyzed because of the navigation device data that were often not reported for regular commutes. Finally, geographical units were tuned to be administrative units (*dong*s) for all three data sets.

The examination was twofold. First, global indices were computed to see how the average statistics of trip frequency, duration and distance were well reproduced by FS using the HTS data with respect to the observed big data of smartcard and navigation. Secondly, local indices were computed to see the matching of trip destination distribution between the simulated and observed trips using GWR. Overall, it can be said that the simulated travel behavior well represented the observed big data of smartcard and navigation.

Nevertheless, the simulator should be further improved to simulate travel behavior that better matches the observed data in particular aspects. The simulated and observed trip destinations did not completely match each other in both cases of smartcard and navigation device data. The activity-based travel simulator reflects land use and network characteristics when it simulates the travel behavior. Therefore the degree of mismatch is affected by land use and network characteristics of TAZs. This tendency becomes stronger with public transport mode use, because travel using a car seems less affected by network provision and land use types. The results imply that accuracy of simulating trips using the public modes should be improved most. The improvement of the travel simulation in the peripheral areas of the city is required for both public and private modes.

The travel behavior simulated by FS should be more concerned with accuracy and develop systematically a method to support the information to validate the simulator using additional data such as navigation, smartcard, and even SNS data. In addition to such behavioral data, the characteristics of geographical area should also contribute to the improvement of the validation quality. This is because the fundamental premise of the activity-based transportation research is that travel is derived from activity participation given the land use settings of the area.

Non-work, flexible trip purposes would be easily distinguished in the context of simple land use neighborhood. However, the study area, Seoul, has highly complex land use characteristics, and many activities are therefore conducted at the same times at the same places, which make it extremely difficult to identify different trip purposes. More elaborated land use information (for example, vertical information of a building block) is required to obtain a better model. Also, activity inference using big data could better validate the destination choice for each activity purpose. The future research agenda should be detailed in this regard.

References

Bellemans, T., Janssens, D., Wets, G., Arentze, T., Timmermans, H.J.P., 2010. Implementation framework and development trajectory of FEATHERS activity-based simulation platform. *Transportation Research Record: Journal of the Transportation Research Board* 2175, 111–119.

Bellemans, T., Kochan, B., Janssens, D., Wets, G., Timmermans, H.J.P., 2008. Field evaluation of personal digital assistant enabled by global positioning system: Impact on quality of activity and diary data. *Transportation Research Record: Journal of the Transportation Research Board* 2049, 136–243.

Bouman, P.C., Lovric, M., Li, T., van der Hurk, E., Kroon, L.G., Vervest, P.H.M., 2012. Recognizing demand patterns from smart card data for agent-based micro-simulation of public transport. *Proceedings of the 7th Workshop on Agents in Traffic and Transportation, Valencia*.

Charlton, M., Fotheringham, A.S., 2009. *Geographically Weighted Regression*. White paper, National Centre for Geocomputation, National University of Ireland Maynooth.

Cheon, S., Kim, H., 2013. An application of car navigation data in transportation. *Monthly KOTI Magazine on Transportation* 183(5), 54–59.

Cho, S., Hwang, J.H., Bellemans, T., Kochan, B., Lee, W.D., Choi, K., Joh, C.H., 2014. A study on data preprocessing for the activity-travel simulator: a case of FEATHERS, Seoul. *Journal of Korean Society of Transportation* 32, 531–543. (in Korean)

Cho, S., Lee, W.D., Hwang, J.H., Kochan, B., Knapen, L., Bellemans, T., Choi, K., Joh, C.H., 2015. Validation of activity-based travel demand model using smart-card data in Seoul, South Korea. *Procedia Computer Science* 52, 707–712.

Devillaine, F., Munizaga, M., Tr´epanier, M., 2012. Detection of activities of public transport users by analyzing smart card data. *Transportation Research Record: Journal of the Transportation Research Board* 2276, 48–55.

Fan, Y., Khattak, A., 2012. Time use patterns, lifestyles, and sustainability of non-work travel behavior. *International Journal of Sustainable Transportation* 6(1), 26–47.

Lee, W.D., Cho, S., Bellemans, T., Janssens, D., Wets, G., Choi, K., Joh, C.H., 2012. Seoul activity-based model: an application of Feathers solutions to Seoul Metropolitan Area. *Procedia Computer Science* 10, 840-845.

Lee, W.D., Joh, C.H., Cho, S., Kochan, B., 2014. Issues in Feathers application in the Seoul Metropolitan Area. *Data Science and Simulation in Transportation Research, IGI*, 71–85.

Lee, W.D., Choi, K., Bellemans, T., Hwang J.H., Cho, S., 2015. *Data mining method for smart card data using household travel survey: a pilot study of public transportation in Suwon, South Korea*. Paper presented at the 14th International Conference on Travel Behaviour Research.

McNally, M.G., Rindt, C., 2000. *The Activity-based Approach*. Center for Activity Systems Analysis, UC Irvine.

Park, B., Schneeberger, J.D., 2003. Microscopic simulation model calibration and validation: case study of VISSIM simulation model for a coordinated actuated Signal system. *Transportation Research Record: Journal of the Transportation Research Board* 1856, 185–192.

Pelletier, M.P., Trépanier, M., Morency, C., 2011. Smart card data use in public transit: a literature review. *Transportation Research C* 19, 557–568.

Pendyla, R.M., Bhat, C.R., 2008. Validation and assessment of activity-based travel demand modeling systems. Innovation in Travel Demand Modeling: Summary of a Conference. *Conference Proceedings of the Transportation Research Board* 2(42), 157–160.

Ramli, M.I., Oeda, Y., Sumi, T., Matsunaga, C., 2011. Accommodating flexible daily temporal constraint on a continuous choice model of departure time for urban shopping travel. *International Journal of Urban Sciences* 15(3), 215–233.

Rasouli, S., Timmermans, H.J.P., 2014. Activity-based models of travel demand: promises, progress and prospects. *International Journal of Urban Sciences* 18(1), 31–60.

Roorda, M.J., Miller, E.J., Habib, K.N.M., 2008. Validation of TASHA: a 24-h activity scheduling microsimulation model. *Transportation Research Part A* 42, 360-375.

Highlights

* The accuracy of an activity-based travel simulator needs to be examined before applying the simulator to the analysis of behavioral sensitivity to policy scenarios.
* The accuracy of travels simulated by a travel simulator was examined against big data of smartcard and car navigation.
* The global and local indices of the matching between the destinations of simulated travels and observed ones suggest the need for further improvements of the simulator to enhance the accuracy of the travel simulation, in particular for the public mode use in the peripheral Seoul.

Title Page

An examination of the accuracy of an activity-based travel simulation against smartcard and navigation device data

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ABSTRACT
Activity-based travel simulators have been experiencing difficulty obtaining high quality activity-travel data and network information, which limits the applicability of the simulator to real world problems. For example, accurate information regarding travel time, link traffic volume and trip distribution is essential for sensitivity analysis using an activity-based travel simulator. Survey data, which relies on respondents' memories, is typically inaccurate. The recent development of big data engineering has enabled us to use passively collected big data such as from smartcards and navigation devices; their travel time and spatial information is highly accurate. Activity-based travel simulation

based on the household travel survey (HTS) can therefore identify inaccuracies in simulated travels by comparing smartcard and navigation device data. This paper aims to examine the accuracy of journeys simulated by an activity-based travel simulator, FEATHERS Seoul (FS), against smartcard and car navigation device data collected in Seoul. The analysis found that the activity-based simulator performs well and reproduces individual travel decisions, as reflected by the overall trip frequency and distance, but it partly fails to correctly reproduce geographical distributions in flexible, non-work trip destinations. The results imply that an activity-based travel simulator needs to improve its incorporation of geographical characteristics using big data engineering to enhance the simulated travel accuracy.

Keywords
FEATHERS Seoul (FS), Household travel survey (HTS) data, Simulated travel, Smartcard data, Navigation device data

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