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The effect of time, passenger age, crowdedness and collective pressure

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Author(s):
Sun, Lijun; Jian Gang, Jin; Lee, Der-Horng; Axhausen, Kay W.

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Characterizing Multimodal Transfer Time Using Smart Card Data: the Effect of Time, Passenger Age, Crowdedness and Collective Pressure

Lijun Sun
(Corresponding author)
Future Cities Laboratory,
Singapore-ETH Centre
Singapore, 138602, Singapore
&
Department of Civil & Environmental Engineering,
National University of Singapore
Singapore 117576, Singapore
Tel: +65-82982976
Email: sunlijun@nus.edu.sg

Jian Gang Jin
School of Naval Architecture, Ocean and Civil Engineering,
Shanghai Jiao Tong University
Shanghai 200240, China
Email: jiangang.jin@sjtu.edu.cn

Der-Horng Lee
Department of Civil & Environmental Engineering,
National University of Singapore
Singapore 117576, Singapore
Email: dhl@nus.edu.sg

Kay W. Axhausen
Institute for Transport Planning and Systems (IVT),
ETH Zurich
Zurich CH-8093, Switzerland
Email: axhausen@ivt.baug.ethz.ch

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ABSTRACT

Understanding passenger transfer behavior is crucial to designing better multimodal transport networks and improving public transport service quality. However, obtaining data for modeling transfer behavior remains a challenge, in particular under complex facility configurations. The recent emergence of smart card data provides us with new and efficient data-driven approaches to modeling public transport systems. In this paper, we present the effect of time of day, day of week, age of passengers, crowdedness at stop/station and collective pressure in determining passenger transfer time. By analyzing transfer profiles provided by smart card transactions, we apply regression models to assess the impact of each factor in determining passenger behavior under different scenarios. Using morning peak period as a base category, we find that passengers are faster during morning peaks even though it is more crowded. In terms of age of passengers, we find that children and senior citizens generally transfer slower than adults. However, children may outperform adults in passing through an overpass. The crowding effect at a bus stop is not substantial unless passenger demand reaches its capacity, while the crowdedness at fare gantries always delays transferring. Finally, we identify the effect of collective pressure by using the number of fastest/slowest passengers around one individual as a proxy. A fast passenger around one individual is found to reduce his/her transfer time, while a slow passenger may delay the transfer significantly. This work presents some empirical evidence in understanding passenger transfer behavior in a multimodal transit network. The results could be incorporated into physical surveys to better model pedestrian behaviors, supporting convenient facility design and public policy making.

Keywords: transfer, multimodal, public transport
INTRODUCTION

Transfer in a multimodal public transport networks refers to passengers’ shifting between different services (e.g. from one bus route to another) and modes (e.g. between bus and metro systems), by walking and waiting between connected stages (1). As a key factor in transit network design and transit service planning, transfer connectivity plays an important role in assessing service quality and affecting user perception (degree of satisfaction) of public transport systems (2). For transit operators, understanding passenger transfer behavior and characterizing factors influencing passenger transfer time are the keys to design better facilities and improve public transport service level, making public transport more attractive to users. Besides its importance for operators, providing better transfer connectivity and improving transfer experience are also common objectives of agencies in urban planning and public health.

For transportation researchers, a bottom-up approach to study passenger transfer behavior is to conduct physical surveys, identifying and quantifying factors influencing individual transfer activities. In the literature, a number of studies have assessed the cost of transfer inconvenience using physical surveys and passenger preference data (2-6). However, conducting such surveys is known to be both labor intensive and time consuming. Despite the high cost, sometimes survey results still suffer from the small sample size. On the other hand, without observations in a microscopic level, little is known about how individual/environmental attributes affect passenger transfer behavior. Recently, the field of public transport research has been benefiting from large-scale smart card data set (7), which provide researchers with data-driven approaches to study various problems about public transport systems, such as bus service reliability and metro network resilience (8; 9). Although the purpose of smart card system is to collect transit fares, the continuous flow of spatial-temporal stamped tap-in/tap-out transactions also enables us to study passenger behavior patterns by reconstructing individual activities from historical transactions (10; 11).

In this paper, we focus on using available information in smart card data on the estimation of bus-to-metro transfer walking time. Essentially, in a network with both bus and metro modes, transfer activities observed in tap-in/tap-out data can be categorized into three types: bus-to-bus, bus-to-metro and metro-to-bus (12). As most metro systems are closed environments, which only register transactions when passengers enter and leave the system, metro-to-metro transfers are usually not captured in smart card data. Thus, we know little about passengers’ activities within a metro system, such as route choice and service-to-service interchanging (13). Metro-to-bus and bus-to-bus transfers are not considered as for these two cases the temporal transactions can only provide us an inter-tapping interval, from which it is difficult to differentiate walking time from waiting time. To avoid the bias from unobserved waiting time, in this paper we stay on local bus-to-metro transfers, which in principle only consist of walking time. The smart card data sets in this study have tap-in/tap-out control for both bus and metro systems, which allow us to assume credibly that the inter-tapping time is a good proxy for transfer walking time. The contributions of this paper are twofold: First, we identify factors influencing passenger transfer behavior using available information in smart card data. Second, we apply linear regression models on different scenarios of bus-to-metro transfers (e.g. with/without restricted walking paths and overpasses/underpasses) to study the impact of each factor, providing in-depth insights on transfer times.

The reminder of this paper is structured as follows. In Section 2, we review existing literature on using advanced data collection techniques to study transfer behavior/activity. In Section 3, we identify factors, which influence passenger transfer behavior from available
information in the smart card data, including time of day, day of week, age category of passengers (e.g. adults, children and senior citizens) and crowdedness at bus stop/metro station. In Section 4, we propose two regression models on passenger transfer times. Besides the mentioned factors, we also quantify the pressure from surrounding people and discuss the results. Finally, Section 5 summarizes our main findings and provides the outlook on future work.

TRANSFER BEHAVIOR

The importance of passenger transfers and transfer behavior have been recognized from diverse points of view, from travel survey design (14), to transportation planning (10; 12), to infrastructure assessment (2; 15). The field has long been relying on surveys to measure the value of various factors using stated/revealed preference data and other aggregated data (16). For example, Liu et al. (5) used revealed and stated data to assess intermodal transfer penalties of New York–New Jersey commute corridors. Iseki and Taylor (17) used survey data to analyze passenger perception on transfer facility. They found that, from the user’s point of view, service reliability and personal safety are more important than the physical characteristics of facilities at transfer stops/stations. However, on a microscopic level, we know little about how passengers perceive various factors and how they behave under different scenarios. To study passenger activity in a more detailed manner, researchers have shifted from questionnaires to physical surveys. For example, using field survey data in Australia, Tirachini (18) studied the effect of different fare collection systems, bus floor level and age of passenger in determining total bus dwell time. Onboard survey data was used to quantify transfer penalty in subway systems of Boston (4; 6). Indeed, such a detailed physical survey could provide us with more information on individual characteristics and other social/environmental factors. However, as mentioned, conducting such surveys is time consuming and labor intensive. As a result, most behavioral studies are limited by their sample size in some way. On the other hand, as physical surveys can become costly when taking additional factors into account, survey-based studies usually have to pre-define the surveying contents, limiting the flexibility of research. Therefore, most studies on transfer behavior mainly focus on age and gender of individuals, while the effect of time of day, weekdays/weekends and pressure from surrounding transfer passengers has received little attention in the literature. This is also the motivation of this study.

To replace physical surveys, video recording devices became widely used in exploring the micro-dynamics of walking behavior. For example, passenger flows were studied using experimental research and experiment-based modeling (19-21). The importance of designing appropriate walking facility in urban environment are discussed based on experimental findings on pedestrian behavior under different circumstances (22; 23). Using similar approach, Jiang et. al. (24) investigated the effect of crowdedness of staircases on passenger evacuation capacity. However, given the considerable human resources and device costs, these experiments are costly to conduct and their application in non-laboratory contexts is still limited.

Recently, with the development of automated fare collection (AFC) systems, the emerging individual-based smart card data has offered transportation researchers a good opportunity to study transit user behavior. For example, Morency et al. (25) identified behavior patterns of grouped users and studied the variability of travel behavior patterns from smart card data. Jang (10) presented that individual transfer information can be obtained more efficiently by using smart card transactions than other conventional approaches. As an efficient way to detect passenger transfers, applying smart card data in transportation planning could also help transportation and urban planning agencies to identify critical
transfer locations in a city. Using smart card data from a multimodal network, Seaborn et al. 
(12) characterized the attributes of different types of transfers (e.g. metro-to-bus, bus-to-
metro and bus-to-bus) in London. Other cities apply flat fare for public transport systems and 
thus users are not required to tap out. Munizaga and Palma (26) focused on reconstructing 
trip information and identifying transfer activities using only boarding transactions in 
Santiago de Chile. Kusakabe et al. (27) studied passenger to train assignment problem in 
closed metro systems where individual train choice information is not available. Taking 
advantage of disaggregated nature of the data, in this paper we aim at filling the gap by 
identifying important factors that influence transfer activities and modeling passenger transfer 
behavior.

DATA COLLECTION

Smart card data

The smart card system in Singapore was first introduced in 2002, as a part of the citywide 
AFC systems. Different from some other systems without alighting (tapping-out) information 
(26; 28), Singapore’s system has a tap-in/tap-out control for both bus and metro systems, 
recording both boarding and alighting activities in order to measure exact travel distance for 
fare calculation. Therefore, once a user taps in/out on a smart card reader, a transaction 
containing his/her card ID, location ID and the exact time will be generated. Given its rich 
content, the data set provides us with a good opportunity to study passenger behavior on a 
microscopic level. For example, using time-stamped individual boarding/alinghting 
information on buses, collective boarding/alinghting dynamics for buses with different 
configurations are studied in (29).

In this study, we use one week’s smart card data (from 6 April 2013 to 12 April 2013) 
to study transfer walking time. The transfer time is measured as the inter-tapping interval – 
from tapping-out from the first stage to tapping-in for the second stage. Note that fare 
gantries are located at entrances of train stations, so the access cost between fare gantries and 
train platforms is not considered. Therefore, metro-to-bus transfers essentially consist of a 
walking segment from exit gantries to bus stops and a waiting segment at bus stops (waiting 
for the bus to board). Bus-to-bus transfers at the same stop consist of a single waiting 
segment, shifting from one service to another. In principle, inter-tapping interval of bus-to-
metro transfers contains only walking time without additional waiting time; thus, we use such 
observations as a proxy to study transfer behavior under diverse scenarios.

Case scenarios

To analyze passenger transfer time, we select four cases of bus-to-metro transfers with 
different characteristics (see FIGURE 1).

- (a) Bus stop 16019 – Station Haw Par Villa (bus stop ‘1’ to entrance ‘A’): alighting 
passengers need to walk about 100 meters (with sidewalk available) and take an 
escalator or stairs to get to the underground floor to tap in at fare gantries. Passengers 
may also take the lift near bus stop ‘1’ to get to the underground floor directly (mean 
observed inter-tapping time is 180.2s). 16019 is the ID of bus stop ‘1’.

- (b) Bus stop 41029 – Station Botanic Gardens (bus stop ‘1’ to entrance ‘A’): alighting 
passengers need to walk about 150m and then have to use an overpass to get to the 
fare gantries (mean observed transfer time is 402.7s). The overpass is equipped with 
lifts on both sides.

- (c) Bus stop 28099 – Station Lakeside (bus stop ‘1’ to all entrances): alighting 
passengers need to walk about 100m (open area without sidewalks) and take either
escalators or stairs to get one floor up to get tofare gantries (mean observed transfer
time is 241.1s).

- (d) Bus stop 18339 – Station Kent Ridge (bus stop ‘4’ to entrance ‘A’): alighting
  passengers are required to take an underpass to cross the street and then get to the fare
  gantries located at the ground level at entrance ‘A’ (mean observed transfer time is
  177.6s).

![Figure 1](http://www.smrt.com.sg)

**FIGURE 1**, Case field scenarios to study passenger transfer time (source:
http://www.smrt.com.sg/)

**FACTORS INFLUENCING PASSENGER TRANSFER BEHAVIOR**

**Time of day**

We first examine whether mean transfer time varies by time of day. **FIGURE 2** shows an
example of the moving average of transfer time with time of day for two cases. For both, we
observe clear and consistent temporal patterns from Monday to Friday, finding that average
transfer time reaches its minimum at 8:00-8:30 a.m. on both weekdays and weekends. In
general, passengers transferred faster in the morning than in the afternoon during the week.
To quantify this temporal effect, we set dummy variables for the time of day in estimating
passenger transfer time.
FIGURE 2, Temporal averaged passenger transfer time of two bus-to-metro pairs

Day of week

Despite the variation with time of day, we also see a clear difference between weekdays and weekends in FIGURE 2. We find that, on average, passengers transfer slower on weekends than weekdays. To quantify this effect, we set a dummy variable to distinguish weekdays from weekends and to capture the relative effect.

Age of passengers

In Singapore’s public transport system, children and senior citizens can enjoy discounts for their transit trips, while adults are required to pay the full fee with some recent exceptions. Because of these differences smart card users can be divided into three groups: children, adults and senior citizens for the later analysis.

Crowdedness

By analyzing all transactions at one bus stop/train station, we can quantify passenger arrival rate. In order to measure the degree of crowdedness at a particular bus stop, we calculate the alighting rate of passengers from all bus routes served by it as an indicator. For the metro station, the crowdedness of fare gantries can be measured in a similar way, by using tap-in rate of all entering passengers. Note that we do not differentiate different entrances for metro stations, as we do not know the exact fare gantry, which a card is tapped in. In this study, the crowdedness for an activity occurred at time $t$ (tapping times) is measured as number of tapping-in/tapping-out passengers from $t-15$ sec to $t+15$ sec (i.e. during 30 sec).
FIGURE 3, Transfer time distributions observed for different scenarios. Panel (a)-(d) corresponds to case field scenarios in FIGURE 1.

TRANSFER TIME MODELS

In modeling passenger transfer time, we only use observations from 6 a.m to 10 p.m. FIGURE 3 shows the distribution of transfer times of all the four cases. Although the inter-tapping interval is supposed to capture only walking time, we still observe long tails in transfer time distributions. In fact, passengers may engage in other time-consuming activities during their transfers, such as staying to answer a phone call, recharging their smart card or buying newspapers. However, without any prior knowledge and field information, we cannot identify such incidental activities from the data set directly. To prevent such incidental cases from influencing our estimation, we constrain the maximum transfer time as the 95\textsuperscript{th} percentile of all observations and disregard the longest 5% observations.

Effect of time, passenger types and crowdedness

To capture the effect of time, weekdays/weekends and passenger types, we set dummy variables to measure their relative differences. The temporal effect is characterized using the following categories:

- 6 a.m. to 10 a.m.
- 10 a.m. to 5 p.m.
- 5 p.m. to 7 p.m.
- 7 p.m. to 10 p.m.
Similarly, we also use dummy variables to capture the effect of weekdays/weekends and passenger types. As categorical variables on time of day and on passenger type contain more than two mutually exclusive categories, we set base classes as ‘6 a.m. to 10 a.m.’ and ‘adults’, respectively. Crowdedness levels at bus stop and train stations are estimated as number of passengers alighting and tapping-in during 30 sec. Taken together, the first estimated model (Model I) is given by Equation (1):

\[ T = C + \beta_{10,5}\delta_{10,5} + \beta_{5,7}\delta_{5,7} + \beta_{7,10}\delta_{7,10} + \beta_{\text{weekends}}\delta_{\text{weekends}} + \beta_{\text{child}}\delta_{\text{child}} + \beta_{\text{senior}}\delta_{\text{senior}}, \]

where transfer time \( T \) is the dependent variable and \( \epsilon \) is the residual or unexplained variance.

The independent variables and their definitions are listed in TABLE 1.

### TABLE 1, Variable definition

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta_{6,10} )</td>
<td>Dummy variable: 1 if the transfer is between 6 a.m. and 10 a.m. (morning peak); 0 otherwise. Dropped as base.</td>
</tr>
<tr>
<td>( \delta_{10,5} )</td>
<td>Dummy variable: 1 if the transfer is between 10 a.m. and 5 p.m.; 0 otherwise. Dummy variable: 1 if the transfer is between 5 p.m. and 7 p.m. (evening peak); 0 otherwise.</td>
</tr>
<tr>
<td>( \delta_{5,7} )</td>
<td>Dummy variable: 1 if the transfer is between 7 p.m. and 10 p.m.; 0 otherwise.</td>
</tr>
<tr>
<td>( \delta_{\text{weekends}} )</td>
<td>Dummy variable: 1 if the transfer is on weekends; 0 otherwise.</td>
</tr>
<tr>
<td>( \delta_{\text{adult}} )</td>
<td>Dummy variable: 1 if the passenger is an adult; 0 otherwise. Dropped as base.</td>
</tr>
<tr>
<td>( \delta_{\text{child}} )</td>
<td>Dummy variable: 1 if the passenger is a child; 0 otherwise.</td>
</tr>
<tr>
<td>( \delta_{\text{senior}} )</td>
<td>Dummy variable: 1 if the passenger is a senior citizen; 0 otherwise. Number of alighting passengers at bus stop (-/+ 15 sec), used to measure crowdedness at bus stop.</td>
</tr>
<tr>
<td>( C^b )</td>
<td>Number of entering passengers at train station (-/+ 15 sec), used to measure crowdedness at train station entrance.</td>
</tr>
<tr>
<td>( C^t )</td>
<td>Number of nearby transfer passengers that are among the fastest 10%.</td>
</tr>
<tr>
<td>( M )</td>
<td>Number of nearby transfer passengers that are among the slowest 10%.</td>
</tr>
</tbody>
</table>

### Effect of collective pressure

For transfer passengers walking in groups, one may expect that walking with a faster person will increase your speed, whereas a slower companion might delay your transfer. We call this effect ‘collective pressure’ in this study. In order to assess the impact of pressure from nearby transfer passengers on individual transfer time, the numbers of fastest \( M \) and slowest \( N \) transfer passengers are added as potential explanatory variables in the regression model. In doing so, we first extract all transfer times and locate the 20th and 80th percentiles. The fast group is defined as the top 20% fastest passengers, while the slow group consists of the top 20% slowest (after disregarding the incidental cases). Note that the fast group and the slow group are obtained from all transactions have equal size.

For an individual, his/her surrounding transfer passengers are those observed at the alighting bus stop \( C^b \) within 30 sec (-/+ 15 sec), going towards the matched train stations. Thus, \( M \) is estimated as the number of surrounding transfer passengers belonging to the fast group. Similarly, \( N \) is the number in the slow group. Note that the subject individual is not counted in measuring \( M \) and \( N \). Taken together, we propose another model by taking
collective pressure from surrounding passengers as explanatory variables. The modified model (Model II) is given by Equation (2):

\[
T = C + \beta_{10.5}\delta_{10.5} + \beta_{5.7}\delta_{5.7} + \beta_{7.10}\delta_{7.10} + \beta_{\text{weekend}}\delta_{\text{weekend}} + \beta_{\text{child}}\delta_{\text{child}} + \beta_{\text{senior}}\delta_{\text{senior}} + \beta_{cb}C^b + \beta_cC^c + \beta_M M + \beta_N N + \epsilon
\]  

where \(C\), \(\delta_{10.5}\), \(\delta_{5.7}\), \(\delta_{7.10}\), \(\delta_{\text{weekend}}\), \(\delta_{\text{child}}\), and \(\delta_{\text{senior}}\) are the intercept, the pressure at station 10.5, the pressure at station 5.7, the pressure at station 7.10, the weekend dummy, the child dummy, and the senior dummy, respectively. \(C^b\), \(C^c\), \(M\), and \(N\) are the coefficients for the costs, the cheapness, the number of passengers, and the number of buses, respectively.

Model estimation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Haw Par Villa</th>
<th>Botanic Garden</th>
<th>Lakeside</th>
<th>Kent Ridge</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\delta_{10.5})</td>
<td>0.28</td>
<td>0.45</td>
<td>0.42</td>
<td>0.49</td>
</tr>
<tr>
<td>(\delta_{5.7})</td>
<td>0.35</td>
<td>0.48</td>
<td>0.28</td>
<td>0.45</td>
</tr>
<tr>
<td>(\delta_{7.10})</td>
<td>0.15</td>
<td>0.36</td>
<td>0.14</td>
<td>0.35</td>
</tr>
<tr>
<td>(\delta_{\text{weekend}})</td>
<td>0.18</td>
<td>0.38</td>
<td>0.16</td>
<td>0.36</td>
</tr>
<tr>
<td>(\delta_{\text{child}})</td>
<td>0.03</td>
<td>0.17</td>
<td>0.37</td>
<td>0.48</td>
</tr>
<tr>
<td>(\delta_{\text{senior}})</td>
<td>0.05</td>
<td>0.22</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>(C)</td>
<td>11.73</td>
<td>10.32</td>
<td>10.83</td>
<td>8.13</td>
</tr>
<tr>
<td>(C^b)</td>
<td>9.26</td>
<td>7.75</td>
<td>6.43</td>
<td>3.83</td>
</tr>
<tr>
<td>(M)</td>
<td>2.54</td>
<td>2.93</td>
<td>1.58</td>
<td>1.86</td>
</tr>
<tr>
<td>(N)</td>
<td>2.12</td>
<td>2.58</td>
<td>1.84</td>
<td>2.43</td>
</tr>
</tbody>
</table>

TABLE 2 summarizes the descriptive statistics of observed data from the four scenarios. Both Model I and Model II are linear regression models and estimated using MATLAB Statistics Toolbox. The final estimation results for both models are provided in TABLE 3. A total of 2%~7% of the variance of passenger transfer time can be explained by the eight explanatory variables in Model I. By taking collective pressure into account, the modified Model II explains about 13%~21% of the total variance.
For Haw Par Villa Station (scenario (a)), we find that passengers at morning peak period (7 a.m. to 10 a.m.) are significantly faster than other time in Model I. Passengers also move slightly slower on weekends. The significant temporal effects are consistent with our previous observations in FIGURE 2: passengers transfer faster in the morning and on weekdays. For the two peaks, passengers are faster during morning peak than evening peak. This trend is consistent with our daily experience: in the morning, people usually have their work/school trips, upon which strong time constraints are usually imposed, such as not being late. On the contrary, people usually do not have strong time restrictions on home and secondary trips. In general, the temporal trend could be also attributed to that regular travelers (such as commuters) transfer faster than other transit users, since regular users are more familiar with transfer facilities. A final possible explanation is that: there might be some inherent temporal difference in human behavior, resulting in that people do things faster in the morning. Children and senior citizens are slower than adults for about 7 sec and 15 sec, respectively. The crowdedness at station entrances slows down transfers by 0.36 s/pax, while the crowding effect is not significant at bus stop. By adding explanatory variables on collective pressure in Model II, we find that these two variables mainly reduce the estimation on the effect of time of day compared to Model I. However, the trend of temporal effects remains the same. In fact, this is due to that fast passenger are more often observed during morning peak hours. Each fast passenger walking around you reduces your transfer time by 2.48 sec, while a slow passenger delays you by about 2.95 sec. The effects of collective pressure both have the expected signs and are statistically significant at 0.1% confidence level. The rest parameters are almost consistent with Model I. The results for Botanic Garden Station (scenario (b)) are basically consistent with Haw Par Villa, except that children are found to be faster than adults. Given the configuration of transfer facility, this may be due to that children are faster when walking up/down the stairs on the overpass.

Lakeside Station shows different estimation results from the prior two scenarios. Weekend transfers do not present significant difference from those on weekdays. In addition, we find that passengers were transferring slower during evening peak (5 p.m. to 7 p.m.). On one hand, the demand at this station is significantly higher than other cases, resulting in additional friction when the high passenger demand cannot be satisfied by the limited escalator capacity. On the other hand, in measuring crowdedness at bus stop, we only use number of alighting passengers as a proxy. In fact, different from the prior two cases, the paired bus stop (28099) of Lakeside Station is not only used to bear the alighting demand, but also heavily used for boarding. In this case, we miss the friction from those passengers waiting to board. Still, the effects of collective pressure both have the expected signs and are statistically significant at 0.1% confidence level.

The temporal effect shows similar trends for Kent Ridge Station; however, the parameters are not significant until 7 p.m. (δ_{7,10}), which is about 5 sec longer than morning peak. Interestingly, we find that children present a significant increase of walking time against adults; while senior citizens do not show significant difference from adults. Bus stop 18339 is similar to 16009, serving only a few bus routes and mainly for passengers going towards train stations. As the bus stop is not busy, the crowdedness does not play a significant role in determining passenger transfer time, while the crowdedness at fare gantries is significant (increasing transfer time by 0.13s/pax). Collective pressure still shows the expected signs at statistical significance level α = 0.1%.
Taken together, we find that time indeed plays an important role in affecting passenger transfer behavior. The influence comes from diverse factors, but can be explained in at least two aspects. Taking trip purpose as an example, passengers for work/school trips may walk faster due to time restrictions; whereas passengers going home or secondary activities such as shopping are usually not in hurry, and thus walk slower. On the other hand, the temporal effect might be also owing to personal attributes. Regular commuters are more familiar with transfer facilities and environment factors, and thus they may transfer faster than other passengers. In addition, regular commuters appear in public transport systems more frequently during morning and evening peaks. This also leads to the reduction of average transfer time at peak hours. Service schedule information is another factor should be pointed out. Passenger may rush the see from the travel information systems that their trains are about to arriving stations. However, such effect is still not clear to given the limitation of the data. The inherent difference in temporal behavior is another explanation, but this effect is difficult to identify without human subject research. In addition, all scenarios show that the crowdedness at train station has a significant impact on transfer time. Taking average observed for each case, the total contribution is about (in terms of Model II): (a) 3.6 sec, (b) 8.8 sec, (c) 1.4 sec and (d) 2.9 sec. The average contribution from collective pressure is: (a) -6.3 sec/+6.3 sec, (b) -16.5 sec/+20.5 sec, (c) -8.5 sec/+11.3 sec and (d) -3.4 sec/+7.1 sec, suggesting that collective pressure is crucial in modeling passenger transfer behavior.

**SUMMARY AND CONCLUSION**

Taking advantage of the emerging smart card data from multimodal public transport systems in Singapore, we studied bus-to-metro transfer walking time using observations from different scenarios. We quantified the effect of specific determinants on transfer time that are available in the data set, including time of day, weekday/weekends, age of passengers, level of crowdedness at stops/stations and collective pressure. Although smart card data set does not provide much information on individual attributes (such as gender: male/female; and loading condition: with/without baggage) and environmental/social factors (such as weather and availability of facilities for passengers to engage in other activities: e.g. a convenience store), the large quantities of disaggregated observations still show huge potential in modeling passenger behavior in a more efficient way than conventional approaches based on physical surveys. To our knowledge, this is the first study that tries to understand determinants of passenger transfer behavior using smart card data as a proxy.

Two models were estimated using inter-tapping time collected from four bus-to-metro transfer scenarios, where different environment characteristics are hypothesized. The estimation results also show variations given different design and configuration of transfer facilities. However, consistent temporal trend and collective pressure effect are observed from all the scenarios. Despite that bus stops and train stations are more crowded during peak hours, we find that passengers walk faster during morning (and evening) peak in general. The effect can be explained by at least two factors: trip purpose and passenger attributes. The diverse types of transfers also enable us to explore how the design and configuration of transfer facilities influences different types of passengers (adults, children and senior citizens). In terms of age of passengers, our estimation results show that (1) senior citizens are essentially slower than adults and children; (2) in general, adults walk faster than children for ground transfer with dedicated escalators; however, children may outperform adults when getting through an overpass. The crowdedness at bus stop does not show significant impact on transfer time, unless its capacity is limited to bear huge demand. However, crowdedness at train station entrance is found significant in determining total transfer time.
As we have not conducted physical surveys for this research, our results are also limited to the available information from smart card data. Although we have tried to incorporate as much individual attributes as possible, there are still some unobserved factors that are not accounted in the regression models. For example, passenger walking behavior is also influenced by travel information systems showing the schedule of coming services. In Singapore, such information is available at the entrances of most train stations. Passengers may rush if they see that a train is arriving station. However, it remains unclear that to what extent passengers are influenced by such information. In all, we see that about 10~20% of total variance can be explained by the extended Model II. We measured collective pressure by only using the fastest and slowest passengers. However, it is not the case for passenger walking in platoon at the same speed. In this case, the effect of collective pressure might be stronger, but not captured by only counting the fastest/slowest passengers. Therefore, there is great potential in combining physical survey with smart card data. On one hand, we may get observations and individual attributes in a more efficient manner. On the other hand, field physical survey can help to identify additional social/environmental factors to build a more sophisticated transfer time model.

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