

Public **JOURNAL OF** Transportation

-
- | | | |
|------------------------------------------------------------------|--------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| ■ Jiana-Fu Wang
Ren-Huei Huang | | Can You Get a Ticket? Adaptive Railway Booking Strategies by Customer Value |
| ■ Philippe Fortin
Catherine Morency | Martin Trépanier | Innovative GTFS Data Application for Transit Network Analysis Using a Graph-Oriented Method |
| ■ Alireza Salavati
Hossein Haghshenas
Bahador Ghadirifaraz | Jamshid Laghaei
Ghodrat Eftekhari | Applying AHP and Clustering Approaches for Public Transportation Decisionmaking: A Case Study of Isfahan City |
| ■ Hojin Jung
Gun Jea Yu | Kyoung-Min Kwon | Investigating the Effect of Gasoline Prices on Transit Ridership and Unobserved Heterogeneity |
| ■ Krae E. Stieffenhofer
Michael Barton | Vikash V. Gayah | Assessing Park-and-Ride Efficiency and User Reactions to Parking Management Strategies |
| ■ Andrea Mather
K.M. Hunter-Zaworski | | Investigation of Wheeled Mobility Device Orientation and Movement on Streetcars and Light Rail Vehicles during Normal and Emergency Braking |
| ■ Dr. Jan Scheurer | | How Intermediate Capacity Modes Provide Accessibility and Resilience in Metropolitan Transit Networks: Insights from a Global Study of 19 Cities |
| ■ Greg Phillip Griffin
Ipek Nese Sener | | Public Transit Equity Analysis at Metropolitan and Local Scales: A Focus on Nine Large Cities in the US |
| ■ Andra Charis Mijares
Mio Suzuki | Tetsuo Yai | Passenger Satisfaction and Mental Adaptation under Adverse Conditions: Case Study in Manila |
| ■ Stefan Foell
Santi Phithakkitnukoon
Marco Veloso | Gerd Kortuem
Carlos Bento | Regularity of Public Transport Usage: A Case Study of Bus Rides in Lisbon, Portugal |
| ■ Yongju Yi
Keechoo Choi | Young-Jae Lee | Optimal Limited-stop Bus Routes Selection Using a Genetic Algorithm and Smart Card Data |
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Can You Get a Ticket? Adaptive Railway Booking Strategies by Customer Value <i>Jiana-Fu Wang, Ren-Huei Huang</i>	1
Innovative GTFS Data Application for Transit Network Analysis Using a Graph-Oriented Method <i>Philippe Fortin, Catherine Morency, Martin Trépanier</i>	18
Applying AHP and Clustering Approaches for Public Transportation Decisionmaking: A Case Study of Isfahan City <i>Alireza Salavati, Hossein Haghshenas, Bahador Ghadirifaraz, Jamshid Laghaei, Ghodrat Eftekhari</i>	38
Investigating the Effect of Gasoline Prices on Transit Ridership and Unobserved Heterogeneity <i>Hojin Jung, Gun Jea Yu, Kyoung-Min Kwon</i>	56
Assessing Park-and-Ride Efficiency and User Reactions to Parking Management Strategies <i>Krae E. Stieffenhofer, Michael Barton, Vikash V. Gayah</i>	75
Investigation of Wheeled Mobility Device Orientation and Movement on Streetcars and Light Rail Vehicles during Normal and Emergency Braking <i>Andrea Mather, K.M. Hunter-Zaworski</i>	93
How Intermediate Capacity Modes Provide Accessibility and Resilience in Metropolitan Transit Networks: Insights from a Global Study of 19 Cities <i>Dr. Jan Scheurer</i>	107
Public Transit Equity Analysis at Metropolitan and Local Scales: A Focus on Nine Large Cities in the US <i>Greg Phillip Griffin, Ipek Nese Sener</i>	126
Passenger Satisfaction and Mental Adaptation under Adverse Conditions: Case Study in Manila <i>Andra Charis Mijares, Mio Suzuki, Tetsuo Yai</i>	144
Regularity of Public Transport Usage: A Case Study of Bus Rides in Lisbon, Portugal <i>Stefan Foell, Santi Phithakkitnukoon, Marco Veloso, Gerd Kortuem, Carlos Bento</i>	161
Optimal Limited-stop Bus Routes Selection Using a Genetic Algorithm and Smart Card Data <i>Yongju Yi, Keechoo Choi, Young-Jae Lee</i>	178

Can You Get a Ticket? Adaptive Railway Booking Strategies by Customer Value

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Abstract

This paper integrates a customer segmentation method with a discrete event simulation model to bridge the gap between identifying customer behaviors and using this knowledge to respond to customers and make the best use of resources. Three strategies are proposed and examined to improve the operation efficiency of a ticket-booking system. Their objective is to assist high-value customers in obtaining the tickets they want and/or reduce cancellations and failure-to-pays from low-value customers. Our simulation results demonstrate that the high-value, customer-friendly strategy beats all in assisting high-value customers and simultaneously improves railway operation performance. Additionally, the indirect, low-value customer abandonment strategy also has improved slightly in all aspects. Applying these strategies is expected to result in a decrease in complaints regarding booking system rejections and an increase in high-value customer satisfaction. On the other hand, the direct abandonment strategy to reject all low-value customers does not make any improvement.

Keywords: Railway, Booking, Simulation, Customer value, Customer segmentation, Customer relationship management

Introduction

Railway companies, with the popularity of e-booking systems, now have access to information on individual customer behaviors. This advantage can enable railway companies to initiate customer relationship management, or CRM, for improved profitability and resource allocation (Venkatesan and Kumar 2004; Kumar and Peterson 2005). According to Stringfellow et al. (2004), the intention of CRM is “understanding customer needs and leveraging that knowledge to improve a company’s long-term profitability.” Railway companies, due to traveler anonymity and the public nature of railway services, had no way to record customer purchase history in the past and could not differentiate their treatments to customers. Currently, with an e-booking system to

retain individual customer data, railway companies can analyze each customer's value and allocate resources accordingly.

Utilizing individual customer purchase data to predict quantities of cancellations and no-shows has been confirmed effective in the field of airline research, as illustrated in the work of Lawrence et al. (2003), Garrow and Koppelman (2004), Neuling et al. (2004), Gorin et al. (2006), and Illiescu et al. (2008). Similar research has been conducted in the railway system, but as far as the authors are aware, there are only the works of Cirillo et al. (2011), Hetrakul and Cirillo (2013), Piening et al. (2013), Hetrakul and Cirillo (2014), and Chen and Wang (2013). However, these two fields are still focused on applying their results to decide the amount of seat overbookings and the allocations of seats among different fare classes, rather than identifying an individual's value to decide how to respond to the individual's request.

Train seating is a valuable resource to a railway company. When a ticket is booked but not yet paid for, the slot is blocked from booking for other customers. Although loyal customers always pay for their booked tickets during the advance ticket-booking period, some ticket holders often hold their reservations for a period of time, frequently cancelling them subsequently. More than 40% of railway ticket bookings ultimately are cancelled in India, Taiwan, and China, according to Bharill and Rangaraj (2008), Chen and Wang (2013), and *China Review News* (2013), respectively. Not only does this high-cancellation situation affect the booking system's operational efficiency, it also incurs complaints about people's inability to book tickets (Zhang et al. 2007; Von Martens and Hilberts 2011). If a customer's booking is rejected because slots are fully booked, yet some or part of those booked slots are eventually cancelled and later booked by others, the customer may be resentful. A loyal customer, frustrated by repeated booking failures, might switch to a competing provider to make his journey possible. This becomes a "lose-lose" situation for both customers and the railway company.

A company should recognize the profitability of loyal customers from the CRM perspective and attempt to know their functional and emotional needs (Stringfellow et al. 2004): they need tickets, and they think they have a priority in making reservations. On the other hand, the company should consider abandoning those who consume a railway company's resources and damage its performance, who may be labeled as "troublemakers" (Van Raaij 2005; Haenlein and Kaplan 2009; Haenlein and Kaplan 2011). The direct abandonment of troublemakers may cause most companies to hesitate; yet, some indirect abandonment strategies can lead to less severe reactions from customers, such as increasing prices and decreasing service levels (Haenlein and Kaplan 2011; Haenlein and Kaplan 2012).

This study aims to use individual-level booking data to implement CRM strategies to improve the performance of a railway ticket booking system. Customers are segmented into three groups, based on a Taiwanese railway agency's ticket booking database. Three strategies then concentrate on assisting high-value customers to obtain tickets, applying an indirect abandonment policy to low-value customers, and using a direct abandonment policy to reject low-value customers in comparison with a base scenario to evaluate their effectiveness. The remainder of the paper is organized as follows: First,

literature on passenger name record (PNR) applications in ticket booking, customer value analysis, and customer management is reviewed. Next, the development of customer segmentation and ticket booking simulation models is introduced. Finally, the implementing of models and conclusions are presented.

Using PNR in Ticket-Booking Services

Early ticket booking papers in railway and airline services primarily utilize aggregated booking data to forecast demand, predict cancellations and no-shows, and allocate seats to various legs and classes. With an increasing number of customer booking databases and improvements in computer calculation speed, a new trend involves utilizing PNRs to increase prediction accuracy (Garrow and Koppelman 2004; Morales and Wang 2010). A PNR is generated when a ticket booking is made. Its typical information includes time of service, time of booking, time of cancellation, ticket type/ fare by class, membership, payment status, origin and destination, reservation channel, group size, day(s) of travel, and number of travel legs, for air travel providers. By using PNRs, customers are heterogeneous agents with their own features, and they interact with others to exhibit aggregate behavior (Khouja et al. 2008).

The application of PNR in ticket booking can be classified into three categories. The first category uses discrete choice models that originate from Talluri and Van Ryzin's (2004) research. Garrow and Koppelman (2004) developed a multinomial logit (MNL) model for the airline industry to predict the percentages of show, cancellation, no-show, and standby for each potential traveler. They concluded that the incorporation of passenger information can improve forecasting accuracy. Iliescu et al. (2008) described a booked ticket's cancellation as a survival process, and the survival percentage of each booking relied on the reservist's characteristics. Graham et al. (2010) used a discrete-time proportional odds model to predict the conditional probability of a ticket surviving from one period to the next. Similar techniques are also applied in the railway industry. Hetrakul and Cirillo (2013) applied three logit-based ticket purchase timing models and compared their suitability to three market segments with different travel distances. Additionally, Piening et al. (2013) analyzed customer choices to upgrade, downgrade, or cancel their ticket discount cards when their cards were due. Their hazard model identified several CRM practices that would affect the discount cards' renewal.

The second category applies data mining techniques to explore meaningful relationships in the customer-booking database. Lawrence et al. (2003) demonstrated that their three data-mining models employing PNRs were superior to a historical model in forecasting airline no-shows. Neuling et al. (2004) introduced how Lufthansa German Airlines applied a decision tree-based model to forecast no-show probabilities. Morales and Wang (2010) tested three decision tree-based models using hotel booking data and found that compared to several traditional statistical methods, they could reduce a 20% forecast error. Its application in the railway industry was developed by Chen and Wang (2013), who used a two-stage clustering model to predict customer values and recommended loyalty program strategies for each customer group.

The final category employs combinatorial methods to forecast customer behavior. Gorin et al. (2006) developed a cost-based, PNR-adjusted approach to find optimal no-show rates for the airline industry. Their objective was to minimize the cost of seat overselling and underselling, while adjusting its no-show probabilities for different customer segments using historical booking data. They concluded that the new approach could improve revenue by up to 10% compared to traditional average no-show rate methods. Cirillo et al. (2011) established an MNL model for the railway industry to explain passengers' choice of booking time, and combined it with a linear-regression demand function to find optimal fares. Hetrakul and Cirillo (2014) further used their logit and demand models to jointly decide optimal ticket prices and seat allocations.

It can be asserted from the above reviews that PNR studies in ticket booking are limited, and the purpose of these studies is primarily to aggregate predicted individual behaviors as parameters to estimate total number of demands, cancellations, or no-shows. The premium benefit of analyzing PNR is not only to predict what might occur, but also to guide a company's actions (Lavalle et al. 2011). The evident link between identifying customer behaviors and using this knowledge to respond to customers is still lacking in ticket-booking literature.

Customer Value Analysis and Customer Management

Several innovative companies have acknowledged that providing differentiated services to customers based on their profitability can be more beneficial, as resources are limited and valuable. For example, investing in the top 1% of customers could earn 50% of a company's revenue, but serving the bottom 20% could cost the company money (Ziethaml et al. 2001; Van Raaij 2005). Therefore, identifying customer value and treating them appropriately is an important avenue for becoming a top performing company.

Customer value can be assessed either by solely using past purchase history or by forecasting future cash flow. The former can be calculated by applying recency, frequency, and monetary (RFM), activity-based costing, past customer value, and share-of-wallet methods (Kumar 2006). The latter is based primarily on the customer lifetime value (CLV) concept proposed by Jackson (1989), a prediction of the net discounted profit obtained from a customer over his or her lifetime with a company. This considers when and how much the customer will purchase, and how the company will invest its resources. A prediction of CLV can be obtained via different types of models, such as the negative binomial distribution (NBD)/Pareto model, the beta-geometric/NBD model, and hazard models (Fader et al. 2005; Gupta et al. 2006).

The RFM method has been used the most frequently among these methods for decades to select customers (Bijmolt et al. 2010). Its fundamental rationale is that those who have recently made purchases, make more repeated purchases, and spend more money are a company's best customers (McCarty and Hastak 2007). Variables other than the original R, F, and M are incorporated in extended studies. For example, Wei et al. (2012) added "relation length" and Khajvand et al. (2011) proposed "count item" in their models. Although CLV is an effective tool to measure direct, or transactional

contributions, it overlooks the non-monetary benefit or harm that customers may carry. As this paper considers customer cancellation and no-show (or failure-to-pay, in the railway scenario) behaviors, an extended RFM model is utilized to segment customers. Therefore, in this study, customer value is defined as the direct and indirect contributions brought by a customer to a company during a period of time (von Martens and Hilbert 2011).

Once customers are categorized by their values, companies can allocate resources differently by group. For example, Reinartz and Kumar (2002) segment customers into four types—true friends, barnacles, butterflies, and strangers—and suggest that companies should implement differentiated strategies for these groups. These strategies include communicating consistently and finding ways to increase the loyalty of “true friends”; promoting up- and cross-selling or controlling costs for “barnacles”; preparing to cease investment in “butterflies”; and making no investment in “strangers.” Likewise, First Union, a US bank, provides extra customer service support to its profitable customers, but it does not grant special favors, such as waiving bounced checks, to those who are unprofitable (Zeithaml et al. 2001). In 2007, Sprint Nextel terminated wireless services to approximately 1,000 customers for making “too many” service calls, with some amounting to hundreds per month (Mittal et al. 2008). Filene’s Basement, a retailer, curtailed all further service to two sisters in 2003 because of their chronic complaints and returning of goods (Haenlein and Kaplan 2009). These cases demonstrate that halting resources, or even abandoning unprofitable or low-value customers, exists in practice.

Although abandoning a customer is not an easy decision for any company, it is considered based on the following reasons: customer profitability, employee productivity, capacity constraint, and target market (Mittal et al. 2008). If a company must abandon a customer, there are direct and indirect abandonment strategies. A direct abandonment strategy refers to a situation in which a company explicitly expresses the intention to end the relationship with the customer, such as the Sprint Nextel and Filene’s Basement cases. On the other hand, a company may choose an indirect abandonment strategy, which terminates the relationship with a customer without explicitly communicating this to the customer (Haenlein and Kaplan 2011). According to Haenlein and Kaplan (2011; 2012), divesting unprofitable or low-value customers can prevent future losses and may improve a company’s image among some types of current customers. However, in the meantime, the company may risk negative word-of-mouth (WOM). Therefore, carefully designing abandonment strategies and managing potential reactions become important.

Model Development

Customer Segmentation Model

Two models were developed during this research for identifying customer values using PNRs and measuring the effectiveness of booking strategies for a railway ticket

booking system in Taiwan. The ticket booking system stores personal ID, date and time of booking, train number, trip origin, trip destination, order quantity, and status, such as purchased, cancelled, or failure-to-pay, for each booking record. Six variables were extracted from these booking data to constitute an extended RFM model.

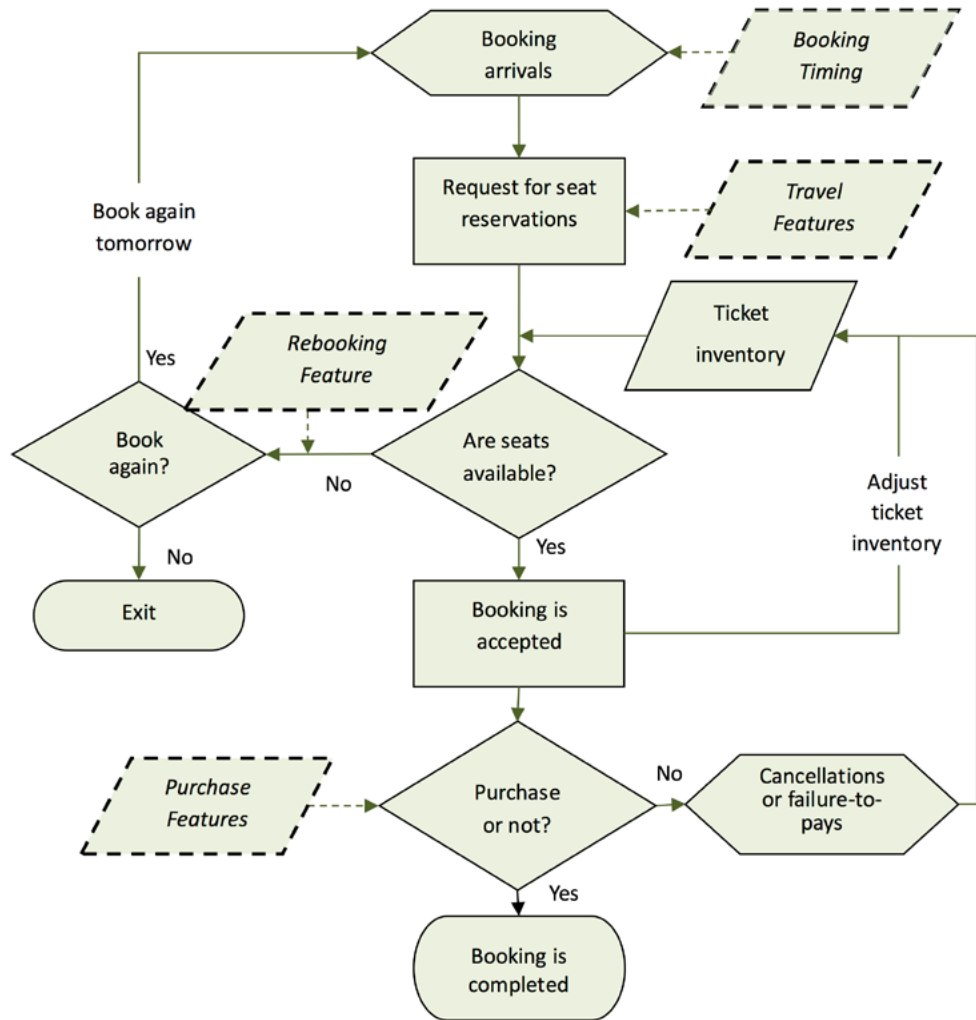
1. Recency (R) – the interval between when a customer last booked and the end of a specified period of time.
2. Frequency (F) – the number of bookings during a specified period of time.
3. Monetary (M) – the average amount of money a customer spends for each booking during a specified period of time, not including cancelled and failure-to-pay bookings.
4. Total Mileage (TM) – the total mileage traveled during a specified period of time, not including the mileages of other passenger(s) travelling along with the customer.
5. Purchase Rate (PR) – the purchase rate of a customer's total bookings during a specified period of time.
6. Average Status Score (ASS) – the average status score of the bookings from a customer during a specified period of time (5 points for a purchased booking, 3 points for a cancelled booking, and 1 point for a failure-to-pay booking).

The customers in the booking database are assigned a number from 5 to 1, according to their rankings for each of the three variables, using the procedure proposed by Hughes (1994). These customers are then grouped by their summed scores. The higher a customer's summed score, the more beneficial the customer is to the company in terms of their loyalty in making repeated purchases and paying for their booked tickets. On the other hand, those who have low scores are labeled as "troublemakers" who consume booking resources and block other customers' reservations but seldom pay for their bookings.

Ticket Booking Simulation Model

A discrete event simulation model is built as the schema in Figure 1, in accordance with actual ticket-booking processes. The model originates with a potential passenger's arrival and request for ticket(s) at the system. The potential passenger is mapped to the properties of a randomly drawn customer from our database, which is based on real customer booking records, to imitate the customer's behavior. If the potential passenger's request for a specific travel section (origin-destination pair, O-D pair) and number of tickets can be met, the booking is accepted. If not, the customer may possibly return to the system the next day for another attempt. The customer's choosing to make a further attempt depends on the customer's rebooking intention. After a booking, one of three possible follow-up actions may occur within a deadline: purchase, cancellation, or failure-to-pay. The customer's action depends on the probabilities of his or her past behavior. If the booking is cancelled, or if there is a failure-to-pay within the deadline, the ticket(s) will be released for subsequent possible booking. However, if the booking is paid for, the booking process is completed.

FIGURE 1.
Base model for ticket-booking processes



Among the aforementioned processes, four decision points exist at which a customer’s personal characteristics, or behaviors, are considered. The relevant characteristics are “booking timing,” “travel features,” “rebooking intention,” and “purchase features,” as noted in Figure 1. The interactions between booking processes and personal actions not only impact the inventory of tickets, but also comprise the dynamics of the ticket booking system. PNRs were collected and managed, as listed in Table 1, to obtain these personal characteristics.

TABLE 1.
Contents and Specifications of
Customer Characteristics

Personal Characteristics		Characteristic Specification Method
Booking timing	Customer segment	Customers categorized into several different segments by RFM analysis
	Customer arrival	Segments' inter-arrival times for each booking day tallied to build their arrival distributions
Travel features	Traveling section	O-D pair most frequently traveled by customer
	Number of tickets booked	Rounded average number of tickets booked each time by customer
Rebooking intention	Rebooking rate	Number of bookings for this train as percentage of total bookings (for all trains); this ratio displays train's importance to customer – the higher the ratio, the more likely that the customer will attempt to make bookings again; there are two maximum attempts to rebook in this study
Purchase features	Purchase rate	Number of purchases as percentage of total bookings
	Cancellation rate	Number of cancellations as percentage of total bookings
	Failure-to-pay rate	Number of failure-to-pays as percentage of total bookings

Ticket-Booking Strategies

The purpose of this study was to propose strategies to improve a ticket booking system's efficiency by helping high-value customers obtain the tickets they want or/ and reducing troublemakers to incur cancellations and failure-to-pays. To meet this objective, we proposed one high-value customer-friendly strategy and two low-value customer abandonment strategies and evaluated their performances along with the base model.

1. High-value customer-friendly strategy: flexible booking limits (FBL) – The goal with this strategy is to facilitate high-value customer bookings by combining two or more available O-D pairs to turn into an O-D pair that the customer had failed to obtain initially because it had been fully booked. Normally, a train's seat allocation is fixed. The disadvantage of a fixed booking limit policy is that it can cause considerable inefficiency when demands are stochastic (Talluri and Ryzin 2004). Hence, when some O-D pairs are fully booked, others may still have vacant seats. High-value customers are reliable, loyal, and profitable for a company; helping them obtain bookings not only raises their satisfaction, but also increases ticket bookings' overall purchase rate.
2. Indirect abandonment strategy: overbooking (OB) – The objective with this strategy is to borrow booked tickets from low-value customers, who have a low purchase rate, and lend them to high-value customers. This method is similar to the airline industry's overbooking strategy. It still provides booking services to low-value customers initially, but these booked seats will be taken away if and once they are cancelled and transferred to overbooked high-value customers. It is expected that this strategy will increase the booking success rate of high-value customers, and lower the overall cancellation rate.

3. Direct abandonment strategy: rejecting low-value customers (RLC) – Although it is difficult to implement in real life, this study builds an extreme strategy to reject all bookings from low-value customers, to observe its impact. When a low-value customer wants to make a booking, the customer will be rejected. This strategy is expected to increase the overall purchase rate, and reduce cancellation and failure-to-pay rates.
4. Base model – The base model follows the booking processes illustrated in Figure 1 and is basically a first-come-first-served scenario. Whether or not a customer obtains tickets is based on both the order of arrival and the availability of seats in the desired O-D pair.

Simulation Results

Experimental Design

The Taiwan Railway Administration (TRA) is the largest railway operator in Taiwan. In its booking system, ticket fares are fixed during its 14-day booking period. A customer can book up to 6 tickets for a train. Customers who book in the system have to make their payments or cancel their bookings (free of charge) before the end of the next day or the booked tickets will be released. An analysis was performed to apply the extended RFM method; 332,584 customers with booking records on TRA’s Western Main Line during the period of August 1–October 31, 2010, were analyzed, with their scores ranging from 6 to 30 points. Further, this study chose the customers who booked Train Number X (the identity of the train number is disguised for confidentiality reasons) during this period as subjects to extract their personal characteristics, as mentioned in Table 1, to use in the simulation model. During this period, there were 13,635 passengers who made 32,647 reservations for Train Number X, and in total they made 186,186 reservations from all 228 trains operated by the TRA. Among these passengers, 725 were graded 6–9 points and 766 were graded 29–30 points. As the number of target customers who are given favors or abandoned should not excessively distort TRA’s daily operations, these two groups were defined as low-value and high-value customers, while the others were categorized as regular customers. The results in Table 2 exhibit the differences among the three customer segments, showing that low-value customers never pay for their booked tickets, and most tend to cancel their bookings; the high-value customers have a high purchase rate, and they spend and travel more than others.

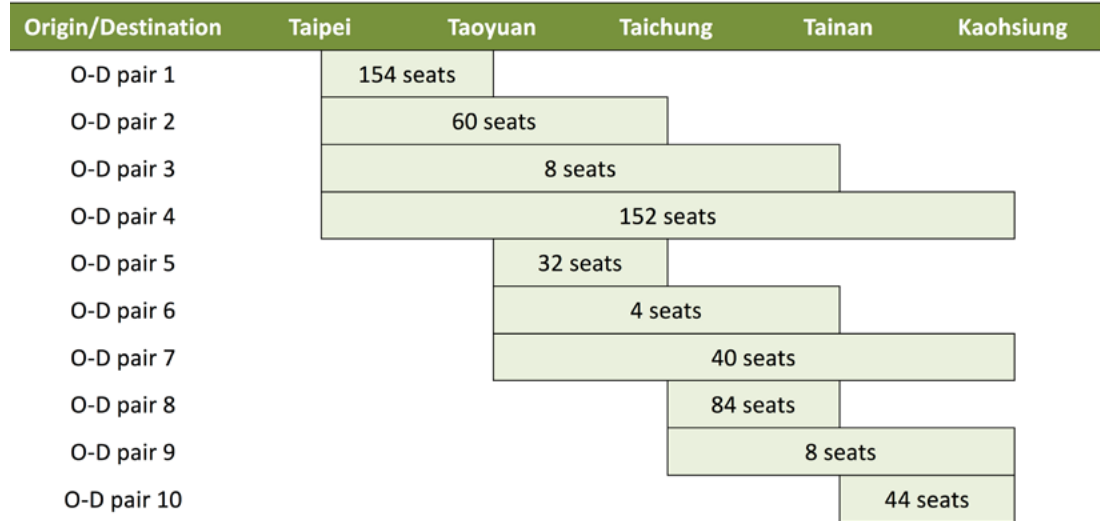
TABLE 2.
Averages of Variables for
Three Customer Segments

Segment	Number of Customers	R (day)	F (times)	M (\$)	TM (mi)	PR (%)	ASS (point)
High-value customer	776	21	16	17	1801	90%	4.76
Regular customer	12,134	41	14	10	695	51%	3.74
Low-value customer	725	75	2	0	0	0%	2.22
Total	13,635						

R = Recency; F = Frequency; M = Monetary; TM = Total Mileage; PR = Purchase Rate; ASS = Average Status Score

The original Train Number X had 18 stops, which gave 153 possible combinations (that is, C_2^{18}) for seat allocations. However, 5 stops were adopted to simplify the situation, as were 10 combinations (O-D pairs). Figure 2 illustrates seat allocations for the train.

FIGURE 2.
Seat allocations for all O-D pairs



Allocations rearranged according to train’s original allocations; distance from Taipei to Kaohsiung is 231 miles.

Our discrete event simulation model was built using the SIMUL8 simulation package. SIMUL8 has the advantage of utilizing modularized blocks to facilitate model building and allows us to incorporate customer segmentation, individual customer behavior, and the intangible booking service process to examine different booking strategies’ impacts. The aforementioned 13,635 customers were randomly chosen to reserve tickets according to their arrival patterns and booking characteristics. Four aspects of performances for each booking strategy were obtained via a 14-day booking period simulation, with 20 replications. These performances included segmental booking results, overall booking results, numbers of unsold tickets, and total revenues.

Segmental Booking Results

The results in Table 3 illustrate that the booking success rates of high-value customers with the first three strategies were all increased compared to the base model. The FBL strategy especially had the largest improvement (from 27.42% to 68.99%), and the success rates in the other two segments did not decrease. This advantage came from the reduction of booking failures by searching combinable tickets for high-value customers. The OB strategy had a smaller improvement (from 27.42% to 35.33%) and did not affect the other two segments’ success rates. On the other hand, the RLC strategy, which blocks all bookings from low-value customers, also generated marginal improvements in the high-value and regular customer segments.

Additionally, the numbers of purchased tickets with the proposed three strategies were all increased, indicating that they can help increase ticket sales. One thing to note in Table 3 is that low-value customers have higher booking success rates in the FBL, OB,

and Base strategies. It is because low-value customers tend to book tickets earlier during the booking period compared to regular and high-value customers in our database and, therefore, have higher chance to get reservations.

TABLE 3.
Booking Results by Segment

Strategy	Customer Segment	Able to Book			Failure to Book	Total	Booking Success Rate
		Cancellation	Failure-to-Pay	Purchase			
FBL	High	20	5	73	44	142	69%
	Regular	208	74	213	1,041	1,536	32%
	Low	43	18	0	70	131	47%
	Total	271	97	286	1,155	1,809	36%
OB	High	10	3	37	91	141	35%
	Regular	205	75	210	1,046	1,536	32%
	Low	41	18	0	71	130	45%
	Total	256	96	247	1,208	1,807	33%
RLC	High	8	2	30	100	140	29%
	Regular	208	76	213	1,038	1,535	32%
	Low	0	0	0	176	176	0%
	Total	216	78	243	1,314	1,851	29%
Base	High	7	2	29	101	139	27%
	Regular	204	74	208	1,050	1,536	32%
	Low	41	18	0	73	132	45%
	Total	252	94	237	1,224	1,807	32%

Overall Booking Results

The overall booking success rates with FBL and OB strategies were higher than the rate in the base model, as noted in Table 3. This means that all customers can benefit from these two strategies helping high-value customers obtain tickets, and the TRA can simultaneously increase customer booking satisfaction.

Further, paired t-tests were used to compare the results of the Base model with other strategies to determine whether the differences are significant. As demonstrated in Table 4, the total number of booking successes (able-to-books) was significantly increased except for the RLC strategy. The reduction in the case of RLC occurred mainly because of the increase in booking rejections by low-value customers. If the possible consequences of successful bookings are considered, it can be noted that purchase rates with the first three strategies were significantly increased, and cancellation and failure-to-pay rates in the cases of FBL and RLC all decreased. This implies that overall efficiency improved, either because of boosting bookings from high-value customers or restraining bookings from low-value customers.

TABLE 4.
Overall Booking Results

Strategy	Able to Book			
	Cancellation	Failure-to-Pay	Purchase	Total
FBL	270* (41.4%*)	96 ^Δ (14.7%*)	286* (43.9%*)	652* (100%)
OB	256 (42.8% ^Δ)	95 (15.9%)	247* (41.3%**)	598** (100%)
RLC	216* (40.4%*)	77* (14.4%*)	242** (45.2%*)	535* (100%)
Base	252 (43.2%)	94 (16.1%)	237 (40.7%)	583 (100%)

* Significantly different from result of Base strategy; $p < 0.001$.

** Significantly different from result of Base strategy; $p < 0.01$.

^Δ Significantly different from result of Base strategy; $p < 0.1$.

Table 5 displays the averages of unsold tickets and corresponding mileages for the 10 travel O-D pairs at the end of the 14-day booking period. The unbalanced results of unsold tickets among these O-D pairs were due to the mismatch of seat allocation and real customer demand, which challenges all kinds of service providers. The FBL strategy was proposed because of this mismatch, to reduce the imbalance. The results in Table 5 confirm the effectiveness of FBL strategy; excess seats from some O-D pairs were added to enable the completion of bookings from high-value customers and thus, more tickets can be sold. The other two strategies do not aim to increase ticket selling. Therefore, these quantities of unsold tickets and mileages do not significantly differ from the base model.

TABLE 5.
Averages of Unsold Ticket and Mileage in Each O-D Pair

O-D Pair	1	2	3	4	5	6	7	8	9	10	Total	Unsold Mileage (mi)
FBL	114.3	1.8	0.7	6.4	1.2	0.3	1.1	38.3	0.7	8.1	173.0*	8,391*
OB	118.0	1.7	0.8	5.7	1.3	0.6	0.7	65.2	0.1	34.4	228.4	11,642
RLC	122.2	1.0	0.5	6.5	1.3	0.5	0.7	65.4	0.2	34.2	232.4**	11,779
Base	118.1	0.8	1.0	6.7	0.8	0.4	1.1	65.4	0.1	34.6	229.0	11,854

* Significantly different from result of Base strategy; $p < 0.001$.

** Significantly different from result of Base strategy; $p < 0.1$.

Total revenue for the above four strategies can be calculated from the prices and numbers of sold tickets. Their average revenues are \$7,287, \$6,892, \$6,874, and \$6,865, respectively. The results demonstrate that the FBL strategy again exhibited more improvement (6.1%), whereas OB and RLC strategies did not significantly differ from the base model.

Conclusions

From a business management perspective, as the best customers are more loyal and profitable, managers should always maintain a good relationship with them, even if it sometimes may be necessary to sacrifice low-value customers' benefits. However, the literature review reveals a gap in the railway industry's linkage between customer value analysis and a responsive CRM strategy. Concerning this inadequacy, this study provided an example of identifying customer profitability, implementing

differentiated strategies for tiered customers, and demonstrating the effectiveness of the differentiated strategies. Through PNR analysis and comprehensive simulation experiments, the following important observations are made.

First, it can be observed that booking strategies responsive to high-value customers are effective. FBL strategy has the best potential to assist high-value customers and simultaneously improves operational performance. Its booking success rate with high-value customers is up 156% (from 27% to 69%, as shown in Table 3), overall booking success rate is up 13% (from 32% to 36%, as shown in Table 3), overall purchase rate is up 8% (from 40.7% to 43.9%, as shown in Table 4), number of unsold tickets is down by 24% (from 229 to 173 tickets, as shown in Table 5), and revenue is up 6% (from \$6,865 to \$7,287 dollars). Additionally, the OB strategy also has slight improvements in all aspects. From booking efficiency and cost-saving perspectives, as “it costs five times more to acquire a new customer than to retain an existing one” (Pfeifer 2005), a wise decision would be for railway managers to favor high-value customers.

Second, some managers may presume that a direct abandonment strategy to reject unprofitable customers is beneficial for their businesses, but that effect is not clearly supported by this study. The RLC strategy has minor improvements in high-value and regular customers’ booking success rate, total purchase rate, and total revenue, but its total booking success rate, total number of successful bookings, and number of unsold tickets do not perform well. Although the RLC strategy provides more booking opportunities for regular and high-value customers, regular customers’ greater quantity and lower purchase rate weaken this strategy’s performance. This direct abandonment strategy does not improve booking efficiency, and risks inducing negative WOM and other costs (Mittal et al. 2008; Haenlein and Kaplan 2011); therefore, managers should consider educating and converting low-value customers to general customers rather than directly abandoning them.

Finally, the RFM analysis reveals that variations in customer booking behavior exist among different customer segments, and railway operators can benefit from allocating seat resources according to customer value. The model is especially applicable for air and railway transportation, which maintains booking data. Further, the concept of linking customer behavior and a company’s operation strategy also can be employed in bus and metro transportation that does not own passenger identifications. For example, some transportation smart cards can be used to pay for parking fees, bike rentals, and store purchases, in addition to bus and metro fares. Cardholder travel data allows transport operators to know their customers’ travel origins and destinations, when they travel, where they stop, and even what they purchase, and transport operators can arrange vehicle resources and advertising strategies accordingly. Along with the development of information technology, the applications of customer analytics to operation strategies will become more and more popular.

As with any research, this study has limitations. First, rebooking rates for rejected customers were estimations in this study because the actual rejected booking data were not recorded by the TRA. More detailed customer booking behavior could be explored were these data available. Second, the costs of customer rejection, cancellation,

and failure-to-pays are difficult to quantify and, hence, were not considered. Future extensions can focus on the appraisal of these costs. Third, possible reactions to the customer-friendly and customer abandonment strategies are not considered, such as positive or negative WOM, or individual purchase rate increments.

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Innovative GTFS Data Application for Transit Network Analysis Using a Graph-Oriented Method

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Abstract

Public transit networks are constantly evolving in the face of frequent economic and social challenges. There exists a large knowledge base on travel demand; however, there is a shortage of information on travel supply and networks. To our knowledge, no analysis tool can, at this point, systematically characterize a network and observe changes over time in a structured and automated manner. This paper addresses this issue and proposes a graph-oriented method for developing an analysis tool that will characterize a single network and then provide the necessary means to compare two distinct networks. A time-expanded model was applied to import General Transit Feed Specification (GTFS) data into a graph database. With built-in algorithms, shortest paths were computed and indicators were derived from these paths. A small case study demonstrates the applicability of the method. This approach still needs to be optimized to process networks that are more complex.

Keywords: GTFS data, Transit Network, Graph Theory, Optimization, Monitoring

Introduction

In many cities, bus network geometry often changes through the addition, withdrawal, or simply modification of an existing bus line. Likewise, schedules and levels of service change through seasons and years. To our knowledge, no analysis tool can, at this point, systematically characterize a network and observes changes over time in a structured and automated manner. Smart card systems provide large quantities of information. They can assist transit agencies in gaining more insights into transit demand. However, to benefit from these rich datasets, transit agencies need up-to-date information and analysis tools to understand transit supply as well.

Understanding the influence of transportation networks on urban life represents an important research topic (Derrible and Kennedy 2011). The interactions between economy, society, land-use, and urban design are critical. As in many areas across the world, Quebec's transit agencies are continuously looking for innovative approaches to improve their services and increase their market share. In this context, many are discussing strategic ways to optimize public transit systems (Société de Transport de Laval 2013).

Derrible and Kennedy (2009, 2011) demonstrated the potential of both graph and network theories for transit network optimization. In addition, Pajor (2009) reported progress on the development of different models to conceptualize transit networks based on a multimodal (car, train, and plane) path calculator (time-expanded model, time-dependent model). Many studies demonstrate the value of graph and network theories. However, very few incorporate both and illustrate their potential when combined. It is important to add that network theories are not completely separated from graph theory and are considered more as a branch of the main subject. Graph theory mainly explores arbitrary questions about graphs, whereas network theory offers a more practical view and is more interested in the interactions among the different components of the graph.

The main objective of this research was to develop a set of indicators for the systematic analysis of transit networks using data from the General Transit Feed Specification (GTFS), structured within a graph-oriented method. These indicators and methodology can assist in characterizing a network and observe changes over time in a structured and automated way.

This paper is divided into four sections. Following this introduction, key concepts are defined through a literature review on transit networks, GTFS, key performance indicators (KPIs), and more advanced indicators derived from the graph theory. Then, the graph-oriented method is described and illustrated through a case study of a local transit network in the Greater Montreal Area (GMA); results from this network are presented and discussed. Finally, a conclusion with research perspectives closes the paper.

Background

The literature review provides a precise context to this research with background information. It describes the importance of transit networks and how dedicated studies can help improve them. It also shows how the GTFS can constitute an efficient source of information for network analysis. A portrait of classical indicators (KPI) and more advanced indicators is also drawn.

Transit Networks

Public transit plays an important role in the mobility of people in all major urban areas. Typical planning processes aim to define the necessary transit supply to fulfill

traveler needs while minimizing operational costs. Two international guidelines have been identified to implement optimal service (Ceder 2015; Kittelson and Associates et al. 2013). These guidelines define measures to describe issues and factors that may result from operational decisions. However, due to the specificity of each service area, some items cannot be applied directly and need to be adapted after an in-depth analysis of the context. Prior research conducted by Fu and Xin (2007) proposed a new performance index for evaluating transit quality of service. Their approach is based on the notion of level of service introduced in earlier versions of the *Transit Capacity and Quality of Service Manual* (Kittelson and Associates et al. 2013) and integrates a number of performance measures.

Voyer (2007) identified some specific features of the GMA and confirmed the major role public transit plays in the planning and development of land use and activity locations. The influence that an efficient public transport network can assert on its environment, including on the travel behaviors of residents, certainly explains the amount of research conducted on the subject.

Still, these studies rely on a rather traditional approach, typically involving post-processing of demand-related data. Several focus on the performance of transit systems, often reflected by the accessibility and equity of the service by population segments (Godin 2012). Studies on network typology remain rare and, according to our understanding, such a concept can provide a new way of looking at the optimization of transit networks.

A study in Beijing highlights a methodology to analyze bus reliability based on three interesting levels of analysis of the public transit supply: stop, route and network (Chen et al. 2009). Although research conducted by these authors has followed mainly the traditional demand-based approach, the analytical levels remain relevant for our research. Some standard key performance indicators have been proposed for diagnosis and monitoring of public transit systems, mostly based on these same levels. TCRP Report 88 (Kittelson and Associates et al. 2003) provides guidelines for developing a transit performance measurement system, including measures focusing primarily on the assessment of service availability (e.g., service density, stop spacing, stop accessibility, hours of operation). Both Shah (2012) and the Institut de la Gestion Déléguée (2008) propose a list of transportation indicators based on urban policy goals to evaluate the impacts and contribution of the transit system in different areas. Finally, Metrolinx, a transportation agency in Ontario, Canada, developed performance network-based indicators. These indicators assess the accessibility and monitor the progress made according to the goals outlined in their Regional Transportation Plan (Metrolinx 2013).

General Transit Feed Specification (GTFS)

This section introduces the GTFS by providing both background and a description of the files defined by the specification. Current studies using GTFS data also are explored along with their limitations.

The GTFS was introduced in 2005 as part of a collaboration between Google and the Portland, Oregon, public transit agency (TriMet). To facilitate data sharing and access to information for users, Google defined a publishing standard for transit agency operational data (e.g., stops, stop times, routes). Due to its simplicity, small transit agencies as well as larger ones can publish their data at a low cost (McHugh 2013).

The specification defines six mandatory comma-separated values (CSV) files and seven optional ones, for a total of 13 in a complete dataset. Together, they describe the stops, routes, and schedules of an entire transit system. These files are provided primarily for developers and can be seen as tables of a relational database. The diagram shown in Figure 1 illustrates the different files and how they are linked.

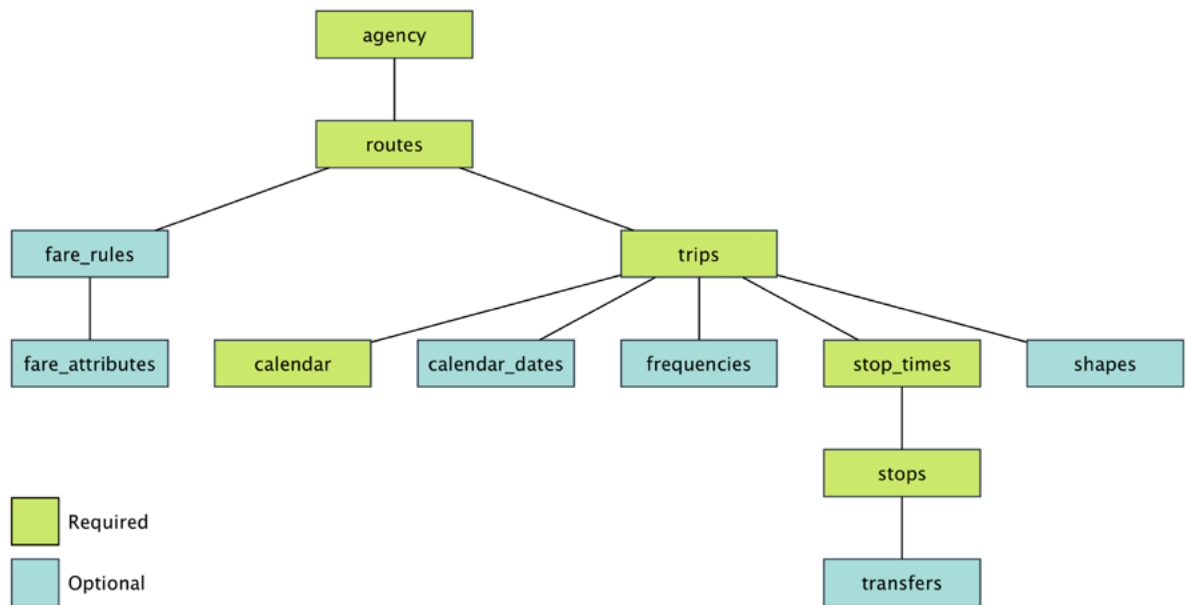


FIGURE 1. Diagram of complete GTFS file dataset

GTFS data are used mostly in online applications to provide route and schedule information to transit users, but their potential goes beyond this use, as already demonstrated by some researchers. The Oregon Department of Transportation published a technical report introducing a proof of concept on how to optimize its transit network using GTFS data (Porter et al. 2014). Also, the Florida Department of Transportation commissioned the National Center for Transit Research at the University of South Florida to identify how GTFS data could help transit agencies in their everyday planning and operational activities (Catalá 2011).

Nonetheless, these data can sometimes contain codification errors or misrepresentations of the actual network. Since they represent planned schedules, inscribed stop times may be wrong due to congestion, or stops could be encoded imprecisely and have incorrect coordinates. To avoid most common errors or to validate that the files adhere to the specification, Google developed the Feed Validator (Google 2015a). Among other things, the Feed Validator identifies missing files, specific columns

or values, overlapping stops, unused shapes or stops, and invalid service dates (Derrible and Kennedy 2011). Prior to any research, a comparison between measures calculated using GTFS data and observed by the agency also should be performed, using a method similar to that proposed by Wong (2013).

GTFS-Realtime

Real-time GTFS is defined as an extension to the general specification. Agencies can provide three different types of live feed—trip updates (delays, cancellation, changed routes), service alerts (stop relocation, events affecting a station, route, or entire network), or vehicle positions (Google 2015b). In our point of view, the vehicle positions feed provides the most useful information. Standard GTFS provides planned schedules and can include codification errors or even planning errors if travel times are overestimated or underestimated. Knowing this, GTFS-Realtime represents the most accurate source of information to compute classic measures and indicators. Most of the transit agencies in the GMA do not yet publish these live feeds of information, and they are not included in this research. They also are more challenging to integrate into a graph database.

Typical Use of GTFS Data

The main purpose of the GTFS standard is to share public transit information. As such, some pre-processing steps are required before it can be used for other needs. Most commonly, a GTFS data set will be imported into a relational database (e.g., MySQL, PostgreSQL, Oracle) from which a developer will be able to query any schedule information to provide it to the end user. Searching the data in a deeper way requires the database to be spatially enabled. A spatially-enabled database has additional features and functions to perform queries using objects (points, lines, shapes) as one would do with any Geographic Information System (GIS). The most common way to do this is to install and activate PostGIS as an extension to the PostgreSQL database system.

Accessibility Assessment

Different measures and indicators of accessibility can be evaluated using GTFS data. These measures assess the proximity of the population or activity locations to the transit network. The proximity typically is estimated using the distance to the nearest transit stop.

Most commonly, a buffer (e.g., 500 m or 0.31 mi as the average acceptable walk distance) is applied around the transit stops. The number or the proportion of individuals living within a certain distance from the transit network then can be identified. This measure can be replicated for various population segments or types of locations to assess the level of accessibility among them and pinpoint where improvements should occur.

The most important identified limitation of such an approach is that it does not account for the travelers' needs (origin-destination). It also does not include service frequency, which clearly affects the level of accessibility—a transit stop with buses every 10 minutes provides a higher level of accessibility than one with service only once per hour. Due to those limitations, some authors have proposed much more complex accessibility measures. For instance, Godin (2012) proposed a typology of accessibility measures as well as new dynamic indicators changing through space and time. Using the shortest path tree from a specific location, Gandavarapu (2012) introduced a different method to compute accessibility measures of the population and employment to each of the traffic analysis zones. Bertolaccini and Lownes (2015) also developed an automated method to evaluate the changes in transit accessibility through the day using only GTFS and population data to make it easier to find relevant datasets. Al Mamun and Lownes (2011) reviewed different methods and proposed weighting factors for individual methods to formulate a composite index of public transit accessibility.

It is generally difficult to include dynamic elements of transit service (e.g., transfers between routes or stops and a bus following a specific route) in most classic indicators. These are based mostly on static data (e.g., stops, schedules, routes) provided by the GTFS and cannot take into account the reachable areas from origin, the paths a user followed, or the variability of service throughout the day, week, and seasons. To render more insights into how transit service can be improved, indicators should provide a way to properly measure the connectivity between the different stops and consider the different stop times and headway for each stop or route.

Graph Theory

Graph theory has been applied in different research fields since its introduction in the 18th century by Leonhard Euler. Today, the foundation of this theory has been proven, and it is now recognized as a mature discipline (Biggs et al. 1986). Therefore, algorithms and indicators calculated using graph theory generally have been optimized and perform well on large graphs.

Graph theory is used to represent real-world situations by a diagram consisting of a set of points with lines joining certain pairs of these points. A graph is made up of vertices (or nodes) connected by edges (lines). The edges may or not be directed, depending if a flow direction is imposed. In the case of a transit network, all edges are directed, as is the global graph (Bondy and Murty 1976).

As part of their literature review, Derrible and Kennedy (2011) proposed a review of all indicators and measures that address the problem of network design using the graph theory. Through time, these indicators have become more complex, implementing the full capability of the graph theory. Some of them can be easily applied to the context of this study— α -index and γ -index (planar, as the graph holds in only two dimensions) and the line overlapping index. Table 1 describes them, along with their pros and cons.

TABLE 1.
Selection of Indicators
Adapted from Graph Theory
to Transit Network Studies

Name (Author) and Description	Equation	Pros	Cons
α-index (planar) (Garrison and Marble) – also known as degree of cyclicality; ratio of actual number of cycles and potential number of cycles in completely connected graph.	$\alpha_{\text{planar}} = \frac{e - v + 1}{2v - 5}$	Directly linked to network design; related to cyclomatic number; consideration of planarity of network.	No consideration for relevance of different cycles or any alternative route.
γ-index (planar) (Garrison and Marble) – also known as degree of connectivity; ratio of actual number of edges and potential number of cycles in completely connected graph.	$\gamma_{\text{planar}} = \frac{e - v + 1}{1/2v(v - 1)}$	Directly linked to network design; consideration of planarity of network.	No consideration of origin-destination of a trip; no consideration of frequency of service.
Line overlapping index (Vuchic and Musso) – ratio of sum of all lines length ($\sum_i R_i$) and total route length of network (R).	$\lambda = \frac{\sum_i R_i}{R}$	Reminds of notion of cycles and alternative routes.	Does not take into consideration origin-destination of lines; does not include ridership data.

E = Number of edges/links

V = Number of vertices/nodes

R = Total route length of the network

Adapted from Derrible and Kennedy, 2011

Table 1 shows that these indicators can be applied directly to transit networks, but they still do not account for some of their unique characteristics such as the planarity of the network, the potential transfer points where two lines cross, or the existence of different lines (e.g., bus or metro) or the existence of different lines overlapping on a network. These limitations also apply to other indicators reviewed by Derrible and Kennedy, who discuss the need to “establish a comprehensive list of network design indicators as a guideline for transit planners” as one of three challenges of developing knowledge on transit system planning.

The study of transit networks rarely uses the graph theory. Alternative methods are best suited and provide a quicker way to obtain interesting results. However, graph theory offers a promising future for transit analysis and is well-suited for GTFS data. The graph-oriented method adopted for this study provides an illustration of this potential.

Methodology

Based on graph theory, the graph-oriented method constitutes a better fit for the needs of this study. The different data elements are expanded into a complete graph, leaving behind the unsuitable table format. The method we propose has four steps: 1) evaluation of classic transit indicators, 2) modeling of a graph for timetable information, 3) importing into a graph database, and 4) development of graph-oriented indicators.

Evaluation of Classic Transit Indicators

The purpose of classic transit indicators is to provide a general description and some basic information on a network. These indicators come in various forms and are widely used in different research fields. In the context of this research, classic indicators were evaluated using GTFS data previously imported into a spatially-enabled PostgreSQL database. Using SQL queries adapted from an extensive work by the World Bank (2013), selected indicators were globally analyzed.

Modeling of a Graph for Timetable Information

The most natural way to represent a graph using GTFS data is to look at every bus stop as a node and every segment between them as edges. However, this representation almost brings us back to the static approach, lacking the integration of time-related information. To achieve the full potential of this method, the data must be organized in a way in which time is fully taken into consideration. Both the time-dependent and time-expanded models were considered to integrate timetable information into a graph.

In the time-dependent model, all nodes of the graph represent a bus stop, linked together by one or more routes. A mathematical function containing a time variable defines the weight of every edge. Each query evaluates the weight according to the time of the query. In the time-expanded model, all nodes represent an event (arrival, departure or transfer) and, thus, it requires more nodes and edges. All weights are directly assigned to the edges when building the graph so no additional calculation is required when querying the database.

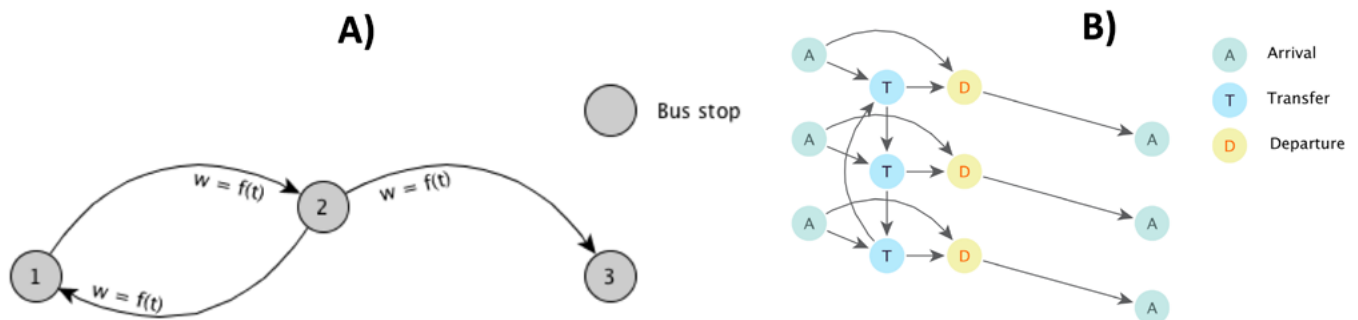


FIGURE 2. Illustration of A) time-dependent model and B) time-expanded model

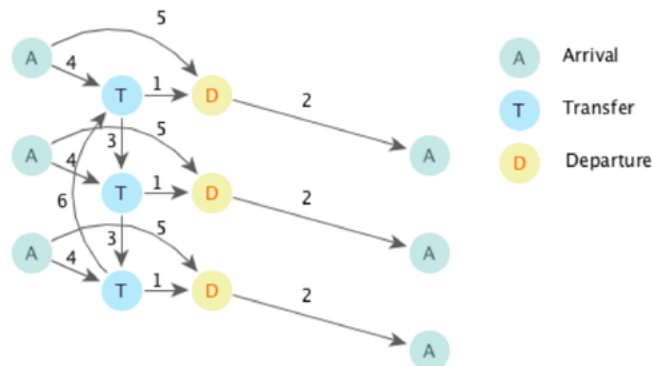
The time-expanded model was selected for this study for two main reasons. First, it presents a more versatile structure to integrate GTFS data and to develop relevant indicators. Also, but most importantly, it works best with the built-in algorithms of the graph-oriented database system used to build and store the graph. Neo4j could not, at this point of development, compute weighted functions on the fly.

Time-Expanded Model

In the time-expanded model, each node of the graph represents an event. Three types of events can occur on a bus network—arrivals, transfers, and departures. Figure 3 illustrates how each event is linked to the others. It shows that for each stop time in the GTFS files, an arrival event is created. Unless the event occurs at a terminal, a transfer event is added, followed by a departure event. To progress in the graph, all events are linked by six types of edges. Edges are characterized by the straight line distance between two connected stops (null if same stop) and the time (duration) between the two events.

1. Departure-Edges [T=>D] – each pair of transfer and departure is linked with a departure edge (weight 0).
2. Connection-Edges [D=>A] – each departure is linked to the next arrival on its path by a connection edge. Properties of this edge contain both the travel time and distance.
3. Station-Edges [T=>T] – each transfer event is linked to the next with a station edge, representing movement at the same bus stop. Weight represents the time between the two related departure events. Distance amounts to zero.
4. Transfer-Edges [A=>T] – an arrival event is linked to the next transfer accessible in its timeline. An arrival can be linked to more than one transfer, considering that a passenger can reach another stop within a 500m radius.
5. Vehicle-Edges [A=>D] – all arrival events associated with a departure are linked by a vehicle edge, representing a passenger staying in the same vehicle along a path. Weight and distance amount to zero.
6. Overnight-Edges – the overnight edge allows for overnight transfers from the last transfer event at a stop, to the first transfer event at the same stop.

FIGURE 3.
Time-expanded model



The combination of nodes and edges portrays the reality observed on a network. A bus arrives at a stop from a departure (Type 1 edge) and the passenger has the option to stay in the same vehicle (Type 5) or transfer to a different stop (Type 4) or a later departure (Type 3) if he has not yet reached his destination. Finally, the bus leaves the current stop to go to the next stop on its path (Type 2).

Importing into a Graph Database

To compute the desired indicators, the GTFS data was modeled using the time-expanded model and imported into a graph database. A graph database, as opposed to a relational database, explicitly stores the links between all elements to scan them more efficiently. It also keeps the context around each node and link, so it does not have to scan all the data, only the relevant parts of the graph. Data are accessed accordingly and returned faster, even with large datasets (Robinson et al. 2013).

Neo4j is a graph database system widely used in the industry (Wolpe 2014). It offers a stable environment with embedded algorithms based on the graph theory, notably to compute the shortest path between two nodes and an application programming interface (API) used by third-party drivers developed for multiple programming languages (e.g., Java, Python, Ruby).

Other experts developed or studied more advanced stand-alone algorithms. Khani et al. (2012) proposed a simple but efficient algorithm for finding the optimal path in an intermodal urban transportation network based on the generalized cost. Dibbelt et al. (2013) introduced a novel algorithm framework called Connection Scan Algorithm that organizes data as a single array of connections, which it scans once per query. This algorithm is simple and versatile, according to the authors.

As opposed to more advanced algorithms, those proposed by Neo4j are not built specifically for computing the shortest path in a transit network. As part of our research, we also wanted to test Neo4j's algorithm and see how it performs in a different environment.

Development of Graph-Oriented Indicators

Most of the indicators presented in the next section are based on the shortest path calculations. All path computations were calculated between a departure node and an arrival node as specified by the time-expanded model. The Neo4j's built-in algorithm for shortest path calculation does not store queries and, thus, must compute an entire cost tree for each run of the Dijkstra algorithm. The time-dependency was taken into account in the GTFS. Travel times were adjusted by the operator with observed values. In peak hours, some inter-stop travels are longer and, thus, return more accurate estimations when using Dijkstra algorithm than when using instantaneous travel time.

Due to the large quantity of departure-arrival pairs, computing all shortest paths in that manner would take an extended amount of time, even for a small network such as the one chosen for the case study. This computation method must be optimized to analyze large networks.

Demonstration

To illustrate the aforementioned concepts, a small network was used from the Conseil Intermunicipal de Transport de Chambly-Richelieu-Carignan (CITCRC), a transit agency

located in the suburban area of the Greater Montreal Area (GMA), Canada. CITCRC operates a local service around Chambly, Richelieu, and Carignan (45,000 inhabitants) as well as a shuttle service to Montreal's Central Business District (CBD) using 10 coaches, 12-city buses, and 2 taxi-buses. Figures 4 and 5 illustrate the network on a weekday and on a Saturday.

FIGURE 4.
CITCRC's network on a
weekday

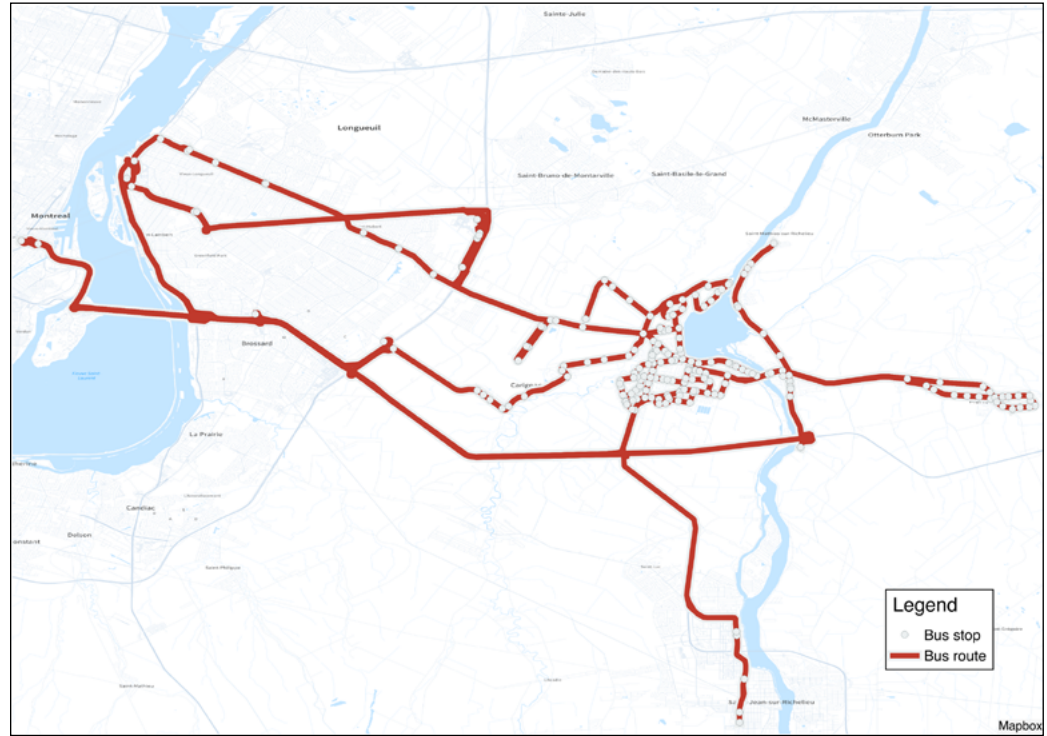
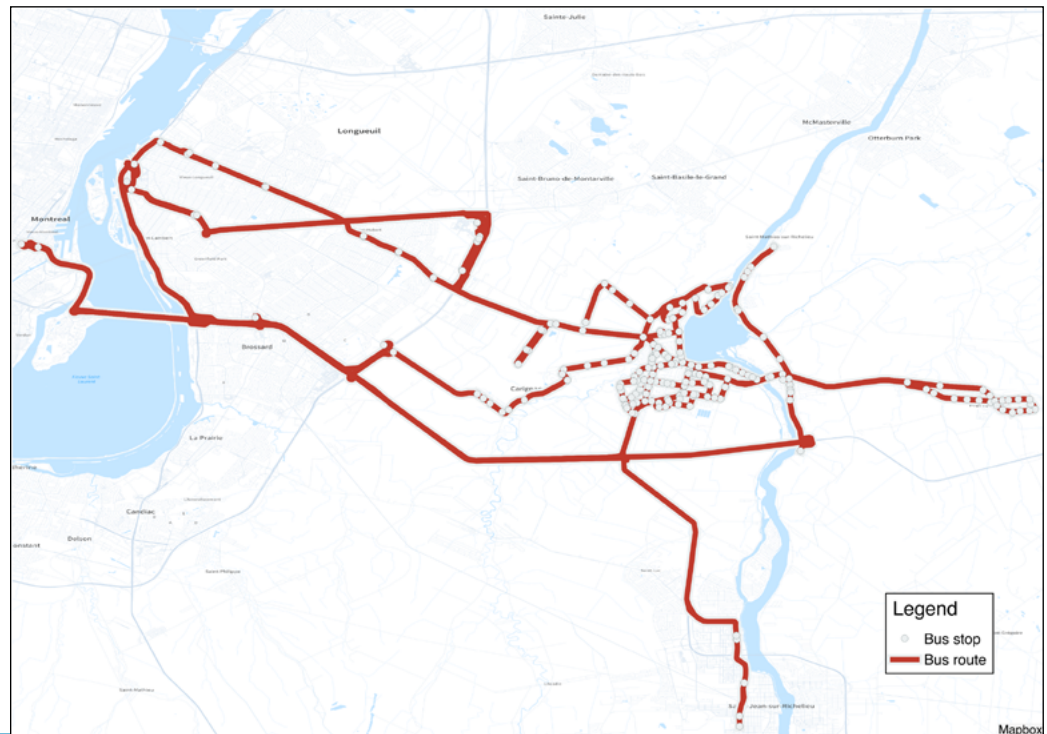


FIGURE 5.
CITCRC's network on a
Saturday



The network’s Saturday service is easily processed since the service level is low on this day. However, the weekday service presents more than 7 million departure-arrival pairs. In this context, the analysis relies on a sampling strategy: samples of 1,000 bus stop pairs were randomly drawn from the entire set of pairs and the shortest path for all possible departure-arrival pairs is computed.

All results from the computation of the Saturday and weekday services were then analyzed following the three levels introduced earlier—stop, route, and network.

Classical Transit Indicators

Table 2 presents a list of indicators and their value. The “Prior Requirements” column lists additional files or sources of information required to compute each indicator.

TABLE 2.
Case Study Indicators
(computed using GTFS data
and SQL database methods)

Indicator	Value	Note	Prior Requirements
Transit system length	40.25 km	Aggregation on routes, route types, or modes upon data availability.	GTFS: Shapes.txt or stop_ distance_traveled field
Number of stops	365	Aggregation on routes, modes, or territories upon data availability.	Territory: Boundary files
Daily number of hours of service (weekday)	19	Aggregation on routes.	N/A
Ratio of number of stops to route-length	1.71 stop/km	Aggregation on routes, modes, or territories upon data availability.	N/A
Average distance between stops	2.15 km	Similar to above indicator.	N/A
Average time traveled between stops	3.49 min	Time traveled between two consecutive stops only.	N/A
Territorial coverage of transit stops (500m radius)	27.5%	Takes into account only stop positions and no frequency of service.	Territory: Boundary files

These results give a general idea of the network, but provide limited information on the interaction between the elements. Even though some indicators could provide a more precise description (e.g., frequency or length of bus lines), they cannot comprehensively characterize a network. Furthermore, the queries that perform the calculations quickly become more complicated as the amount of additional required information grows. In addition, producing highly-detailed indicators often requires additional sources of information.

Graph-Oriented Indicators

The graph-oriented indicators are based on three different levels of analysis (stop, route, and network analysis), as presented earlier. The analyses on the stops and routes levels are presented in this section. The analysis at the network level is mostly a generalization of similar indicators and, thus, is not part of this paper.

Stop Level

Bus stops (or any other station) represent the access point for all public transit travelers. As users interact with these stops, often on a daily basis, it is important to understand their impact on the efficiency and productivity of the network. We focused on two main concepts: connectivity and frequency.

First, we developed the dynamic connectivity between pairs of stops throughout the day. In this case, a pair of stops was defined as the combination of any two bus stops in the network, regardless of their position, the routes they serve, or their connectivity to one another. Two distinct stops actually can generate two pairs, as direction is considered (e.g., Stop A/Stop B and Stop B/Stop A). A pair of stops was determined to be active if the stops are linked by at least one path. A maximum duration of two hours was set as the threshold for inclusion in the indicator. The maximum duration was set according to the period of validity of a single ticket sold by the STO. The results were then assembled according to departure time. The percentage of active stop pairs was computed upon the subset of data. Figure 6 illustrates the proportion of active stop pairs across a typical weekday (using estimations from 10 independent samples) and a Saturday.

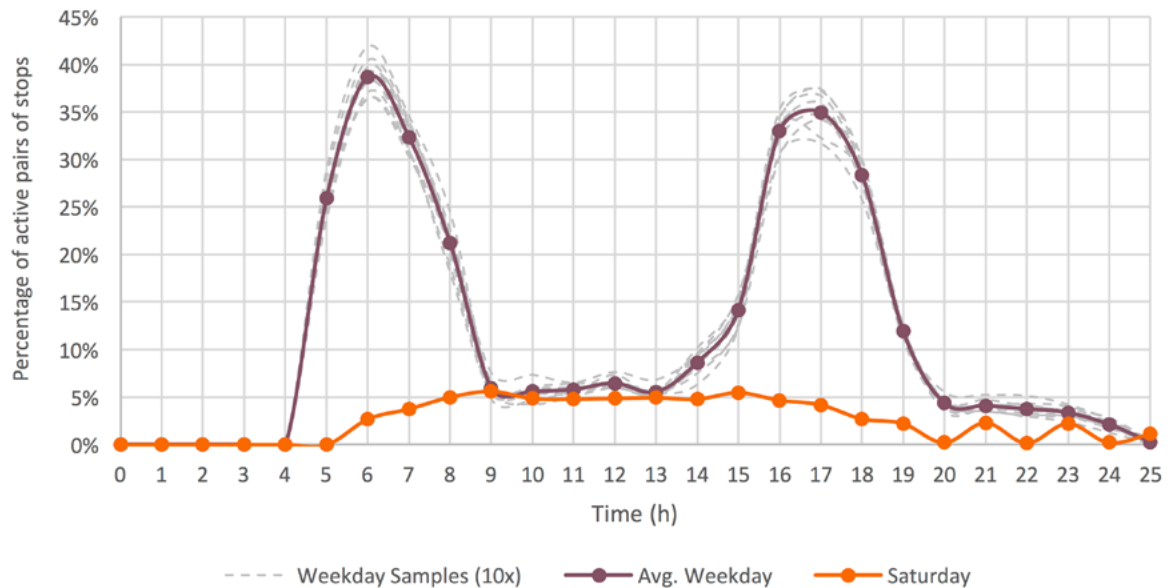


FIGURE 6. Active pairs of stops throughout day

Figure 6 highlights some interesting observations:

- Weekday samples presented a similar pattern with some variability.
- As expected, the weekday line exposed the two peak periods; the morning peak was more concentrated than the afternoon peak. The observation is consistent with typical profiles of weekday travel demand in the GMA.
- The variation of active pairs on Saturday evenings was due to a sparse service.

Due to headways being unevenly distributed, a drop in service for certain hours is visible.

- Bus stops are mostly located in one of the three municipalities, with some in Downtown Montreal. When the percentages of active pairs of stops on the graph were high, a better local transit service is offered, whereas lower percentages indicated more direct lines to Montreal and less passages at local stops.
- Percentages peak at almost 40% during the week and 6% on Saturday. Considering that this is a small network that mostly connects travelers from small cities to Montreal's CBD, it indicates that many local stops are not interconnected, reducing global connectivity.

The second indicator relates to the extent of the service offered at each stop. In this context, the existence of a path between two stops for a given departure time defines an opportunity. Accordingly, a single departure could generate multiple opportunities, heading to different destinations. Figure 7 presents trip opportunities to various stops for an entire day (for Saturday service). The results revealed some interesting findings:

- For the overall service, the pattern of departure and arrival opportunities are similar, with some differences in quantities.
- This opportunity measure accounts for frequency of service and reachable destinations within a set time frame.
- It would be possible to produce interesting analysis such as comparing a sector's accessibility based on different origins or segmentation according to a time range by using a complex network or a complete weekday dataset. However, the algorithm used for this research paper does not support such large datasets.

FIGURE 7.

Extent of service at each stop
(Saturday service)
a) Departure opportunities

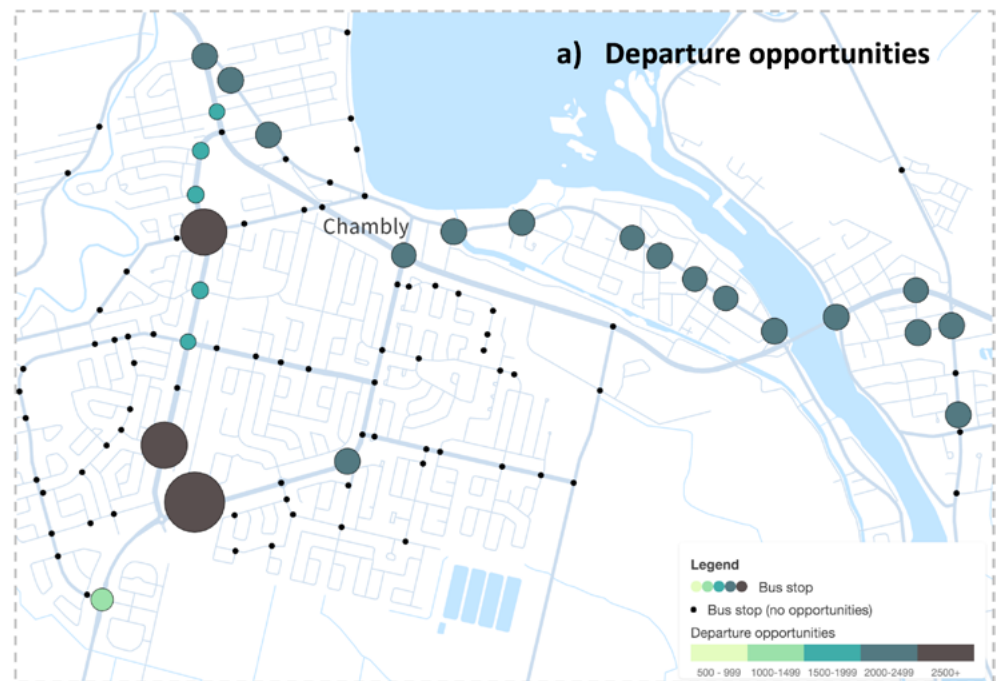
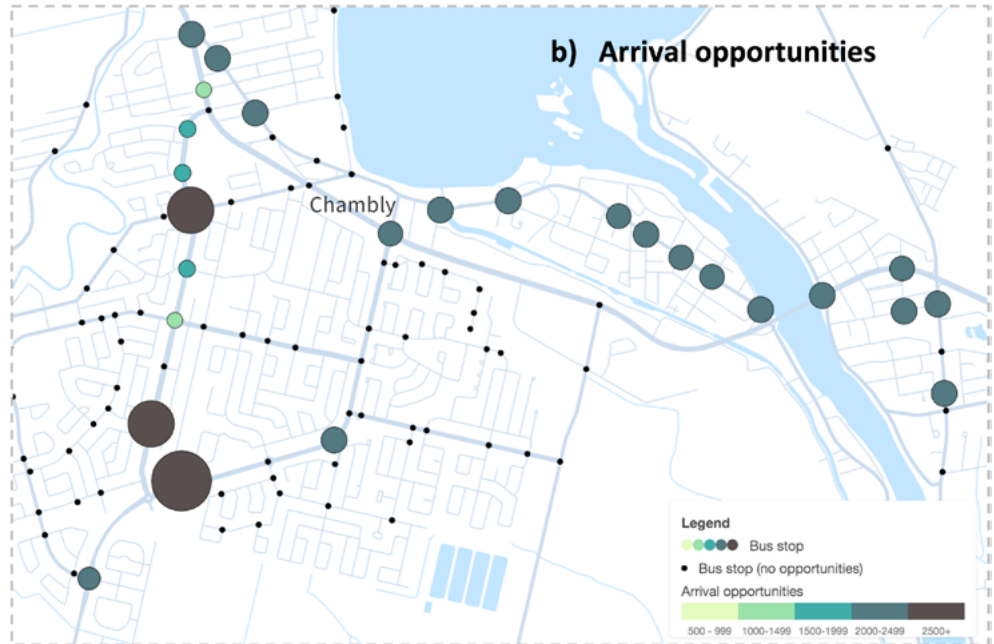


FIGURE 7 (cont'd).
Extent of service at each stop
(Saturday service)
b) Arrival opportunities

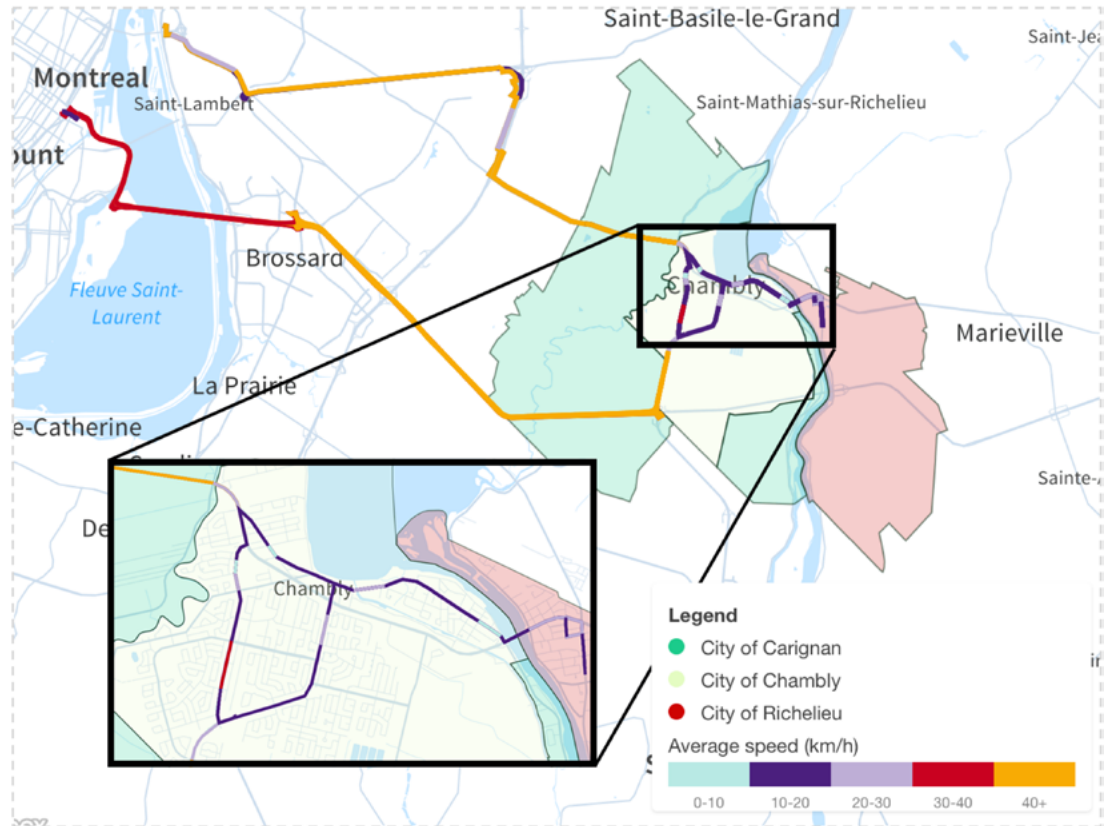


Route Level

Different pairs of stops may be connected by more than one bus route. Total trip distance and duration of the trip vary according to the selected route, so the service speeds vary, depending, for instance, on the number of stops or road conditions.

For operational reasons, it is interesting to analyze the service speeds by road sections according to the time of departure. Transit agencies want to increase service speed, and customers equally want to avoid segments with low speeds. As such, service speed provides a good point of comparison to assess the effectiveness of a network during a typical day and also to monitor evolution over time. A benefit to this analysis is it helps to verify if the data included in the GTFS is consistent during peak periods or changes hourly due to local road conditions. Figure 8 shows the average service speed per segment for the Saturday service.

FIGURE 8.
Service speed for Saturday service



The results show an apparent difference in speeds along the route segments. The service speeds remain considerably lower for the local routes (near Chamby) and slightly higher for the longest segment where buses drive on highways. Nevertheless, the maximum service speed observed remains under 70 km/h (45 mph), and it may be improved on some highway segments. Service speed is the result of many factors, including stop location and route conditions. By highlighting the problematic road sections and overlapping the results with external data (e.g., traffic conditions, exclusive bus lane), such analysis provides relevant information to optimize the service and inform the strategic planning process.

Conclusion

The research presented in this paper demonstrates how GTFS data can serve purposes other than delivering schedule information to travelers. In addition, the paper illustrates the benefits of graph theory for transit network analysis. Based on these observations, a new intuitive graph-oriented method is proposed to improve existing indicators and develop new ones for characterizing and analyzing a transit network. A selection of indicators mostly based on connectivity and service speeds was presented as a proof of concept and constitute a small part of a scheme to measure and understand the complexity of a transit network.

The experimentation helps put forward current limitations of the graph-oriented method. Even though graph theory is promising for the study of transit networks, its implementation into a graph database raises some issues. The way the shortest path algorithms are built into Neo4j increases computation burden since previous results are not stored. Graph database technology is quite new; hence, third-party drivers are of unequal quality among programming languages and documentation remains limited. Moreover, at this time, the graph-oriented method does not take into account the quality of transfers from a bus line or bus stop to another. Safety, ease of transfer, transfer location, or universal accessibility could influence the choice to transfer or not when other options are available.

Future research will focus on validating GTFS data with planned and real-time data. Additionally, two options are being examined to reduce computation time: 1) a hybrid solution—modifying the Neo4j algorithm to change the way it stores and publishes its results; all intermediate routes calculated when computing the shortest path query can be stored externally in a cost matrix, which would limit the computation burden on the system and overall calculation time should be substantially reduced; and 2) a conventional path calculator using a relational database; the graph database would then be used to pre-compute some parameters.

Finally, we are currently developing other, more precise indicators on various spheres of analysis, including connectivity, stop location, and accessibility. These indicators will facilitate the characterization of a global transit network and its comparison with other networks. For the long term, our objective is to integrate all these components into a transit network analysis tool that will allow systematic network analysis and monitoring, as well as observe changes through time in a structured and automated way. Although this proof of concept is set on a specific state of the network, further analyses will focus on the comparison of networks after a change in supplied service.

Acknowledgment

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Applying AHP and Clustering Approaches for Public Transportation Decisionmaking: A Case Study of Isfahan City

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Abstract

The main purpose of this paper is to define appropriate criteria for the systematic approach to evaluate and prioritize multiple candidate corridors for public transport investment simultaneously to serve travel demand, regarding supply of current public transportation system and road network conditions of Isfahan, Iran. To optimize resource allocation, policymakers need to identify proper corridors to implement a public transportation system. In fact, the main question is to adopt the best public transportation system for each main corridor of Isfahan. In this regard, 137 questionnaires were completed by experts, directors, and policymakers of Isfahan to identify goals and objectives in the field of urban transportation. In the next step, objectives were prioritized by a multi-criteria decisionmaking method. Afterward, for the main 35 corridors of the city, available information, including trip demands toward main destinations of studied corridors derived from Isfahan comprehensive transportation studies and number of passengers of bus lines, were collected. Finally, 3,906 taxi passengers were interviewed at the end points of each corridor. The role of each policy in improvement of the objectives was assessed by expert choices, and suitable public transportation policies in studied corridors were defined by clustering parameters and converting them into weighted criteria. Mass transportation and implementation of road space rationing policies had

the most influence on achieving prospected objectives in the city's urban transportation system. Findings of this paper present a general evaluation of each implemented policy for the studied corridors.

Keywords: Policy-making, public transportation, AHP, clustering

Introduction

Public transportation is a type of transportation in which the vehicle does not belong to the traveler (Simpson 1994). Any vehicle that is openly used to move people around is a part of a public transportation system. Regarding social equity, public transportation is more important for special groups of users such as older adults, youth, and low-income populations (UITP 2015). Generally, we can divide existing public transportation systems into two groups: regular and irregular. A regular public transportation system or transit system is defined as a system that has fixed origins and destinations and serves passengers on a schedule. This type of transportation includes large and small buses, double-decker buses, articulated buses, trolleybuses, some mini-buses, bus rapid transit (BRT) systems, tramway systems, light rail transit (LRT), monorail, subway, and commuter rail systems (Armstrong-Wright 1993). Unlike a regular transport system, an irregular public transportation system, known as light transportation or paratransit, usually carries passengers on unfixed routes without schedules. Paratransit, which includes private taxis, jitneys, mini-buses, vehicles for hire, ferry, and PRT, is popular in developing countries (Vuchic 2007). Variations of taxis are taxicab, taxi service, airport taxi, radio-dispatch taxi, jitney, rush-hour taxi, vans, and passenger transporters (UITP 2015).

Generally, policymaking is the process of providing a balanced response to different social group demands. Normally, various interested groups seek their own benefits, which could contradict other groups' interests (Schiefelbusch and Dienel 2009). Therefore, to be effective, decisionmaking in the Isfahan metropolis requires consensus among City managers. Zhou (2012) explained that public transportation policies can be categorized in two parts: those that respond to existing demand of public transportation and those that increase the public transportation share in serving total daily trips (Zhou 2012). The decisionmaking process for public transportation could also be self-detrimental. For instance, de Bruijn and Veeneman (2009) indicated that decisionmaking for light rail involves great technical and social complexity that leads to obstacles in the decisionmaking and demand strategic choices by the decisionmakers. Applying a multi-criteria decisionmaking (MCDM) method is a way to overcome this issue. A popular method of MCDM used by many researchers worldwide (Abbaspour et al. 2015; Jozi et al. 2011; Kheirkhah et al. 2010; Lai et al. 2015; Nosal and Solecka 2014) is the Analytic Hierarchy Process (AHP). AHP has been introduced as a fast, easy, and effective technique for the decisionmaking process that has a powerful ability to handle planning problems with a systematic approach.

Mass transportation includes transporting a large number of people among predetermined places. Subway, LRT, tramway system, monorail, regional train, and BRT are variations of mass transportation systems. Rail systems—in particular, heavy rail systems—are more popular in developed countries these days. In developing countries, either there is no urban rail system or the network coverage is poor. In these countries, suburban, heavy, and light trains have been operated in small parts of cities for which most expenses could not be covered by cities. One of the most important sorts of public transportation in developing countries is bus because of economic issues. In developed countries, buses operate beside rail transportation systems and usually operate at a fraction of their capacity. In developing countries, there is either no rail transportation system or limited rail lines. On the other side, in developing countries, the car ownership rate is low, and the only available regular transportation system is bus; consequently, buses usually operate above their capacity in rush hours (Armstrong-Wright 1993).

Implementing a BRT network is part of an emerging public transportation policy around the world, which is different in details depending on each city's characteristics such as pathways, population, resources, and texture of the city, although it has similarity in many aspects. A BRT system is formed of different parts including exclusive lanes, stations with intelligent doors and appropriate facilities, terminals, low-floor vehicles for easy and quick boarding and alighting, beautiful interior and exterior design, passenger comfort facilities, advanced fare collection system, extended time service with low headways, and embedded adaptive bus preemption signal control system. This system is simple and has lower expenses in comparison with rail systems. Additionally, in recent years, BRT systems have gained the ability to transport up to 20,000–30,000 passengers per hour per direction. To date, there are several successful dedicated bus lines, such as Porto Algeria with 26,100 passengers per hour per direction and Sao Paulo with 18,600 (OECD 1995). According to EIU (2010), one of the best-operated BRT systems is in Curitiba Brazil. The role of BRT is different in developed and developing countries. In developing countries, BRT moves a huge number of passengers at its capacity; in developed countries, BRT is a system with high-level of technology and high-level of services that competes with private automobiles (TCRP 2007).

One of the important subjects in public transportation policy is choosing an appropriate system, considering the economic conditions and city status or proper place. Therefore, by focusing on different references during a comparison of alternatives, we briefly explain the effective factors in choosing a public transportation system:

- *Financial-economic factors* – costs of implementation, operation, equipment, and unit expense per trip unit; improving productivity via development of feeder lines; total subsidies paid on public transportation; total fare collected; and flexibility in operation.
- *Social factors* – supporting development of a city via applying a modern transportation system, serving urban transportation demand through a good quality public transportation, increasing urban mobility, improving safety, and reducing accidents, enhancing passenger comfort, establishing high capacity

urban feeder lines, offering cheaper services, increasing passenger satisfaction and reliability of the system, reducing waiting time, providing affordable means of transportation between every origin and destination for all levels of income.

- *Environmental elements* – air and noise pollution, energy consumption, water and soil pollution, land occupation, and visual effects (Vuchic 2007; Carmen et al. 2002).

A systematic approach in this paper is applied to define appropriate criteria for evaluating and prioritizing public transportation strategies to serve travel demand and regarding the supply of current public transportation system and road network conditions of Isfahan. The aim of this paper is to define a set of criteria to choose an appropriate public transportation system as the established goal. Criteria are objective measures of the goal to measure how well each alternative achieves the goal. According to Baker et al. (2002), criteria should be able to discriminate among the alternatives and to support the comparison of the performance of the alternatives. Hence, the procedure of defining criteria is based on the current public transportation supply and demand and road network status. For optimal allocation of available city resources, it is necessary to obtain local priorities and preferences through a public transportation decisionmaking process. The main question in this paper is that what kind of policy is appropriate for public transportation in each city corridor in a unified framework? Undoubtedly, implementation of policies involving mass transportation, road space rationing, bus service enhancement, improvement of roundabout geometric design in urban squares and building park-and-ride facilities, improvement of taxi systems, establishment of exclusive taxi lines with taxi stops, shared taxis, van paratransit systems, and urban minibuses can play an important role in the facilitation of urban mobility. However, it should be mentioned that each city has its own limitations. Accordingly, there should be particular consideration about Isfahan's road network characteristics. This paper intends to present a contribution toward development of unified framework for city public transportation decisionmaking with a capability for the systematic practice of similar policies in other cities. In this paper, the necessity of a general procedural implication of public transportation decisionmaking is illustrated by a practical case study. Accordingly, this paper provides a method in the selection of BRT corridors for Isfahan in 2013. Brief steps of this paper are as follows:

1. Asking Isfahan policymakers, managers, practitioners, and experts were asked their opinions about the most important objectives (criteria) in the field of urban transportation. Priorities of objectives were determined using AHP.
2. Considering main transportation corridors of the city, available data were collected, including trip attraction to principal destinations, obtained from comprehensive transportation and traffic studies of Isfahan by Isfahan University of Technology (IUT 2008), performance data, and a survey from some bus users.
3. Interviews were conducted with taxi passengers at the end destinations of desired corridors.

4. A data bank was compiled in Microsoft Access from the interview results for primary evaluation and further analysis of data as an innovation in public transportation sector of city.
5. Each alternative role was determined as a definite policy in improvement of objectives by surveying from experts.
6. Appropriate criteria were determined based on clustering available parameters in supply and demand data of transportation systems to clarify suitable alternatives of public transportation systems in studied corridors.
7. Proper alternatives were offered as feasible policies of public transportation for the studied corridors.

Quick Review of Isfahan

In Isfahan, with a 260-square-kilometer area and a population of about 2,000,000, more than 4 million trips are performed every day. Isfahan is a city with many tourist attractions that are mostly centered in downtown, and more than 30% of daily trips are attracted to downtown. There are shortages in city transportation such as inefficient orientation of sustainable urban transportation, fundamental weakness and shortage of the road network because of the impossibility of network expansion, widening of roads, and large expenses of releasing real estate for road construction. Moreover, the historical and valuable texture of the city leads experts to find solutions based on optimal application of public transportation to solve the city's traffic difficulties. For optimal allocation of available city resources, it is necessary that officials apply appropriate policies to public transportation. For this purpose, 35 main corridors of Isfahan in which public transportation policymaking is a feasible solution were considered for this study. Taxi and bus services are the only available public transportation systems in Isfahan, for which demand data have been updated in comprehensive transportation and traffic studies of the city. The current public bus system of the city has lacked effectiveness for quite a long time. Long travel time, long headways, and congested buses gradually have led to the formation of taxi lines, which constitute a paratransit network. In essence, taxis have predetermined origins, destinations, and paths. Passengers are boarded at an origin station or on their path (who share the same route) up to the taxi's capacity (four passengers in a sedan) and are dropped off on their way or eventually at a destination point. This form of taxi service, similar to jitney, is very common in many developing countries; however, it is obsolete or different from services in many developed countries. In addition, supply information of public transportation in these corridors exists in comprehensive transportation and traffic studies (EIU 2010). Features of transportation supply and operation of public transportation, including number of passengers, trip time, travel speed, and waiting time for each section and station, are collected by Isfahan's public transportation corporation.

Surveys of City Managers and Experts

To determine the objectives of city transportation, managers, directors, and experts in the field of transportation and urban traffic completed 137 questionnaires. These forms included 12 objectives describing fair distribution of transportation services among various income levels, environmental pollution alleviation, building expenses of rapid public transportation systems, alleviating traffic congestion in city streets and highways, traffic safety improvement especially pedestrian safety, and reliability improvement in transportation systems regarding schedule adherence. In addition, trip comfortability, accessibility to transportation systems, attractiveness of the transportation system, facilitation of a sense of living in a modern city, mode choice diversity in city trips, efficient response to transportation demand, reducing energy consumption in city transportation sector, reducing travel time, and trip cost in the city were other objectives. Respondents were mid-level managers and experts from public organizations who are relevant to city traffic management, such as multiple divisions of Isfahan Municipality, the Provincial Bureau of Road and Transportation, the Bureau of Transportation Terminals, the Police Department, the Department of Housing and Urbanization, and all major universities in the city. All responses were treated equally regardless of the position of respondents.

In this study, after separating the problem into its components, the AHP method was used mainly to allocate weights or rate the selected objectives for transportation policy appraisal. The AHP method is a multi-criteria decisionmaking technique proposed by Saaty (1990). To make comparisons between defined criteria, a scale of numbers is needed that indicates the relative importance of a dominant element over other elements with respect to the criterion or property to which they are compared (Saaty 2008). Saaty and Hu (1998) pointed out that the relative importance is stated based on a 9-point scale or weight of criteria that is determined with the robust method of estimation in AHP (Saaty and Hu 1998). Results are presented in Table 1 in normalized priorities for the defined objectives (criteria), showing the relative importance of objectives. As indicated, traffic congestion reduction, trip cost reduction, increase in safety, and pollution reduction are the most important objectives in the selection of appropriate transportation system respectively.

TABLE 1.
Final Priorities of Objectives
Based on Survey of Managers
and Experts

No.	Objective	Score	No.	Objective	Score
1	Traffic Congestion Reduction	0.179	7	Travel Time Reduction	0.085
2	Trip Cost Reduction	0.114	8	Trip Comfortability	0.084
3	Traffic Safety Improvement	0.108	9	Energy Saving	0.054
4	Pollution Reduction	0.108	10	Efficient Response	0.046
5	System Attractiveness	0.086	11	Fair Distribution	0.026
6	Increase of Reliability	0.085	12	Costs of Implementation	0.023

Prioritization of Transportation Policies with Respect to Objectives Ranking

Effective policies for improving urban public transportation in terms of mass transportation alternatives or solutions are categorized as implementing BRT or tram, traffic demand management, enhancing bus service, precise improvement of bus lines' start/end stations in urban squares such as organizing the traffic situation, and building park-and-ride facilities near origins and destinations of bus lines. Improvement of common available taxi systems in a city such as taxi service, taxicab, shared taxi, and paratransit system are other policies in public transportation. To determine the influence of each policy with respect to city transportation objectives, it was requested from responders to carry out a pairwise comparison to construct matrices expressing the relative preferences of a set of alternatives with respect to 12 objectives to classify alternatives based on their relative merits. Next, the AHP methodology was applied to identify the true order of priorities such as in similar studies (Leskinen et al. 2005). Finally, each corresponding number of the seven policies preferences for improving transportation system was multiplied by the priority relating to each objective of Table 1. All numbers were then summed, and global priorities of alternatives were calculated. Table 2 presents the global transportation alternative priorities with respect to all transportation objectives.

TABLE 2.
Global Priority of Alternatives

Global Priority	Proposed Alternatives
Mass transit (BRT, ¹ tram, monorail)	0.258
Traffic demand management (road space rationing, exclusive bus lanes ²)	0.213
Improvement of bus system (improvement of bus line, exclusive bus and taxi lines ³)	0.160
Implementation of complementary facilities (building park and rides-terminals, improvement of urban squares traffic condition)	0.137
Improvement of shared taxi system (provide exclusive lines)	0.112
Paratransit system (van or urban minibus)	0.070
Taxi service and taxi for hire (private taxis ⁴)	0.050

¹ BRT is a bus system with dedicated lanes, low-floor buses, and fare collection at station gates.

² In some sections, bus has dedicated lane; fare collection and fleet are same as conventional bus lines.

³ Exclusive bus lines, also called express bus, skip some stations and stop only at major stations on their route.

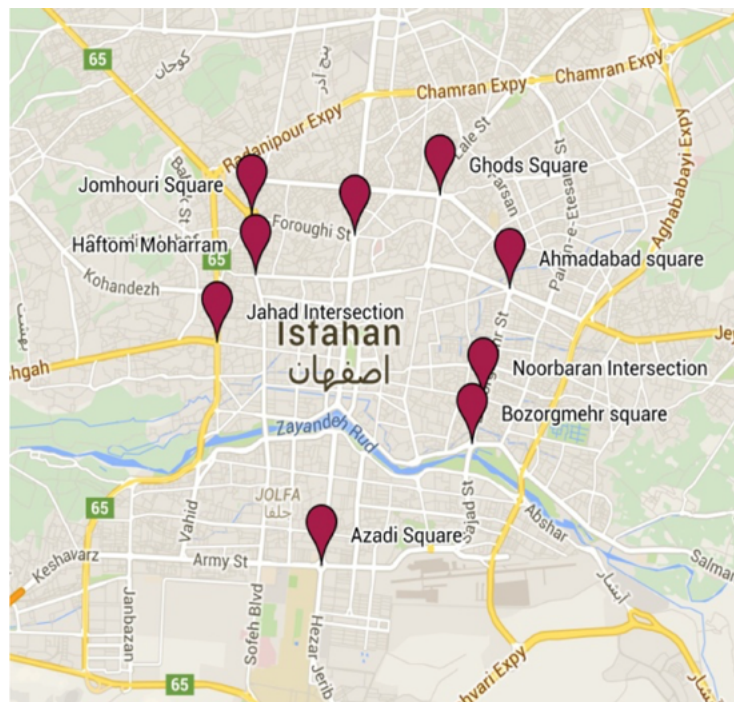
⁴ Exclusive taxis also move passengers between origin and destination points without stopping on their way to board passengers.

Table 2 results indicates that mass transit and traffic demand management, which score 0.258 and 0.213, respectively, seem to have significant role in terms of their ability to meet the public transportation sector needs of Isfahan. Paratransit, taxi service, and taxi for hire would do rather badly at satisfying the city's requirements in this case study.

Interviews with Taxi Passengers

Because there is a shortage of information about taxis, which accommodate more than half of the city's public transportation trips, field studies were conducted via interviews with passengers and taxi drivers in nine main city squares that are major origins and destinations of city trips. The intended locations were selected beyond the central zones of the city to cover large peaks of trip attraction in the central zones based on transportation comprehensive studies. Furthermore, at selected points, an unsynchronized combination of different public transportation systems exists. Surveying points were selected to illustrate a general overview of taxi routes and trip objectives, which are done inside the city by taxi. Whereas the majority of intra-city trips by taxi end in one of the squares or intersections in the second traffic ring of Isfahan, surveying points and surveyor locations for interviews with dropped-off passengers were located in major squares and intersections (1–Azadi Sq, 2–Noorbaran int, 3–Bozorgmehr Sq, 4–Ghods Sq, 5–Ahmadabad Sq, 6–Shohada Sq, 7–Jomhoury Sq, 8–Jahad int, 9–Haftome Moharram int), as presented in Figure 1.

FIGURE 1.
Map of selected survey locations



Questionnaires were designed in three sections—1) passenger information; 2) trip purpose, including primary origin and final destination and portion of route traveled by taxi, waiting time, and taxi fare; and 3) maximum fare for taxi for hire and substituted vehicle for taxi in situations in which there was no taxi or passengers desired not to use taxi. Surveying for this research was conducted on three weekdays in May 2013, with 3,906 passengers interviewed in the nine main squares and intersections of the city.

Primary results of this interview emphasized the existence of problems in the urban taxi system, especially in early morning and at noon. The main causes of dissatisfaction

among passengers were the inability to control and supervise the taxi system, lack of proper scheduling, unbalanced distribution, and non-optimal allocation of the city taxi fleet. For instance, taxi service for schools in the morning and at noon and the unbalanced distribution of taxi fleet leads to inefficient service during these hours. In the evening, there is a deficiency in performance of the urban taxi system due to the decreased number of active taxis. Additionally, findings indicate that a majority of exclusive taxi lines in the city satisfy passenger demands at origins, but passengers may be confronted with many inconveniences in the middle and at the destinations of trips.

Integrated Data Bank

The substantial gathered data from the interviews on urban roads of the city public transportation corridors were entered into a research data bank after necessary corrections. These data consist of personal information of responders, trip objective, address of origin and destination of trips, and length traveled from origin to destination by taxi (whole trip, more than half of trip, less than half of trip, less than one-third of trip). In addition, waiting time to get a taxi, taxi fare, number of family members traveling by taxi, maximum proposed fare for booking a taxi for hire, and hired vehicle when no available taxi were included. Data from a comprehensive transportation study of the city were updated and consist of total demand for trips ending at a main destination of the studied roads and demand for public transportation trips by bus and taxi. Bus service information such as passengers traveling, passengers per kilometer, efficiency, daily waiting time, peak-hour waiting time, average running speed, average trip speed, running speed before square, trip speed before square, running speed after square, trip speed after square, and the number of picked-up and dropped-off passengers in the studied squares was added to the integrated data bank. Finally, the integrated data bank was entered into Microsoft Access.

Clustering Effective Factors in Choosing Each Policy

Clustering is the common term for a variety of numerical methods used to create objective and firm classifications (Everitt et al. 2001). Jain et al. (1999) defines clustering as patterns or observations that are grouped based solely on the data. The primary objective is to find groups of similar entities in a sample of data (Aldenderfer and Blashfield 1984). Clustering groups different observations whose patterns of scores on variables are similar. Consequently, clustering is a promising tool for data analysis whose aim is the separation of members to homogenous groups. Moreover, clustering can be applied in situations in which primary recognition of relationships between observations does not exist and, therefore, is counted as data mining.

Similarity and dissimilarity of members based on desired factors are described according to the quantity concept of distance between members and is the main key to identifying clusters. There are different methods of clustering, depending on various factors such as kind of distance definition, consideration of distances between cluster centers, farthest and nearest members, members' average, and comparison of

members with each other to determine the degree of similarity, which then is divided into two general groups of hierarchical and K-means clustering. One of the most applicable methods of clustering is K-means clustering, which is used for numerical variables. In this method, the number of clusters is selected initially and members are arranged in clusters in a way such that their distance from the centroid of the cluster would be minimum. Accordingly, by changing the number of clusters and proficient interpretation of each clustering, the best results would be obtained (Johnson and Wichern 2007).

In this study, to choose an appropriate transportation system for studied corridors, effective factors in the selection of each policy were determined. By applying the clustering method, effective variables in choosing policies as feasible alternatives were divided into meaningful groups. The K-means clustering method was applied by using IBM SPSS statistics software. Accordingly, corridors were categorized into meaningful groups based on variables. Table 3 represents clustering based on variables and influence of each cluster in choosing public transportation policies concluded through the judgment of professionals and experts.

Identifying Appropriate Corridors for Policy Implementation

Applying results from Table 3 and scoring the studied corridors in case of existing an appropriate objective for each public transportation policy, total scores of policies were obtained for each corridor. Corridors with higher priority for each policy were identified as shown in Table 4. To go further into detail and as an example, note that a corridor such as Jomhuri Sq-Jahad Int-Hakim Nezami St-Azadi Sq, which has high travel demand, long-ride bus users yet low travel speed, and considerable taxi fare, has the highest priority to implement a mass transit system. Regarding the economic conditions and budget of Isfahan, policymakers tend to select BRT rather than rail systems due to its lower costs of implementation.

TABLE 3. Cluster Influence of Each Variable on Policy Selection

Source of Information	Variable	Influence of Cluster's Type in Choosing Policy							
		Number of Clusters	Mass Transit	Service Quality Improvement of Bus System	Service Quality Improvement of Taxi System	Improvement of Corridors' Origin	Implementation of Road Space Rationing	Taxi for Hire	Paratransit
Bus Corporation Studies	Passengers traveling	4*	very high	high			high		high
	Passengers per kilometer	4	very high	high					
	Efficiency	3**		low					
	Daily waiting time	3		high					
	Peak waiting time	3		high					
	Daily trip speed	3	low				low		high
	Running speed before square	3							
	Difference in two speeds	3					high		
	Running speed after square	3					low		
	Dropped-off passengers	3					high		
	Route length	3	high	high	low				
	Picked-up passengers	3							
	Total trips demand	4	very high					high	
	Bus demand	4	very high						
Taxi demand	3			high					
Taxi demand versus bus demand	3	low	High	low					
Public transportation demand share of total demand	3	High				high		low	
Waiting time	3			high				high	
Taxi fare	3	high	high					high	
Desired Taxi fare	3	low	low					high	
Total trip by taxi	3	high							
Less than half of trip by taxi	3							high	
Alternative mode for bus	3	high	low						
Alternative mode for minibus	3			high				high	
Alternative mode for vehicle for hire	3							high	
Alternative mode for taxi service	3							high	

*Four clusters: very high, high, average, and low

**Three clusters: high, average, and low

TABLE 4.
Priority of Corridors for Policy Implementation

Score	Endpoint	Corridor	Policy
Mass Transit	Jomhuri Sq-Jahad Int-Hakim Nezami St-Azadi Sq	Jomhuri Sq	10
	Azadi Sq-Bozorgmehr Sq-Ahmadabad Sq-Qods Sq	Azadi Sq	6
	Ahmadabd Sq-Takhti Int-Haftom Moharram Int	Ahmadabad Sq	6
	Shohada Sq-Malekshahr	Shohada Sq	6
	Azadi Sq-Qaemiyah	Azadi Sq	5
	Qods Sq-Zeinabieh	Qods Sq	5
	Ahmadabad Sq-Khorasgan	Ahmadabad Sq	5
Service Quality Improvement of Bus System	Shohada Sq-Malekshahr	Shohada Sq	10
	Jomhuri Sq-Robat Blvd	Jomhuri Sq	7
	Ahmadabad Sq-Khorasgan	Ahmadabad Sq	6
	Modarres St – Qods Sq	Qods Sq	6
	Shohada Sq-Qarazi Hospital	Shohada Sq	5
	Qods Sq-Haftoon	Qods Sq	5
	Azadi Sq-Margh	Azadi Sq	6
	Azadi Sq-Sepahanshahr	Azadi Sq	6
Azadi Sq-Enghelab Sq	Azadi Sq	6	
Road Space Rationing	Jomhuri Sq-Jahad Int-Hakim Nezami St-Azadi Sq	Jomhuri Sq	4
	Jomhuri Sq-Shohada Sq-Qods Sq-Ahmadabad Sq	Jomhuri Sq	4
	Bozorgmehr Sq-Enghelab Sq	Bozorgmehr Sq	3
	Ahmadabad Sq-Emam Hossein Sq	Ahmadabad Sq	3
	Ahmadabad Sq-Takhti Int-Vafae Int	Ahmadabad Sq	3
	Shohada Sq-Jomhuri Sq	Shohada Sq	3
Paratransit	Jomhuri Sq-Esteghlal Sq	Jomhuri Sq	9
	Ahmadabad Sq-Khorasgan	Ahmadabad Sq	8
	Azadi Sq-Baskool	Azadi Sq	8
	Azadi Sq-Hotelpol	Azadi Sq	7
	Jomhuri Sq-Simin Int	Jomhuri Sq	7
	Azadi Sq-Enghelab Sq	Azadi Sq	7
	Jomhuri Sq-Rehnan	Jomhuri Sq	7
	Shohada Sq-Qarazi hospital	Shohada Sq	6
	Azadi Sq-Margh	Azadi Sq	6
	Azadi Sq-Sofeh Terminal	Azadi Sq	6
	Jomhuri Sq-Robat St	Jomhuri Sq	7
	Azadi Sq-Bozorgmehr Sq-Ahmadabad Sq-Qods Sq	Azadi Sq	7
	Qods Sq-Haftoon	Qods Sq	6
	Ahmadabad Sq-Khorasgan	Ahmadabad Sq	6
	Azadi Sq-Baskool	Azadi Sq	6
	Khaju-Qods Sq	Qods Sq	6
Khane Esfahan-Jomhuri Sq	Jomhuri Sq	5	
Shohada Sq-Malekshahr	Shohada Sq	5	

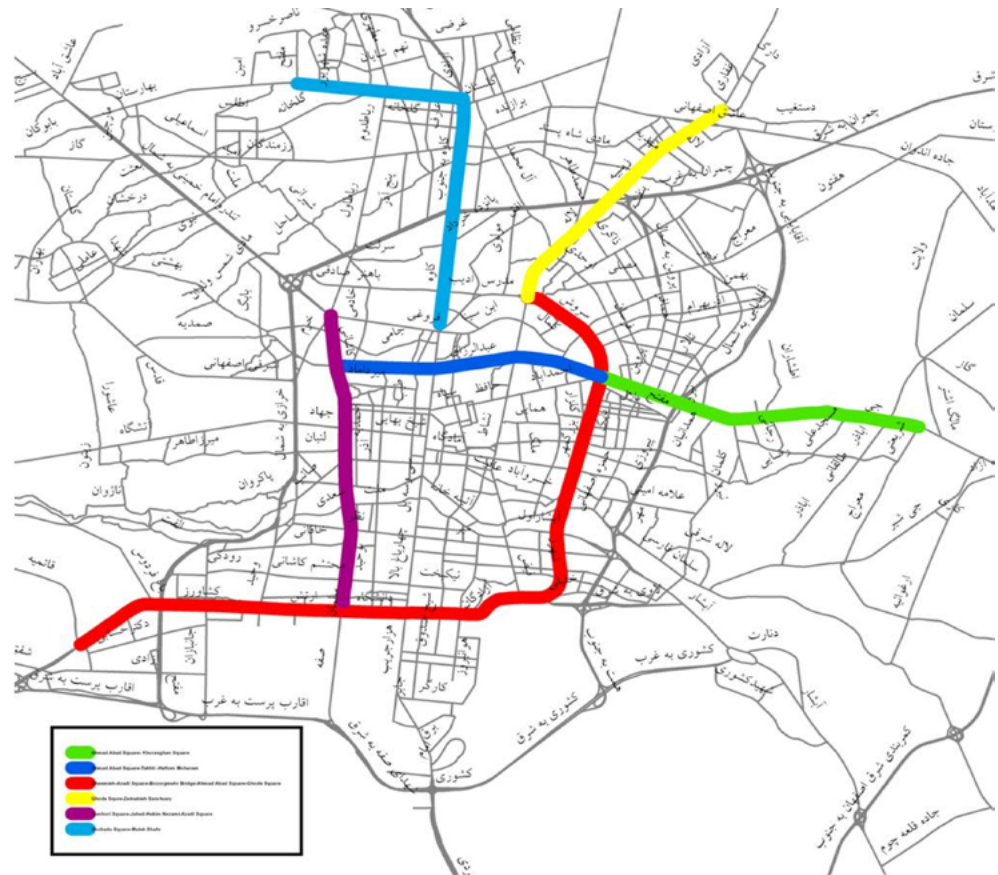
TABLE 4. (cont'd.)
Priority of Corridors for Policy Implementation

Score	Endpoint	Corridor	Policy
Paratransit (cont'd.)	Allameamini St-Baghgoldaste St	Noorbaran Int	5
	Azadi Sq-Margh	Azadi Sq	5
	Jomhuri Sq-Esteghlal Sq	Jomhuri Sq	5
	Azadi Sq-Sepahanshar	Azadi Sq	5
	Jomhuri Sq-Modarres St	Jomhuri Sq	5
	Jomhuri Sq-Zeinabieh	Jomhuri Sq	5
	Jahad Int-Zeinabie	Jahad Int	5
Service Quality Improvement of Taxi System	Jomhuri Sq-Ashoora	Jomhuri Sq	6
	Bozorgmehr Sq-Ayenehkhaneh Blvd	Bozorgmehr Sq	6
	Jomhuri Sq-Modarres St	Jomhuri Sq	5
	Azadi Sq-Amirieh	Azadi Sq	4
	Jomhuri Sq-Amirkabir Blvd	Jomhuri Sq	3
	Ahmadabad Sq-Sarhang Bridge	Ahmadabad Sq	3
	Azadi Sq-Sepahanshahr	Azadi Sq	3
	Noorbaran-Shahrestan Bridge	Noorbaran Int	4
	Haftom Moharram Int-Ashoora	Haftom Moharram Int	4
	Ahmadabad Sq-Atashgah St	Ahmadabad Sq	4
	Haftom Moharram Int-Montazeri St	Haftom Moharram Int	4
Taxi for Hire	Jomhuri Sq-Khaneesfahan	Jomhuri Sq	6
	Shahrestan Bridge-Bozorgmehr Sq	Bozorgmehr Sq	6
	Azadi Sq-HotelPol	Azadi Sq	5
	Azadi Sq-Rahahan	Azadi Sq	5
	Bozorgmehr Sq-Khorasgan University	Bozorgmehr Sq	5
	Jomhuri Sq-Zayandehrood Terminal	Jomhuri Sq	4
	Haftom Moharram-Zayandehrood Terminal	Haftom Moharram Int	4
	Azadi Sq-Sepahanshahr	Azadi Sq	4

The AHP results imply that policies including mass transit and implementation of traffic restriction measures have the highest influence on achieving the objectives for city transportation. According to Table 4, the main corridors of mass transit of the city connecting the zones with significant trip generation and attraction in Isfahan are presented in Figure 2. Because the proposed mass transit corridors are partially or totally located downtown, implementing them would necessitate traffic limitations for private vehicles. In addition, traffic restrictions for private vehicles in the central area of the city could lead to a revival of tourism and historical streets, thanks to giving priority to pedestrians. Constructing park-and-ride facilities and terminals or improving the traffic condition of squares at the start/end points of bus lines, even at a small scale, has high priority to boost the condition of significant corridors. Furthermore, deploying shared taxi and improving its system could help to transport a large number of passengers between major origins and destinations who are waiting at stations to catch a shared taxi in the city streets. It is observed that passengers are willing to pay

more money to avoid a long waiting time. Taxi for hire is more likely to be used in Azadi Sq, Rahahan, Sepahanshahr, Bozorgmehr Sq, Shahrestan Bridge, and Khorasgan university stations, because passengers residing in these locations have a high income level and expectation. Small stands for passengers and taxis could be installed on the city streets; taxi service should not necessarily have a fixed station if communication with a navigation system from a permanent place via a wireless system, telephone, or cellphone is possible.

FIGURE 2.
Proposed corridors for mass transit system in Isfahan



In spite of deficits and problems, a bus system is still the best public transportation system for passengers, so a bus system improvement policy for the studied corridors should have the highest priority; however, other paratransit systems such as vans and minibuses should not be ignored. Considering taxi system limitations such as short life cycle and low passenger capacity, a paratransit system could be new and efficient in Isfahan. This system would increase the beauty of the city, decrease environmental pollution, and occupy three times less space than roads in comparison with taxis, considering the number of passengers transported. Establishing stations for picking up and dropping off passengers without any interference in a square's traffic is an important issue in planning paratransit system in Isfahan.

Conclusions and Further Study Suggestions

Different policies of public transportation as feasible alternatives play an important role in achieving objectives of sustainable development as the goal in each city. Policies such as developing mass transit and implementing traffic demand strategies such as road space rationing have the most influence on attaining the city's transportation objectives. Because of expenses and resource limitations, some corridors and special areas of the city were identified to be the most appropriate for assigning the policies. In this paper, the priorities of public transportation corridors were determined for policy implementation via available data from the city transportation system, interviews with passengers, and polling of experts, practitioners, planners, and city managers. The findings indicate that the general evaluation of corridors that are suitable for performing each policy as a practical alternative. In essence, each corridor may be suitable for implementing some policies, which should be analyzed technically and economically in detail at the level of installation and performance. Finally, the authors recently proposed the studied corridors to the City Council to get approval for implementation of a BRT system based on our findings. Support for a BRT system was approved unanimously by the City Council in July 2015. It is also worth noting that the overall assessment of the approved BRT corridors should be considered precisely as an implication of policy in future.

Although the proposed approach is flexible, additional policies that are suitable for different public transportation corridors can be included to the model and can be evaluated for specific corridors. The approach of this article can be used in other cities, and the importance of the objectives and policies for selection of an appropriate transportation system for each city can be compared and evaluated. In addition, in further studies, more technical and economic aspects of one or more policies should be considered in more detail.

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Investigating the Effect of Gasoline Prices on Transit Ridership and Unobserved Heterogeneity

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Abstract

Based on a unique scanner panel data set on debit and credit card transactions, we examined the effect of gasoline prices on individual choices between private vehicle use and public transit ridership. The unique feature of our data allowed us to address possible heterogeneity in the effect of gasoline prices and to explicitly incorporate the link between private vehicle use and public transit ridership. A series of empirical analyses reveal that there is significant heterogeneity in the effect of gasoline prices on fuel consumption and that financial constraints and commitment to vehicle use determine individual sensitivities to the price of gasoline. The substantive empirical knowledge provided about individual decisions concerning transit modes contributes meaningful implications and effective guidance for practitioners and policymakers.

Key words: *Public transit ridership, private vehicle use, gasoline prices, heterogeneity*

Introduction

In accordance with growing concerns about increasing levels of carbon and energy security, many industrialized nations and organizations have begun to advocate for transformation of the energy market, and firms have begun to make extensive investments in sustainable energy products and services. However, many parts of the globe still heavily rely on oil, coal, and natural gas, and such fossil fuels are the primary resources used to heat homes, run vehicles, and power industry. In particular, fossil fuels meet 85% of the total energy requirement and 95% of transportation-sector consumption in the US (Economy Watch 2010). Similar patterns also are witnessed in other industrialized countries—for instance, in 2014, 66% of the total electricity generated in Korea, which was investigated in this paper, was accounted for by fossil fuels (U.S. Energy Information Administration 2015).

Under such circumstances, recent fluctuations in gasoline prices reignited interests in understanding gasoline demand, and numerous studies in different fields have been compiled to predict the impact of policy interventions on gasoline consumption (e.g., Dahl 1996; Dahl and Sterner 1991; Drollas 1984; Espey 1997; Sterner 1990). One particular object of these studies has been to understand how the price of gasoline influences ridership on public transportation, focusing on shorter time horizons in which it is not feasible for people to alter their commitment to fuel consumption or to buy more fuel-efficient cars (Golub 2010; Mattson 2008). Such a discussion is important because the use of fossil fuels by private and public transportation systems has been increasing significantly over the years, and fossil fuels currently account for 44.9% of the total refined products derived from crude oil. Furthermore, those affected by the resultant costs of private vehicle use, such as noise emission and increased levels of pollution, are not limited to motorists (Economy Watch 2010; Institute for Energy Research 2015).

However, studies in this stream typically are conducted at an aggregate level, and the link between private vehicle use and public transit ridership has hardly been addressed explicitly. As a result, little is known about how individuals react to gasoline prices or to policy interventions or about how the individual mode choices are made. Yet the literature shows that there is significant heterogeneity in individual responses to fluctuations in prices (e.g., Kim and Rossi 1994; Wakefield and Inman 2003) and that the purchase decision of a product is directly related to that of its substitutes in many other contexts (Allenby et al. 2004; Anderson and Simester 1998; Dube and Gupta 2008). Thus, the common restriction imposed in these studies allows only limited implications about the demand for gasoline and ridership on public transit to be extrapolated.

Such an absence is surprising, considering that the environmental problems resulting from fossil fuel use and related industries are of extreme importance to the economy. A key contributing reason for the limited work exploring individual responses to fluctuations in gasoline prices is the lack of microdata on individual decisions in the two categories. Unlike in many other retail industries for which scanner panel data have been used extensively in research on differences in individual behaviors, panel data on purchases of or expenditures on fuel and transit ridership have not been widely accessible to academics.

In this study, we examined the effect of gasoline prices on individual choices between private vehicle use and public transit ridership based on a unique scanner panel data set on debit and credit card transactions. Through a series of empirical analyses, we explicitly addressed possible heterogeneity in the effect across individuals and present robust evidence that, with significant heterogeneity across individuals, gasoline prices have a statistically and economically significant effect on fuel consumption and public transit ridership. The substantive empirical knowledge provided herein about individual decisions concerning transit modes contributes meaningful implications and effective guidance for practitioners and policymakers.

The paper proceeds as follows. Section 2 discusses the relevant literature, and Section 3 explains the data. Section 4 presents the empirical models and their results. Section 5

describes robustness checks of our findings, Section 6 addresses the implications of our findings, and Section 7 concludes.

Related Literature

Extensive studies have been conducted to explore how the demand for gasoline changes in response to fluctuating or rising gasoline prices. A wide range of assumptions and model specifications has been employed to investigate data across different time periods and regions, yielding predictions about the impact of policy interventions and explanations about differences in gasoline consumption (Dahl 1986; Dahl and Sterner 1991; Drollas 1984; Schipper et al. 1993; Sterner 1990). Several meta-analyses have summarized the estimates of price or income elasticities in past research and explained the variations in the results across studies (Assmus 1984; Espey 1997; Espey 1998; Tellis 1988).

An interesting feature of such efforts is that researchers tend to pay particular attention to different margins over which different market players make adjustments. For example, Donna (2010), Wang and Chen (2014), and Goldberg (1998) investigated how, in the short run, drivers alter how much they drive when gasoline prices change; Busse et al. (2012) examined whether car buyers buy more fuel-efficient cars in response to increasing gasoline prices in the medium run; and Gramlich (2009) explored whether gasoline prices impact decisions of automobile manufacturers concerning the fuel economy of vehicles they produce in the long run. Because the adjustments that can be made over different time horizons can differ considerably, no simple answers can describe how gasoline prices affect gasoline usage completely. Nonetheless, conventional wisdom is that the demand for gasoline is fairly inelastic over short time horizons, on which we focus in this paper.

Beyond the demand for gasoline, ridership on public transit also has been examined in systematic research investigating the impact of gasoline prices. A noteworthy finding presented in many of these studies is that an increase in gasoline prices has a statistically-significant but economically-marginal effect on transit ridership in the short run (e.g., Agathe and Billings 1978; Masayuki and Allen 1986; Navin 1974; Nizlek and Duckstein 1974; Rose 1986; Wang and Skinner 1984; Wolff and Clark 1982). For example, cross-elasticity estimates for transit ridership due to gasoline prices typically fall below 0.15 in the short run, whereas longer-run estimates range from 0.12 to 0.40 (Mattson 2008).

However, there are mixed empirical findings about how the short-run impact of gasoline varies across the population. For example, McLeod et al. (1991) modeled gasoline price as an important determinant of transit ridership but found no evidence that it is a significant factor. Kitamura (1989) raised the issue of interrelationship between car use and transit ridership and found that a change in car use influences transit use.

To explain such mixed empirical results, researchers consider that various factors such as parking, fuel, transit quality, and transit fare prices have some interaction with ridership on public transit under conditions of changing gasoline prices. For example,

the low-income population suffers more from rising gasoline prices as a result of limited transit options; substantial transit systems enable a realistic alternative for large segments of the population, resulting in a larger mode-choice response to gasoline price changes; and the modal shift to public transit first occurs among travelers making the most expensive automobile trips (Currie and Phung 2007; Haire and Machemehl 2007; Litman 2004; Mattson 2008; McFadden and Talvitie 1977; Sanchez 1999; Sanchez and Peng 2004; Wang and Skinner 1984).

We contribute to these lines of research, in that our analyses allow for a comprehensive understanding of the individual decisions between the use of one's private vehicle and ridership on public transit during periods of fluctuating gasoline prices. Given the significant role of transportation agencies in the transit ridership (Agathe and Billings 1978; Horowitz 1982; Navin 1974; Sagner 1974), the considerable advantage of our data provides important implications about how policy changes would influence members of the population with different characteristics.

Data

Our data came from a company that developed a household account-book application. The application automatically records credit and debit card transactions based on text messages its users receive on their cell phones. The information collected from the text message includes for each transaction the customer's individual identifier, date and time, amount paid, name of the retail store, and retailer type (identified based on its name). The application exclusively serves Koreans, and, thus, our data were limited to transactions of Korean customers. Yet, given the construct of the data collection process, transaction information included in the data is not limited to particular categories, and the application records data for an extensive range of expenses.

Our data set included the records of retail transactions of 12,000 individuals in 2014. The sample was randomly drawn by the company from its entire customer pool. Examining transaction information for these 12,000 individuals, however, we identified that only 1,521 individuals had made at least one purchase of a transit card or an individual trip by public transit (bus or rail). Because our study aimed to investigate the impact of gasoline prices with a particular focus on public transit ridership as well as on the demand for gasoline, we restricted our attention to these 1,521 individuals for further empirical analyses.

Table 1 describes the transaction information of 12,000 (full sample) and 1,521 (estimation sample) individuals. Of a total monthly expenditure of 832,538 won, an average individual in the estimation sample spent 74,284 won on gasoline and 43,513 won on public transit. Similarly, an average individual in the full sample spent 73,874 won on gasoline out of total monthly expenditures of 824,283 won, although the expenditures on public transit in this group were much smaller than those of the estimation sample. Given the construction of the estimation sample, the considerable differences in expenditures on public transit are intuitive.

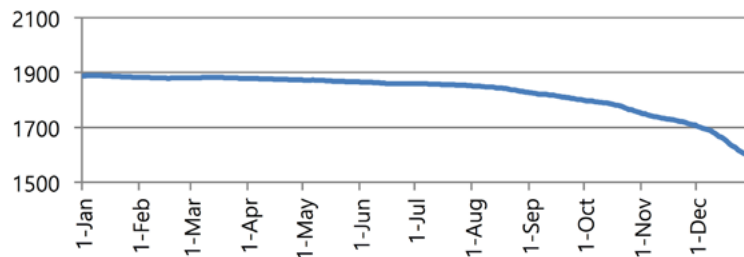
TABLE 1.
Descriptive Statistics for
Monthly Expenditures

Average Weekly Expenditures	Estimation Sample (won)	Full Sample (won)
Total expenditures	832,538	824,283
Gasoline	74,284	73,874
Public transportation (bus, subway, or train)	43,513	5,515

Descriptive Analysis

In 2014, oil prices dropped dramatically. Beginning at \$107.33 on January 2, benchmark crude fell below \$100 in March and, in July, reached \$66.90, its lowest value since 2008. By December, the price of benchmark crude oil dropped to \$62.75, representing a 40% decrease for the year. As a net importer of crude oil, Korea exhibited similar patterns in the price of gasoline, and retail prices in Korea consistently fell throughout 2014, as described in Figure 1. Although Figure 1 suggests, compared to the drop in oil prices, a relatively small decrease in the retail price of gasoline in 2014, note that gasoline prices retreat slowly when oil prices fall.

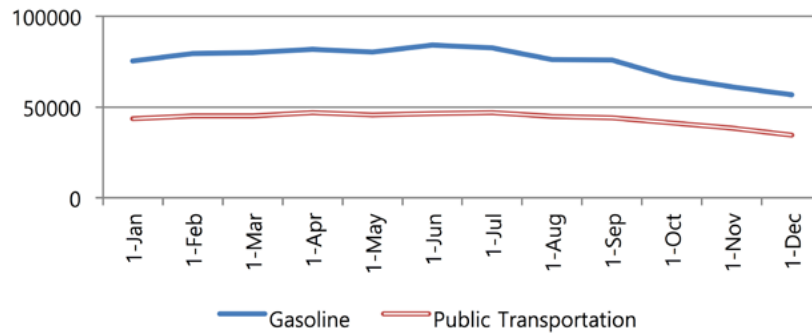
FIGURE 1.
Median gasoline prices, 2014
(won per liter)



Upon finding the considerable and consistent drop in gasoline prices throughout 2014, we focused on the effect of gasoline prices on fuel consumption and transit ridership. In particular, we first calculated individual monthly expenditures on gasoline and transit ridership and examined whether any particular patterns were to be found in relation to the persistent decrease in gasoline prices. According to the extant literature on the effect of gasoline prices, the population should switch to private vehicles from public transit, although not to a dramatic extent, and transit expenditures, therefore, were expected to decrease during the sample period.

Figure 2 shows graphs of the two types of expenditures. The first interesting feature to be noted in Figure 2 is that the average monthly expenditures on public transit gradually decreased throughout 2014, as predicted based on the decrease in gasoline prices. Considering that fares for public transportation remained stable during the sample period, the gradual but steady decrease in expenditures on public transit empirically support the argument that the demand for public transport decreased during the period with falling gasoline prices.

FIGURE 2.
Average monthly expenditures, 2014 (won)



Turning to the average monthly expenditures on gasoline, Figure 2 implies that the population generally reduced their gasoline expenditures during 2014. Such a decrease in gasoline expenditures may seem to imply a decrease in fuel usage at first glance. However, note that the decrease in gasoline expenditures was modest relative to the dramatic decrease in retail gasoline prices in 2014. Together with the decrease in expenditures on public transit, this suggests that the population increased their gasoline consumption as retail gasoline prices decreased by switching to private vehicle use from transit ridership. However, we caution that the approach we adopted in this subsection is more descriptive and may not be well suited to conclusively validate this conclusion.

Given the descriptive evidence about the impact of gasoline prices on transit mode choice, we noted that transit commuters often use transportation cards to avoid the hassle of purchasing single-journey tickets. Although many credit and debit cards provide transit card services, the absence of a concrete link between the expenditure and transit ridership could introduce a bias into our result. Thus, we calculated summary statistics for transactions made for public transportation and compared them with the public transportation fares. Table 2 shows that the three quartiles of these transactions were fairly similar to minimum transit fares, whereas the average was approximately three times the minimum bus fare. We, therefore, considered the that summary statistics reported in Table 2 provide empirical evidence that transit riders used their debit and/or credit cards as transit cards and ensured that the expenditures on public transit could serve a proxy for transit ridership.

TABLE 2.
Descriptive Statistics for
Public Transit Transactions

	Public Transit Fares (Minimum)	Transaction for Public Transportation	
Bus	1,200 won	1 st Quartile	1,550 won
Subway	1,250 won	Median	1,200 won
		3 rd Quartile	1,200 won
		Average	3,786 won

Gasoline Prices and Individual Decisions of Transit Modes

Based on the descriptive evidence for the effect of gasoline prices, we developed models of weekly expenditures on gasoline and public transit as a function of gasoline prices. The models examine how the changes in gasoline prices influenced weekly

expenditures on gasoline and public transit, respectively, after explicit controlling for other explanatory variables. Beyond the price of gasoline, the models include two groups of explanatory variables. The first group controls for the effect of heterogeneity in preferences across individuals, using demographic information and individuals' value of the dependent variable during an initialization period (Briesch et al. 2009; Bucklin et al. 1995; Ma et al. 2011). More specifically, data during the first four weeks of our sample period were employed to construct the initialization period dependent value and then excluded in the further analyses to avoid a possible endogeneity. Finally, the second group accounts for time trends and general economic conditions.

Turning to the effect of gasoline prices, we noted that it may have taken more than a week for people to react to the changes in gasoline prices and that gasoline prices may have influenced individual transit mode-choices with a time lag. Although we considered that the advanced public transit system enabled a realistic alternative in the very short run, we, thus, included the lagged gasoline prices and tested the effect of lagged gasoline prices on their gasoline consumption and transit ridership.

The model of gasoline expenditures employs log-log form, and the estimation results provide coefficients in percentages instead of absolute terms. This is because considerable variations are present in the magnitude of the expenditures on gasoline and public transit across individuals. Log-log linear specification is widely employed by studies exploring the effect of gasoline prices on consumer expenditures in different categories (Gicheva et al. 2010; Ma et al., 2012). The model is in the following form:

$$\log GasExp_{it} = \alpha_1^1 + \beta_1^1 \log GasExp_{0i} + \beta_1^2 Demog_i + \gamma_1^1 \log Price_t + \gamma_1^2 \log Price_{t-1} + \delta_1^1 X_t + \varepsilon_{1it}^1 \quad (1)$$

The dependent variable, $GasExp_{it}$, is individual i 's expenditures on gasoline for week t ; $GasExp_{0i}$ is individual i 's value of the dependent variable during the four-week-long initialization period; $Demog_i$ is a group of demographic variables, including dummies indicating gender and age; $Price_t$ and $Price_{t-1}$, the variables of primary interest, are the average retail price of gasoline at week t and $t-1$; and X_t is a set of controls, including dummies for time trends and age groups.

Similarly, the model of expenditures on public transit is specified as a function of the same explanatory groups, with individual i 's expenditures on public transit for week t , $PubExp_{it}$, as the dependent variable. This model is also specified in log-log form:

$$\log PubExp_{it} = \alpha_2^1 + \beta_2^1 \log GasExp_{0i} + \beta_2^2 Demog_i + \gamma_2^1 \log Price_t + \gamma_2^2 \log Price_{t-1} + \delta_2^1 X_t + \varepsilon_{2it}^1 \quad (2)$$

Table 3 summarizes the estimation results based on 1,521 individuals who had made at least one purchase of a transit card or an individual trip by public transit. First focusing on the impact of gasoline prices on gasoline consumption, a decrease in gasoline prices was associated with a statistically-significant decrease in gasoline expenditures. In particular, weekly gasoline expenditures decreased by 0.65% for a 1% decrease in the retail price of gasoline, implying that the elasticity of demand for gasoline is -0.35

$(\frac{1 - \frac{1-0.0065}{1-0.01}}{1-0.99} = \frac{-0.0035}{0.01})$. This is consistent with the extensive literature on gasoline demand,

in which the elasticity of gasoline demand turns out to be between 0 and -1.36 (Espey 1998). Turning to the effect of lagged gasoline prices, γ_2^2 also turned out statistically-significant, showing that a 1% decrease in the retail gasoline prices would result in a 0.10% decrease in the gasoline expenditures for the following week.

TABLE 3.
Estimation Results for Log
Expenditures Models

	Gasoline	Public Transportation
Expenditures during initialization period	0.4982** (0.0065)	0.1865** (0.0248)
Gasoline prices	0.6257** (0.1854)	0.1714** (0.2014)
Lagged gasoline prices	0.1054** (0.0425)	0.0854** (0.0352)
Gender dummy	0.0015 (0.0385)	0.0063 (0.0284)
2nd quarter	0.1247* (0.0524)	0.0021 (0.0725)
3rd quarter	0.0854 (0.0695)	0.0254 (0.0621)
4th quarter	0.2148* (0.0895)	0.0084 (0.0685)
30s	0.6257** (0.0485)	-0.2857** (0.0254)
40s	0.8571** (0.0621)	-0.4965** (0.0758)
50s	0.7848** (0.0895)	-0.4896** (0.1054)
60s	1.2147** (0.4254)	-0.8745** (0.0895)
Intercept	-1.2547* (0.4785)	0.4258** (0.0895)
N	72,479	72,954
Adjusted R-squared	0.108	0.076

* $p < 0.05$; ** $p < 0.01$

Note: Standard errors are shown in parentheses.

In the model of expenditures on public transit, the coefficient of gasoline prices also turned out to be statistically-significant and positive. The results suggest that weekly expenditures on public transit decrease by 0.17% for a 1% decrease in the retail price of gasoline for an average individual, implying that cross-elasticities for transit ridership are 0.17. Finally, similar to the model of gasoline expenditures, the effect of lagged gasoline prices also was statistically significant but smaller than the effect of gasoline prices.

The cross-elasticities for transit ridership were somewhat higher than those reported in the extant studies (Mattson 2008). Remember that Korea has one of the world's most advanced public-transportation infrastructures, and local urban taxis, buses, and subways provide exceptionally good and punctual service at fairly low fares. Thus, we considered our estimation results to be in line with our prediction. To summarize, our

interpretation of the statistically-significant effects of gasoline prices in the two models is that the population switches to private vehicle use from ridership on public transit when gasoline prices increase.

In addressing the effect of gasoline prices on gasoline consumption and transit ridership, we understand that different factors such as the availability of parking, gasoline prices, transit quality, and transit fares have considerable impact on mode choices (Bhat et al. 2009; Litman 2004; Taylor and Fink 2003; Wang and Skinner 1984). Although, among these factors, only the effect of gasoline prices is incorporated in our empirical analyses, our analyses focused on a short time horizon over which no particular systematic changes in the availability of parking, transit quality, or transit fares were likely to occur. Thus, we concluded that although our empirical analyses could not account for the effects of other factors, concerns about the omitted variable bias are not valid, despite that the findings cannot provide implications about the effects of other factors.

Finally, upon finding the intuitive results, we evaluated the robustness of our findings. We noted that there were different lengths of initialization periods or other model specifications that we could consider. Thus, we replicated the analyses by varying the length of the initialization period and using alternative model specifications. In particular, we used a six-week-long initialization period (Model 3) and a fixed-effects estimation to control for heterogeneity in preferences across individuals (Model 4).

Tables 4 and 5 report the findings for all of the replications. To summarize, the effects of gasoline prices are all statistically significant and positive despite the loss in the model fit in terms of *R*-squared, showing that the results after these adjustments were qualitatively unchanged. Our findings survived all the above robustness checks and provide strong empirical evidence that gasoline prices have statistically significant effects on gasoline expenditures and ridership on public transit.

TABLE 4.
Estimation Results for
Competing Models
(Fixed Effect)

	Gasoline	Public Transportation
Gasoline prices	0.5214** (0.2014)	0.1685** (0.0621)
Lagged gasoline prices	0.1102** (0.0036)	0.0632** (0.0221)
2nd quarter	0.1247** (0.0501)	0.0042 (0.0510)
3rd quarter	0.1301 (0.0701)	0.0421 (0.0681)
4th quarter	0.2014* (0.1109)	0.0041 (0.0874)
Intercept	2.8921** (1.0852)	5.8654** (1.2014)
N	72,479	72,954
Adjusted R-squared	0.0009	0.0008
F	8.65	4.87

* $p < 0.05$; ** $p < 0.01$

Note: Standard errors are shown in parentheses.

TABLE 5.
Estimation Results for
Competing Models (6-week
initialization period)

	Gasoline	Public Transportation
Expenditures during initialization period	0.4847** (0.0084)	0.1758** (0.0249)
Gasoline prices	0.6244** (0.2044)	0.1687** (0.1994)
Lagged gasoline prices	0.1001** (0.0357)	0.0862** (0.0301)
Gender dummy	0.0018 (0.0412)	-0.0052 (0.0251)
2nd quarter	0.0987 (0.0702)	0.0047 (0.0621)
3rd quarter	0.0725 (0.0709)	0.0321 (0.0471)
4th quarter	0.2111** (0.0987)	0.0074 (0.0687)
30s	0.4214** (0.0387)	-0.4461** (0.0451)
40s	0.8541** (0.0701)	-0.6582** (0.0541)
50s	0.7214** (0.1541)	-0.5650** (0.0922)
60s	1.0974** (0.2417)	-0.6939** (0.1759)
Intercept	-1.8741** (0.1587)	0.6820** (0.2126)
N	69,492	69,914
Adjusted R-squared	0.101	0.052

* $p < 0.05$; ** $p < 0.01$

Note: Standard errors are shown in parentheses.

Heterogeneity in Consumer Responses to Changes in Gasoline Prices

There is ample evidence that individual characteristics have a significant effect on price sensitivities in many purchase contexts (e.g., Hoch et al. 1995). Studies on gasoline demand and public transit ridership also have addressed different individual characteristics and have particularly focused on the role of income. For example, Golub (2010) noted that, in addition to ownership costs, marginal costs during periods of rising gasoline prices become particularly significant for low-income households and affect their ability to use vehicles for commuting to a considerable extent. Thus, we incorporated the effect of financial constraints into our consideration and explored the interactions between income and gasoline prices. Without a direct measure of income in the data, we found a variable that could approximate the financial constraints with which individuals are faced. More specifically, based on the recognition that consumption expenditures are closely related to financial constraints (Cutler and Katz 1991; Johnson and Smeeding 1998), using the total amount of expenditures for a

four-week-long initialization period, we constructed a measure of individual financial constraints.

We also note that, apart from the effect of income, substantial variations are present in individual gasoline expenditures, as described in Table 6. More specifically, the top 25% of the sample in terms of gasoline consumption spent more than 12 times as much on gasoline as the bottom 25% of the sample. We posited that an increase or decrease in gasoline prices, therefore, likely would not influence the population equally, as large variations in gasoline expenditures should lead to considerable heterogeneity in individuals' incentives to adjust their fuel use. For example, the population exhibiting greater gasoline consumption would be faced with a larger increase in gasoline expenditures for a won increase in gasoline prices and would therefore have larger incentives to adjust. However, at the same time, we also considered the possibility that individuals with a strong commitment to vehicle usage would maintain a high level of gasoline consumption and would therefore remain less sensitive to changes in gasoline prices. Thus, we explicitly address this particular aspect and empirically examine how baseline gasoline consumption interacts with the price of gasoline in this subsection.

TABLE 6.
Average Weekly Gasoline Expenditures

	Weekly Gasoline Expenditures (won)
1st Quartile	11,238
Median	58,754
3rd Quartile	138,524

In the presence of large differences in total and gasoline expenditures in the estimation sample, we constructed two categorical variables identifying the baseline levels of gasoline and total expenditures. "Baseline" expenditures are defined as the average weekly expenditures in the four-week-long initialization period, and the 25th, 50th, and 75th percentiles of gasoline and total expenditures were used as cutoff points for two categorical variables.

$$Group_i^{total} / Group_i^{gas} = 1 \text{ if below the 25th percentile}$$

$$Group_i^{total} / Group_i^{gas} = 2 \text{ if between 25th and 50th percentiles}$$

$$Group_i^{total} / Group_i^{gas} = 3 \text{ if between 50th and 75th percentiles}$$

$$Group_i^{total} / Group_i^{gas} = 4 \text{ if above the 75th percentile}$$

To address the possible heterogeneity in the effect of gasoline prices, we included the interaction effects between the retail price of gasoline and each of two categorical variables. Using the same explanatory variables employed in the initial analyses, we developed the following model specification:

$$\begin{aligned} \log GasExp_{it} = & \sigma_1^1 + \tau_1^1 \log GasExpe_{0i} + \tau_1^2 Demog_i + \sum_{m=1}^4 v_{m1}^1 I(Group_i^{total} = m) \\ & + \sum_{n=1}^4 v_{n1}^2 I(Group_i^{gas} = n) + \sum_{m=1}^4 v_{m1}^3 \log Price_t \cdot I(Group_i^{total} = m) + \\ & \sum_{n=1}^4 v_{n1}^4 \log Price_t \cdot I(Group_i^{gas} = n) + \sum_{m=1}^4 v_{m1}^5 \log Price_{t-1} \cdot I(Group_i^{total} = m) + \\ & \sum_{n=1}^4 v_{n1}^6 \log Price_{t-1} \cdot I(Group_i^{gas} = n) + \varphi_1^1 X_t + \omega_{1it}^1, \end{aligned} \tag{3}$$

$$\begin{aligned} \log TotalExp_{it} = & \sigma_2^1 + \tau_2^1 \log GasExpe_{0i} + \tau_2^2 Demog_i + \sum_{m=1}^4 v_{m2}^1 I(Group_i^{total} = m) + \\ & \sum_{n=1}^4 v_{n2}^2 I(Group_i^{gas} = n) + \sum_{m=1}^4 v_{m2}^3 \log Price_t \cdot I(Group_i^{total} = m) + \\ & \sum_{n=1}^4 v_{n2}^4 \log Price_t \cdot I(Group_i^{gas} = n) + \sum_{m=1}^4 v_{m2}^5 \log Price_{t-1} \cdot I(Group_i^{total} = m) + \\ & \sum_{n=1}^4 v_{n2}^6 \log Price_{t-1} \cdot I(Group_i^{gas} = n) + \varphi_2^1 X_t + \omega_{2it}^1, \end{aligned} \tag{4}$$

where $I(Group_i^{total} = k) = 1$ if $Group_i^{total} = k$ and $I(Group_i^{total} = k) = 0$ otherwise. This specification allowed us to distinguish among individuals according to their individual total and gasoline expenditures during the initialization period. For an individual with $Group_i^{total} = m$ and $Group_i^{gas} = n$, $v_{m1}^3 + v_{n1}^4$ measures the change in gasoline expenditures for a 1% price increase and $v_{m1}^5 + v_{n1}^6$ measures the change in gasoline expenditures for a 1% price increase in the past week.

Table 7 reports the coefficient estimates and their standard errors. The first overarching point to be noted in the estimation results is that an increase in gasoline prices was associated with statistically-significant changes in gasoline expenditures for all groups, whereas considerable heterogeneity in individual responses to the change in gasoline prices was witnessed. More specifically, individuals with larger baseline gasoline consumption and higher income level turned out to maintain more inelastic demand for gasoline. The current findings confirm the role of income in how gasoline prices affect fuel consumption and, at the same time, empirically supports the argument that the population with a strong commitment to vehicle usage maintains a high level of fuel consumption and remains less sensitive to changes in gasoline prices.

TABLE 7.
Estimation Results for Model
with Segmentation Variables

	Gasoline	Public Transportation
Expenditures during initialization period	0.4844** (0.0058)	0.1961* (0.0214)
Gasoline prices* Segment1	0.2429** (0.1014)	0.0824** (0.0147)
Gasoline Prices * Segment2	0.3428** (0.1011)	0.0842** (0.0186)
Gasoline Prices* Segment3	0.4069** (0.1041)	0.0862** (0.0156)
Gasoline Prices* Segment4	0.4829** (0.1078)	0.0837** (0.0181)
Gasoline Prices* Income1	0.0624** (0.0286)	0.0481** (0.0117)

TABLE 7. (CONT'D.)
Estimation Results for Model
with Segmentation Variables

	Gasoline	Public Transportation
Gasoline Prices* Income2	0.0856** (0.0284)	0.0307** (0.0106)
Gasoline Prices* Income3	0.1239** (0.0297)	0.0287** (0.0104)
Gasoline Prices* Income4	0.1526** (0.0298)	0.0267** (0.0110)
Lagged Gasoline Prices* Segment1	0.0104** (0.0017)	0.0014** (0.0001)
Lagged Gasoline Prices* Segment2	0.0121** (0.0018)	0.0018** (0.0001)
Lagged Gasoline Prices* Segment3	0.0111** (0.0017)	0.0019** (0.0002)
Lagged Gasoline Prices* Segment4	0.0118** (0.0017)	0.0014** (0.0002)
Lagged Gasoline Prices* Income1	0.0128** (0.0042)	0.0012** (0.0004)
Lagged Gasoline Prices* Income2	0.0132** (0.0041)	0.0009** (0.0004)
Lagged Gasoline Prices* Income3	0.0134** (0.0042)	0.0013** (0.0004)
Lagged Gasoline Prices* Income4	0.0137** (0.0046)	0.0008** (0.0003)
Segment2	0.1042** (0.0324)	-0.0542** (0.0217)
Segment3	0.1524** (0.0317)	-0.0841** (0.0208)
Segment4	0.1874** (0.0318)	-0.1012** (0.0209)
Income2	0.2079** (0.0241)	-0.0447** (0.0081)
Income3	0.2748** (0.0249)	-0.0487** (0.0087)
Income4	0.2821** (0.0236)	-0.0514** (0.0084)
Gender dummy	0.0174 (0.0219)	0.0110 (0.0121)
2nd quarter	0.1047 (0.0698)	0.0044 (0.0224)
3rd quarter	0.1001 (0.0687)	0.0084 (0.0217)
4th quarter	0.1406** (0.0694)	0.0074 (0.0268)
30s	0.0472** (0.0100)	0.0625** (0.0218)
40s	0.0849** (0.0098)	0.0625** (0.0214)

	Gasoline	Public Transportation
50s	0.0684** (0.0099)	0.0647** (0.0217)
60s	0.0842** (0.0101)	-0.0841** (0.0219)
Intercept	-1.6847** (0.283)	0.5471** (0.217)
N	72,479	72,954
Adjusted R-squared	0.154	0.068

* $p < 0.05$; ** $p < 0.01$

Note: Standard errors are shown in parentheses.

Turning to the model of transit expenditures, there was limited heterogeneity in individual responses across segments. Yet, for the decrease in gasoline prices, individuals with low income generally decreased their transit ridership to a greater extent, and, more interestingly, the effect of gasoline prices decrease monotonically with baseline gasoline expenditures. We interpret the results as low-income populations made sufficient adjustments in their gasoline consumption to retain persistent gasoline expenditures irrespective of the retail prices of gasoline and switched to public transit to reduce their vehicle use.

To sum up, after explicitly controlling for heterogeneity across individuals, we found empirical evidence that financial constraints and commitment to vehicle usage have significant interaction effects with the price of gasoline. Our results confirm that the population switches between private vehicle use and ridership on public transit and identify how the effect of gasoline prices differs across segments of the population. Adding substantive empirical knowledge about public transit ridership and the demand for gasoline, our findings provide important guidance for policymakers and practitioners, and we address the implications of our findings in the next section.

Discussion

In an empirical investigation using unique panel data on individual expenditures, we found that gasoline prices had a statistically-significant effect on gasoline and transit expenditures, with the presence of considerable heterogeneity. Confirming the moderating effect of financial constraints, the analyses yielded empirical evidence showing that commitment to vehicle usage also plays an important role in determining sensitivities to the price of gasoline and ridership on public transit.

Our findings have an important implication for policymakers. With growing concerns about carbon emissions and energy security, higher gasoline prices have been imposed to induce a shift from private vehicle traffic to public transit in many industrialized countries. However, as described in the previous section, relatively inelastic demand for gasoline implies only a limited regulative effect despite the strong fiscal effect.

In particular, a noteworthy feature is that individuals with inelastic gasoline demand generally consume the largest amount of fuel. Given that vehicle use is considered more essential for work and business trips (e.g, Storchmann 2001), such findings indicate that the relative inelastic demand of these segments can be closely linked to the productivities of other sectors in the economy. This particular aspect also was confirmed by our data, in that the individuals with high levels of gasoline consumption purchased significantly more often during weekdays (see Table 8)—which is important because drivers usually follow weekday routines and trips for leisure or recreation during weekends can be greatly reduced, particularly in comparison to work commutes. Raised fuel taxes, therefore, can have an adverse effect on productivities and induce deficits in different sectors. This aspect should not be overlooked, especially because a substantial increase in gasoline prices often accompanies a significant negative shock to the economy.

TABLE 8.
Average Number of Gasoline Purchases

	During Weekdays	Total
Gas Expenditures 1	0.1625 (62.69%)	0.2592
Gas Expenditures 2	0.5415 (60.52%)	0.8947
Gas Expenditures 3	1.3006 (82.38%)	1.5789
Gas Expenditures 4	2.3574 (94.59%)	2.4923

Given these considerations, to reduce environmental problems, alternative means of transportation must be provided for individuals with a strong commitment to vehicle use. In addition to subsidies for public transit services or reduced fares for worker or student tickets, for example, investment in and policies advocating for more fuel-efficient or alternative-fuel vehicles are necessary. Government incentives to promote or develop fuel cell or electric vehicles using profits from higher fuel taxes help reduce the levels of carbon in the atmosphere without further disrupting productivities. The restricted scope of our paper does not allow us to counterfactual such policy intervention; rather, the primary objective of this discussion is to present a particular implication for practitioners and policymakers. Thus, we hope our research stimulates further efforts to investigate our argument.

Conclusion

Based on panel data on gasoline and transit expenditures, we examined how gasoline prices impact gasoline consumption and ridership on public transit. The unique feature of our data allowed us to address possible heterogeneity in the effect of gasoline prices, and our analyses yielded strong empirical evidence that financial constraints and commitment to vehicle use determine individual sensitivities to the price of gasoline and modal shift between private vehicle use and public transit ridership. In particular, the low-income population reduced gasoline consumption and increased their transit ridership during the period of rising gasoline prices; the high-income population with a

strong commitment to vehicle use maintained fairly inelastic demand for gasoline and public transit.

Our findings contribute substantive empirical knowledge about individual decisions between public transit and private vehicle use. Extensive studies have been compiled to address the effect of gasoline prices on gasoline consumption and transit ridership. However, such studies are typically conducted at an aggregate level based on data for either fuel consumption or transit ridership. As a result, less is known about individual responses to changes in gasoline prices and how decisions concerning fuel consumption and transit ridership relate to each other, and our study concerned itself primarily with this issue.

We note that our findings concern the short-run effect of gasoline prices and provide limited implications about how gasoline prices influence gasoline consumption and ridership on public transit over longer time horizons. Nevertheless, we have witnessed that short-run changes in gasoline prices have a significant effect on the economy, and, therefore, it is important to understand the effect in the short run.

Acknowledgments

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Assessing Park-and-Ride Efficiency and User Reactions to Parking Management Strategies

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Abstract

Increasing the number of spaces at overutilized park-and-rides often is not possible due to budgetary and other constraints. Instead, transit agencies may instead seek to maximize the number of people that are able to use the existing spaces through various parking management strategies. Unfortunately, the efficiency of park-and-rides is difficult to measure, so agencies cannot accurately quantify existing use or improvement after parking management strategies have been applied. This study proposed and tested a method to measure the person-efficiency of park-and-ride lots through an onsite audit. Additionally, a user survey was proposed to confirm the audit results and unveil reactions to parking management strategies to increase person-efficiency. The onsite audits and user surveys were conducted at several overutilized park-and-ride lots in the Central Puget Sound Region of Seattle, Washington. The results show that the person-efficiency can be measured easily, and several potential avenues to increase person-efficiency of park-and-rides are identified.

Keywords: Park-and-ride lots, parking management, parking pricing

Introduction

Park-and-ride lots have become a prominent feature of dense metropolitan regions in the United States since their emergence in the 1930s (Noel 1988). These facilities are used to promote the use of higher-occupancy transit vehicles in urban areas by providing commuters with a more convenient means—driving—to access transit service (Turnbull 1995). Although there are some mixed findings in the literature (Meek et al. 2008, 2010), increased transit use generally is related to decreased vehicle miles traveled and other negative externalities associated with automobile use (van der Waerden et al. 2011). Park-and-rides also are associated with additional benefits to users and transit agencies, including convenience, reduced trip costs, increased travel comfort,

aggregation of transit demand, and faster commercial transit speeds (Bowler et al. 1986; Noel 1988). Although some disadvantages exist—specifically, transfer of congestion from one area to another, underutilization, increased congestion due to induced travel demand, and contribution to sprawling land use patterns (Parkhurst 2000)—park-and-rides are generally viewed positively in urban transportation systems.

Existing practitioner guidebooks provide well-established guidelines for implementing park-and-ride facilities (Bowler et al. 1986; Bullard and Christiansen 1983; Turnbull 1995). The majority of more recent research literature focuses on methods to optimally locate these facilities within an existing network (Aros-Vera et al. 2013; Faghri et al. 2002; García and Marín 2002; Horner and Groves 2007) or idealized network structures (Liu et al. 2009; Wang et al. 2004). However, little guidance exists to address a rapidly-emerging problem: the overutilization of capacity-constrained park-and-rides. This is a significant issue that affects many major metropolitan regions with well-developed transit and park-and-ride systems. For example, an audit of existing lots in the Puget Sound Region reveals that approximately 19,700 of the available 25,367 parking spaces at park-and-ride lots (78%) are used on a daily basis, and over half of these lots are either full or nearly so (King County Metro Transit 2014). The average lot utilization rates in Snohomish and Pierce counties are 87% and 77%, respectively. Historical data also reveals that the demand for these facilities is steadily increasing and is likely to continue in the future. Another documented example (Shirgaokar and Deakin 2005) suggests that overutilization is a problem within the San Francisco Bay Area, where 4 of 7 surveyed locations had utilization rates greater than 90%.

Whereas full parking spaces are a sign of well-used facilities, lack of parking space availability means that the lots are not able to serve additional commuters. A potential solution to address this problem is to increase the number of parking spaces; however, doing so is expensive and can be unpopular in some neighborhoods. Instead, agencies are beginning to recognize the need for other types of parking management strategies at park-and-rides to increase the number of people that are able to use the overutilized facilities to access transit (Habib et al. 2013; Hendricks and Outwater 1998). Agencies are considering strategies that prioritize multiple-occupant vehicles over single-occupant vehicles (SOV) so that the same number of spaces can serve more people. Although such policies might cause some choice transit users to abandon transit altogether, the net benefit still might be positive if these policies increase the total number of people who are able to use the park-and-rides to access transit.

Unfortunately, agencies generally have little to no data on the number of people served by parking spaces at park-and-rides since there is no well-established methodology to estimate the person-efficiency of these lots. Agencies also do not know how users may react to potential parking management strategies. In light of this, the purpose of this study was to propose a method to measure the person utilization of parking spaces at existing commuter park-and-ride lots and assess user feedback to strategies designed to increase the number of people who can be served by these facilities. The estimates of person utilization were obtained through an onsite audit of the use of existing facilities, and these estimates were confirmed using user intercept surveys conducted at these facilities. Additionally, the intercept survey provides more insight on how existing park-

and-rides are used and user feedback on proposed parking management strategies. Both were tested as some of the busiest park-and-ride lots in the Central Puget Sound Region.

The remainder of this paper is organized as follows. The following section describes the audit methodology used to assess park-and-ride passenger efficiency. Next, the user survey and general results are described. Then, user responses to parking management strategies are summarized. Finally, concluding remarks are provided.

Audit to Assess Park-and-Ride Passenger Efficiency

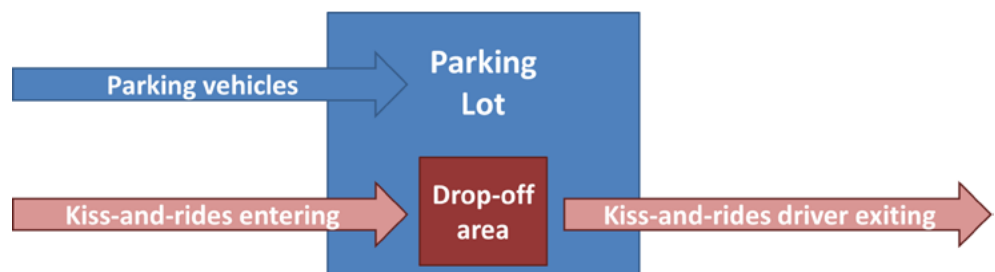
Transit agencies typically measure park-and-ride lot utilization as the fraction of parking spaces occupied by vehicles or the total number of transit boardings per parking space. However, the former does not measure how many people use the lot, and the latter includes transit boardings by users that did not use a parking space.

In this study, we focused on the average number of people served by each parking space, which we define as the person-efficiency. This person-efficiency also is equal to the average passenger occupancy of vehicles that actually park at the lot for transit purposes. Unfortunately, agencies do not have a well-established methodology to calculate the person-efficiency of park-and-ride lots. In this paper, an onsite audit is proposed to measure person-efficiency of park-and-ride spaces. The remainder of this section describes the audit procedure and summarizes the results of a set of case studies performed at park-and-rides in the Puget Sound region of Seattle.

Methodology

In this methodology, observers track the movement of people and vehicles into the park-and-ride facility during a peak period. An observer is placed at each of the vehicle entry points into the park-and-ride lot such that they can see how many people are inside each entering vehicle. The observers record the total number of entering vehicles and number of people within these vehicles for the observation period. Observers also are placed near well-used drop-off locations to record the total number of kiss-and-ride drop-offs, K , that occur within the parking areas. Figure 1 provides a schematic that illustrates how vehicles use the lot and what vehicles should be observed.

FIGURE 1.
Schematic of audit to assess person-efficiency of park-and-rides



Denote the number of vehicles and people entering the park-and-ride facility during the observation period as C_{in} and P_{in} , respectively. A simple estimate for the person-efficiency of parking vehicles is provided by:

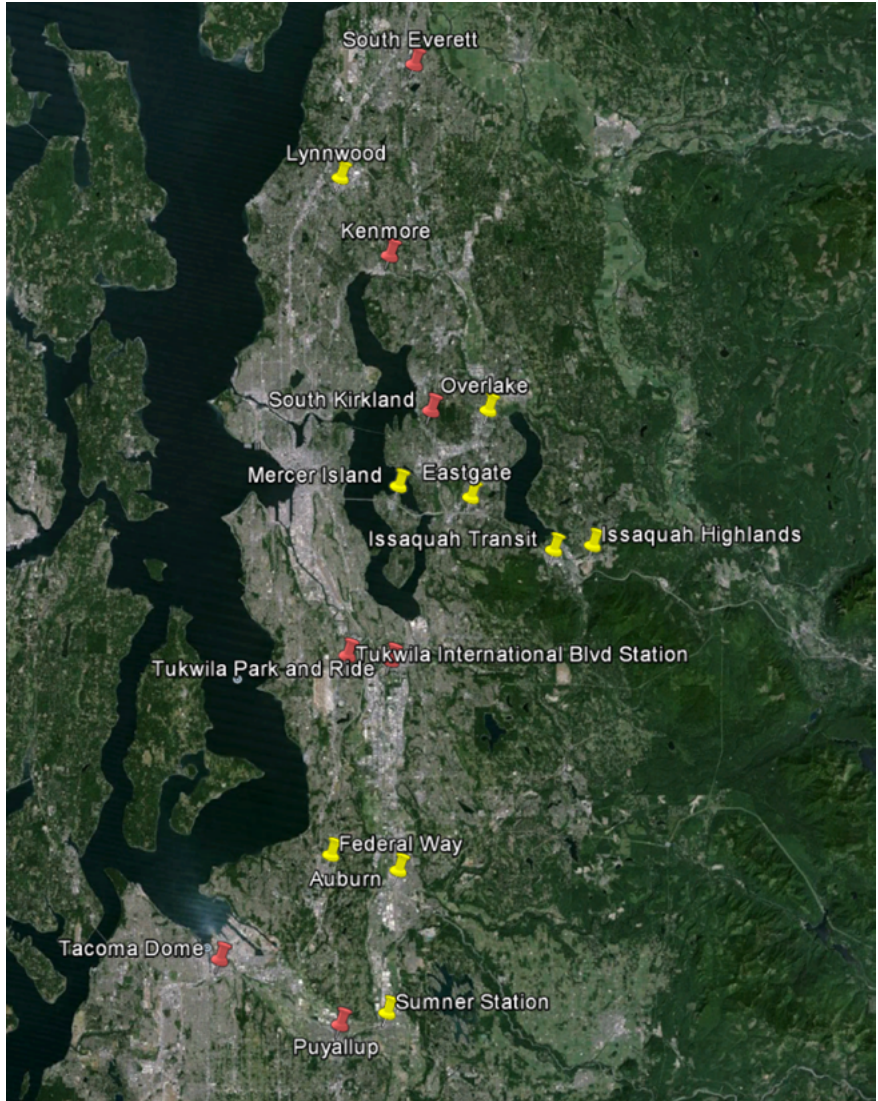
$$\text{Person-Efficiency} = (P_{in} - 2K)/(C_{in} - K) \quad (1)$$

The denominator in Equation (1) represents the number of vehicles parking at the lot during the observation period. It is equal to the difference between the total number of vehicles entering and the number of kiss-and-ride vehicles that enter but do not park. The numerator represents the total number of people using parking spaces and is equal to the number of people entering in a vehicle minus the number of people involved in kiss-and-ride drop-offs. For this latter number, we assumed that each drop-off involves just two people: the driver and the passenger being dropped off. The data collection team noted that this was the case for almost all kiss-and-ride maneuvers that were observed. Note that, in this procedure, the estimate of person-efficiency includes drivers of carpools/vanpools that pick up passengers inside the park-and-ride lot and leave. In reality, these drivers park only temporarily before leaving and they should not be included in the person-efficiency measurement. A more complicated procedure to account for these carpools/vanpools is provided in (Gayah et al. 2014). However, the two values are remarkably close; therefore, the more straightforward method is provided here for practitioners to estimate person-efficiency for existing park-and-ride lots.

Results

The onsite audit procedure was conducted for nine commuter park-and-ride lots in the Puget Sound area (see Figure 2 for a map of the lots). The audits were conducted in the AM peak hours of weekdays during the weeks of October 21 and November 4, 2013. Table 1 presents the raw data and estimates of lot utilization, defined as the fraction of parking spaces filled at the end of the data collection period (which generally took place from 5:00-10:00am), and estimated person-efficiency of parking spaces at each of the lots. These lot utilization values account for vehicles present during the lot at the start of the audit and already-parked vehicles that exit during the audit time period (e.g., night shift workers returning home from work). As can be seen, the majority of the facilities became completely filled (described as 100% of the parking spots being occupied by vehicles) during the data collection period. Of the three lots that did not completely fill, two (Auburn Station and Issaquah Transit Center) were audited on a Friday, when travel demands can be expected to be lower than normal. Even so, more than 80% of the spaces at these locations were used, suggesting that they are at or near capacity on typical weekdays.

FIGURE 2.
Map of park-and-ride facilities considered



Red pin indicates survey only; yellow pin indicates survey and onsite audit.

TABLE 1.
Summary of
Onsite Audit Data

Lot	Parking Spaces	C_{in}	P_{in}	K	Lot Utilization	Time Lot Completely Filled	Person-Efficiency (EQN 1)	Fixed-Route Transit Users
Auburn	633	549	594	23	85.8%	–	1.042	96%
Eastgate TC	1,614	1,643	1,795	125	90.8%	–	1.018	96%
Federal Way TC	1,190	1,334	1,578	149	100.0%	7:40 AM	1.080	92%*
Issaquah Highlands	1,000	1,160	1,322	122	100.0%	9:10 AM	1.039	84%
Issaquah TC	819	741	832	62	82.3%	9:15 AM	1.043	95%
Lynnwood TC	1,368	1594	1,880	213	100.0%	7:25 AM	1.053	88%*
Mercer Island	447	530	639	74	100.0%	7:50 AM	1.077	95%
Overlake TC	222	282	333	47	100.0%	7:35 AM	1.017	99%
Sumner	343	288	318	20	100.0%	5:40 AM	1.037	88%*

* Estimates may be inaccurate due to lot geometry.

In general, the person-efficiency values are very near 1; the highest is just 1.080 passengers per parked car. This suggests that the majority of people parking at these facilities arrive at the park-and-rides in an SOV. Although such a result is not surprising, it provides quantitative data with which lot managers can use to justify the implementation of parking management strategies designed to promote carpooling and multi-occupant vehicle use at these facilities.

Table 1 also provides an estimate of the fraction of people who parked and went on to use fixed-route transit options (bus, train, or local fixed-route shuttles). This was determined by members of the audit team, who observed where vehicle occupants went after parking at the park-and-ride facilities. Only about 2% of users were noted as leaving the lot for non-transit purposes. Users that did not proceed to the transit boarding area or adjacent offsite establishments were identified as using flexible transit options such as carpools or vanpools. At some locations, the lot geometry made it difficult to estimate the fraction of parking users that used fixed transit options; these lots are denoted with an asterisk in Table 1.

User Intercept Survey

A user intercept survey was conducted to learn more about park-and-ride users at each of the lots, as well as to capture their feedback/reactions to the implementation of new parking management strategies to increase person-efficiency. This section describes the survey tool and its coverage, the characteristics of park-and-ride users who responded, travel information, and reasons for using the park-and-rides. A detailed overview of the full survey results can be found in Gayah et al. (2014).

Description of Survey and Coverage

The primary goal of the survey was to collect information on how park-and-ride users actually use these facilities (i.e., to confirm the audit results) and their reactions to potential parking management strategies. The survey was broken down into several thematic categories:

- Transit Pass Ownership
- Origin and Destination
- Travel Time
- Mode Entering and Mode Exiting
- Current Park-and-ride Use Preference
- Bicycle and Pedestrian Preference
- Pricing Strategy Preference
- Carpooling Preference
- Socioeconomic Information

The survey was distributed at 17 sites, including the 9 at which the onsite audit was performed, in the AM peak hours of weekdays during the weeks of March 4 and March 11, 2014 (see Figure 2). To maximize the number of responses, users were provided with two options to complete the survey: a paper survey that could be completed onsite or a card with website link to a mobile-phone-friendly electronic copy of the survey that could be completed later. The data collection team was located near the primary transit stops at each lot (since this location had the largest congregation of people); however, the team strived to provide every park-and-ride user with an opportunity to complete the survey. Carpoolers/vanpoolers were the most challenging groups to survey onsite, as they tended to gather at the more remote locations of the park-and-ride lot. To address this, the website link also was emailed to the set of registered vanpool users for several of the lots (Eastgate TC, Issaquah Highlands, Kenmore, South Kirkland, and Tukwila) via emails from King County Metro.

A summary of the survey distribution by lot is provided in Table 2. More than 3,300 unique surveys were collected; about 2,000 were paper surveys, and the remaining 1,300 were completed online. The last column of Table 2 presents the ratio of the total number of surveys collected to the total number of parking spaces available at each lot, which was used as a measure of survey penetration. The survey had an average “penetration” of about 25% of the total number of parking spaces across all facilities. At individual park-and-ride facilities, the penetration rate ranged between 11% and 40%.

TABLE 2.
Summary of Survey Data
Collection

Lot Name	Total Completed Surveys	Paper Surveys	Online Surveys	Lot Capacity	Penetration Rate
Auburn	172	121	51	633	27.2%
Eastgate TC	348	146	202	1,614	21.6%
Federal Way TC	283	217	66	1,190	23.8%
Issaquah Highlands	396	217	179	1,000	39.6%
Issaquah TC	284	197	87	819	34.7%
Kenmore	121	20	101	603	20.1%
Lynnwood TC	305	221	84	1,368	22.3%
Mercer Island	108	53	55	447	24.2%
Overlake TC	80	54	26	222	36.0%
Puyallup	165	105	60	432	38.2%
South Everett	148	132	16	397	37.3%
South Kirkland	223	159	64	852	26.2%
Sumner	138	75	63	343	40.2%
Tacoma Dome	262	88	174	2,283	11.5%
Tukwila International Blvd.	199	159	40	600	33.2%
Tukwila P&R	33	11	22	255	12.9%
Tukwila Station	76	45	31	208	36.5%
Total	3,341	2,020	1,321	13,266	25.2%

User Characteristics

The majority of survey participants were between the ages of 25 and 55. Participants were evenly split by gender. About half lived in households with two or fewer members. Household income was fairly uniformly distributed between annual salaries of \$30,000–\$150,000+; only 3% of participants made less than \$30,000 per year. More than 99% of participants had at least a high school diploma, and 67% of participants had some form of college degree. There was no apparent link between education level and preference toward public transit use. The majority of survey participants had access to a working vehicle, with 98% of respondents having at least a single working vehicle in their household, and 86% of respondents having at least two working vehicles in their household. The average auto sufficiency—defined as the number of cars per household member—was 1.02 vehicles/person, and nearly 60% of respondents had more than one car per household member. Across individual modes, those that drove to the park-and-ride had average auto sufficiency values of 1.02 vehicle/person, and kiss-and-ride drop-offs had very similar average auto sufficiency values (about 0.98 veh/person). These metrics indicate that the vast majority of park-and-ride users were not captive transit users.

The majority of the participants (94%) indicated that they had an ORCA (One Regional Card for All) card, used to pay bus and train fares in the Puget Sound region. Of the ORCA cardholders, 77% received some form of transit subsidy, which supports the finding that park-and-rides are used because they help save money. Subsidized transit users might not be as sensitive to pricing strategies as others, since a significant portion of their transit fare was being subsidized. Since so many received ORCA cards at a reduced rate, allowing users to pay for parking with their ORCA card might not significantly disincentivize SOV use, as many individuals would not experience the full pricing effect.

Travel Information

As expected, the majority of trips at the park-and-ride lots were commute trips to work (94.4%), with the next highest trip purpose being commute trips to school (3.2%). This would suggest that park-and-ride users regularly used the lots, confirmed by the fact that the average use of park-and-rides by survey respondents was nearly 4.5 times per week. This usage frequency was quite consistent across all individual facilities, as statistical t-tests confirmed that the mean value at each lot did not significantly differ from the overall mean value across all lots. Trip origin information was used to estimate distances traveled to the park-and-ride location. The majority of origins (71%) were located within 5 miles of the park-and-ride facility, and the average distance traveled to the park-and-ride lots was 4.1 miles. Those who parked at the lot had a slightly smaller mean travel distance (3.7 miles), but the distribution between those who parked and all other users was similar.

The clear majority (nearly 74%) of participants arrived to the park-and-ride in an SOV. Of the remaining participants, the highest uses appeared to be bus (indicating the park-

and-ride is a transfer location) (8%) and kiss-and-ride drop-off (7%). The ratio of drop-offs to entry in a parked vehicle (SOV, carpool or vanpool) was about 0.085, which is generally in line with the ratio of K to P_{in} in Table 1. These data also suggested that the lots are being used primarily for their intended purpose, which is to access transit. The majority of the users surveyed exited the lot by a fixed-route transit mode: either bus (72.2%) or train (20.4%). Flexible transit—e.g., carpool (0.5%) and vanpool (2.8%)—use was about half that indicated by the onsite audit; however, as previously indicated, these users were the most difficult to reach with the survey. Finally, the fractions of fixed and flexible transit users were consistent across both the set of total users and the set of users who parked a vehicle at the facility.

Since we specifically were concerned with the person-efficiency of the park-and-ride lots, we also examined the distribution of entry modes considering only those participants arriving by modes that required both a car and parking space: drive alone, carpool, or vanpool. For this set of parked vehicles, 93% entered in an SOV, which is consistent with the onsite audit results. Table 3 provides a comparison between the fraction of SOVs parking at the lots estimated from the survey and onsite audit. In most cases, this fraction is between 90–100%; however, Overlake TC and Sumner have single-occupant parking percentages near 85%, indicating that higher levels of carpool/vanpool activities may occur at these locations. A chi-square test was performed to see if this fraction was statistically equal across all lots. The resulting p-value was >0.01 , which suggested that the distribution was not statistically different across all facilities. Therefore, there is not enough statistical evidence to suggest that Overlake and Sumner are statistically different from the average distribution of all lots.

The estimated SOV parking fractions obtained from the onsite audit data also are provided in Table 3 for comparison with those obtained through the surveys. In most cases, SOV fractions obtained from the audit are slightly higher than the fractions obtained from the survey; however, in general, the two values are consistent. The audit estimates do not fall within the 95% confidence interval obtained from the survey data for Auburn, Eastgate TC, Issaquah Highlands, Overlake TC, and Sumner. Of these, only Eastgate TC, Sumner and Overlake TC have significant differences (i.e., differences greater than 6%) between the audit and survey data. Reasons for these discrepancies might include self-selection bias for the users who chose to respond to the surveys, differences in park-and-ride facility during the audit and survey periods, and estimation inaccuracies during the onsite audit process.

TABLE 3.
Fraction of Single-Occupant
Vehicles Parking at Each Lot

Lot Name	SOV Fraction (Survey)	LB of 95% CI	UB of 95% CI	SOV Fraction (Audit)
Auburn	91.3%	84.2%	95.3%	95.5%
Eastgate TC	91.7%	87.8%	94.4%	98.1%
Federal Way TC	93.1%	89.0%	95.7%	89.8%
Issaquah Highlands	92.9%	89.7%	95.2%	95.8%
Issaquah TC	95.4%	92.1%	97.3%	96.0%
Kenmore	93.1%	86.4%	96.6%	---
Lynnwood TC	92.8%	88.3%	95.7%	94.3%
Mercer Island	93.2%	85.9%	96.8%	91.9%
Overlake TC	84.2%	72.6%	91.5%	98.3%
Puyallup	93.0%	86.9%	96.4%	---
South Everett	96.5%	91.4%	98.6%	---
South Kirkland	93.4%	88.5%	96.3%	---
Sumner	84.1%	75.0%	90.3%	94.7%
Tacoma Dome	96.4%	93.1%	98.2%	---
Tukwila International Blvd.	95.0%	90.0%	97.5%	---
Tukwila P&R	100.0%	-	-	---
Tukwila Station	90.4%	81.5%	95.3%	---
All	93.0%	92.0%	94.0%	---

LB = Lower Bound; UB = Upper Bound; CI = Confidence Interval

Use of Park-and-Rides

Survey participants were asked to identify all the reasons they used park-and-ride facilities from the following list:

- No parking at destination (34.9% agreement)
- Driving takes too long (44.9% agreement)
- Environmental reasons (36.1% agreement)
- To save money (77.1% agreement)
- Can relax on transit (59.6% agreement)

Unsurprisingly, a majority of users indicated that they use park-and-rides for the convenience and relaxation opportunity provided within transit vehicles. A third of respondents indicated that they used park-and-rides because of the lack of parking availability at the destination. This category included three potential options that a park-and-ride user might experience: the complete lack of parking spaces, the lack of employer-provided parking spaces, or the lack of free parking. Further differentiation among these three options was not included in the survey to simplify its presentation. About half of participants indicated that they used park-and-rides because driving takes too long. Since transit trips typically take longer than driving (in terms of door-to-door

travel time), this further suggests that people value transit for longer trips since they can focus on other tasks. For example, they can work and relax on the transit vehicle on the way to work, which is generally not possible while driving.

Survey participants also indicated reasons they used a specific park-and-ride lot. It appears that convenience was the primary reason for selecting a particular park-and-ride lot, since users generally selected park-and-ride lots that were closer to their origin (64.3% agreement) and those that provided express transit service (39.2%). Many also indicated that they selected the park-and-ride simply because it was the closest transit station (24.9%). Very few (4.5%) indicated that they selected a particular lot because they could not find parking at their desired lot, which suggests that park-and-ride users might not try new lots if their preferred lot becomes full. This was verified, as only 31.0% of users indicated that they would drive to another park-and-ride if parking was not available at the lot at which they were surveyed. The remaining participants indicated they would park nearby and walk to the lot (19.7%), drive directly to their destination (29.5%), or were either unsure or would use another method (21.6%). Only 2% of participants indicated that they would not make this trip if parking was not available at the park-and-ride, which is reasonable since these are primarily commute trips to work or school.

User Response to Efficiency Strategies

The user intercept survey also included several questions to assess user reaction to various parking management strategies that might be considered by the Washington State Department of Transportation (WSDOT) and related agencies for parking management at park-and-rides in the future. One set of questions focused on willingness to pay for parking, another focused on carpooling alternatives, and another focused on bicycle/pedestrian alternatives.

Willingness to Pay for Parking

Three questions were included to gauge willingness to pay: (1) to park at the facility (general parking fee); (2) to reserve a guaranteed space; and (3) to reserve a guaranteed space located a 10–15-minute walk offsite. The first question directly asked respondents if they would still park at the park-and-ride facility if a parking fee was implemented and, if they answered yes, how large a fee would they be willing to pay to park (\$1–\$5/day in \$1 increments). Similarly, users were asked the maximum amount they would be willing to pay to reserve a guaranteed parking space at the park-and-ride facility or a guaranteed parking space located a 10–15-minute walk away from the facility. The guaranteed spaces would be reserved for use only by the users that paid for these spaces (in advance), as if they were able to “rent” the spaces ahead of time. Pricing of guaranteed spaces located a 10–15-minute walk away from the park-and-ride facility was included to assess how much users might pay for parking spaces at multi-family developments near park-and-rides, a strategy being piloted by WSDOT. If a user was not willing to pay anything or not willing to park a 10–15-minute walk away, a value of

\$0.00 was used. This direct method was used to reduce the time required to take the survey and to alleviate concerns that pricing was imminent at these locations (which was a concern of WSDOT and the other agencies that supported the survey). This was a limitation of the pricing questions, as users could simply state that they would not be willing to pay anything to park at these facilities. For this reason, the magnitude of the willingness to pay might not represent actual willingness to pay. Instead, the relative magnitudes across different types of willingness to pay are likely to reveal preferences among different pricing strategies.

Unsurprisingly, park-and-ride users were generally unwilling to pay for the (currently free) parking spots. Only 28% were willing to pay for existing spots or guaranteed spots located at an offsite location. That fraction increased to 46% if the parking fee would guarantee a parking space within the lot itself. Of those willing to pay, respondents indicated they would pay an average of about \$1.50 for existing spots at the lot or guaranteed spots a 10–15-minute walk away and \$1.83 for a guaranteed spot at the lot itself. Thus, it appears that whereas almost twice as many people are willing to pay for a guaranteed space, they are not willing to pay significantly more for these guaranteed spaces. However, the provision of guaranteed spaces might make the implementation of parking fees more palatable to park-and-ride users.

Alternatives to Avoid Parking Fees and Promote Carpooling

Survey participants were asked if they would be willing to (1) carpool to a lot if carpools were exempt from paying a parking fee, (2) carpool to a lot if carpools were provided guaranteed parking spaces, and (3) park 10–15 minutes away if a guaranteed free parking space was available there. The results of the first two questions were about the same: half of the respondents indicated they would not consider carpooling to avoid parking fees or to obtain guaranteed parking spaces, about one-quarter indicated they would be willing to consider carpooling if carpools did not have to pay a parking fee or were provided guaranteed “carpool-only” parking spaces (which is promising since current carpooling rates to these facilities were very low, about 5% based on the survey responses), and the remainder indicated they either already carpool (5%) or were unsure (20%).

Since these locations are already overutilized, providing guaranteed parking spaces for carpool users would take spaces away from single-occupant drivers. However, about 40% of the respondents indicated that they would be willing to park at a satellite location a short walk away to obtain a guaranteed space. This suggests that if increasing capacity at the park-and-ride itself is not an option, offsite capacity improvements nearby could be beneficial to accommodate overflow demand. Therefore, it might be a good idea to entice SOVs to park at these locations to free up carpool-only spots at the main lot. It should be noted that this strategy is especially promising, as conversations with park-and-ride users during the survey process revealed that many users already do this when the lot is full; i.e., park-and-ride users already park either on the street or in nearby parking lots when the park-and-ride is full and walk to the station. Formal

overflow parking at adjacent locations might be an efficient strategy to increase the use of park-and-rides without significant infrastructure investments.

Bicycle/Pedestrian Alternatives

Another potential strategy to reduce SOV parking is to add bicycle lockers and/or to improve bicycle and pedestrian access at the individual park-and-ride facilities. Participants were asked if these improvements would make them more willing to bike/walk to the park-and-ride. Overall, the responses suggested that these improvement strategies are not promising: only 12% would be more willing to bike if bicycle lockers were provided, and only 17% would be more willing to bike/walk if better pedestrian/bicycle access were provided.

Potential for Transit Access to Park-and-Ride Facilities

In general, transit access to the park-and-ride facilities is very small (only about 8% of users arrive to the lots using local transit options). One potential strategy to improve the person-efficiency of park-and-ride lots is to entice more SOVs to access the park-and-ride through local transit vehicles (e.g., buses). However, local buses may not be a feasible option for many travelers due to their trip origin and location of current local transit routes: if transit service is not available at their origin, users must drive (often alone) to the nearest park-and-ride to access transit service.

To assess the potential for transit use to increase parking efficiency, maps of the set of origins of all single-occupant drivers were created using the origin information from the user intercept survey for each park-and-ride facility. These maps were then used to determine what fraction of single occupant drivers had feasible transit alternatives. As an example, consider the trip origins identified for the Tukwila International Boulevard Station shown in Figure 3. Each unique origin is shown by the red marker on the figure, and the relevant portions of the local bus lines serving this facility are drawn on the map. Only bus routes that provided service during the AM peak hours that these trips were actually made were considered. Figure 3 reveals that a significant fraction of origin markers lie either directly on existing transit lines or very close by. Drivers at these locations potentially could be served by transit if bus stops along these lines were located near the origin markers. Several origins are isolated and located well away from the park-and-ride facility, e.g., the set of origins directly east and southwest of the park-and-ride marker; it probably would not be feasible to dedicate transit service to serve these origins. Although not perfect, maps such as these created using detailed survey data from park-and-ride users could provide agencies with vital information on how many parking spaces could be freed up by enticing park-and-ride users to use local transit service to access the park-and-ride.

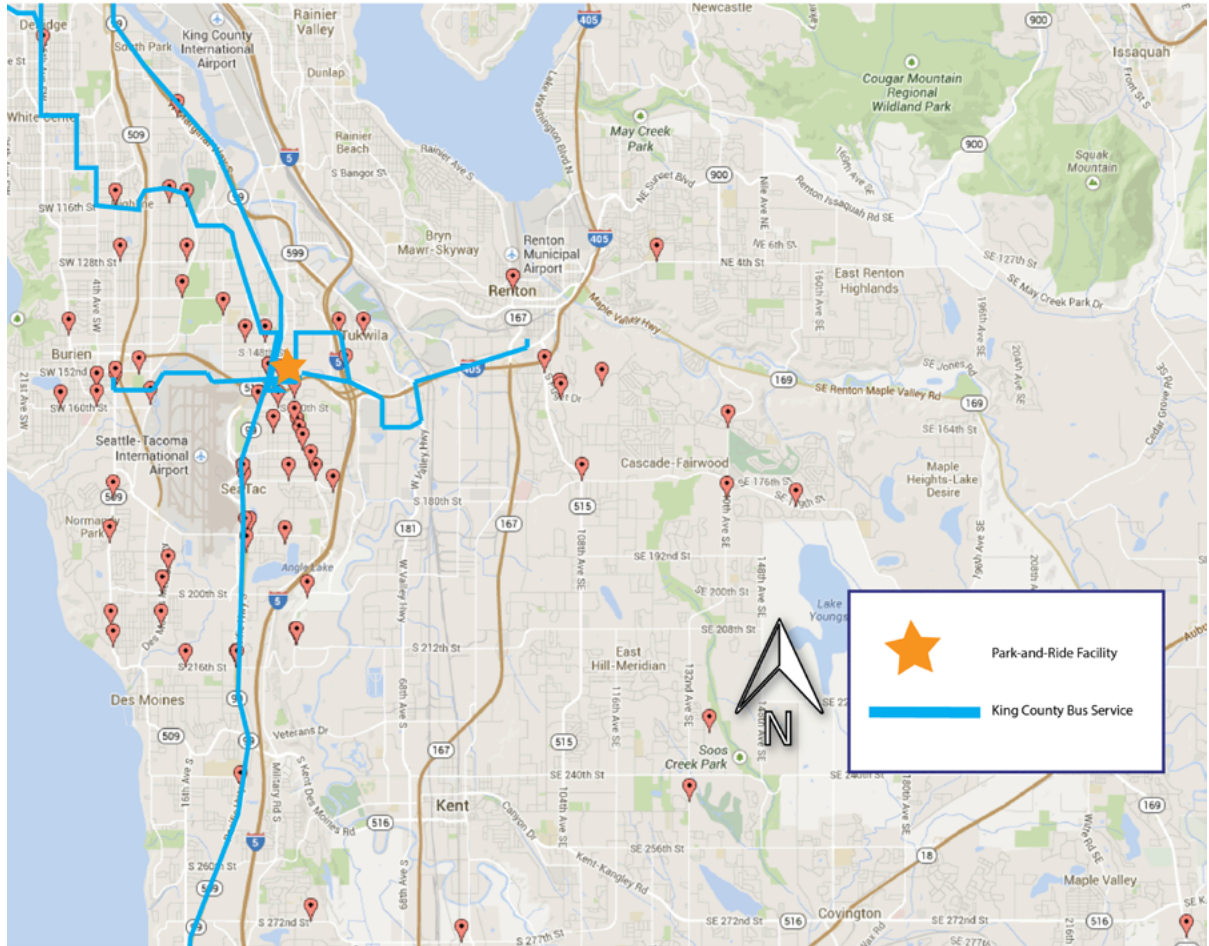


FIGURE 3. Tukwila International Boulevard Station with origins and transit routes

For each lot, the fraction of SOV origins that lie along existing local transit routes was estimated (see Table 4). Note that origin markers often overlap, as survey participants were asked only for the nearest major intersection to their origin. Since each marker near a transit line was counted only once, the results in Table 4 are conservative. The origins initially were disaggregated by the number of trips made from that origin per week; however, the vast majority of users were commuters that made 4–5 trips per week, so this disaggregation did not offer any additional insights. Furthermore, we considered only origins directly on transit routes or within 0.1 miles of the route.

TABLE 4.
Summary of Origins with
Potential Transit Service

Lot Name	Number of Unique Origins	Number of Origins along Existing Transit Lines	Fraction with Potential Transit Access
Auburn	60	15	25.0%
Eastgate TC	207	67	32.4%
Federal Way TC	150	48	32.0%
Issaquah Highlands	219	27	12.3%
Issaquah TC	181	37	20.4%
Kenmore	78	14	17.9%
Lynnwood TC	135	24	17.8%
Mercer Island	69	34	49.3%
Overlake TC	37	18	48.6%
Puyallup	86	23	26.7%
South Everett	88	2	2.3%
South Kirkland	126	38	30.2%
Sumner	52	5	9.6%
Tacoma Dome	162	33	20.4%
Tukwila International Blvd.	90	20	22.2%
Tukwila P&R	33	7	21.2%
Tukwila Station	39	4	10.3%

Several facilities have very high fractions of origins for which transit access may be possible: Eastgate TC, Federal Way TC, Mercer Island, Overlake TC, and South Kirkland. At these locations, the promotion of transit to access the park-and-rides may be a feasible way to improve park-and-ride efficiency. Furthermore, pricing strategies at these locations could be supplemented with transit map information to provide users with an alternative to avoid the parking fee and still use transit at the park-and-ride. Several other facilities have very little potential for transit as an alternative access mode: Sumner, South Everett and Tukwila Station. At these locations, pricing might be less palatable, as users do not have feasible transit alternatives to avoid paying the parking fee.

Of course, these results are not perfect. We were not able to identify if these routes were sufficiently “connected” to the origins by sidewalks or bicycle lanes. This would be critical for users to access the bus line. Furthermore, information was not available on the passenger occupancies of these buses, so we could not identify if sufficient space was available on these buses to serve new passengers. Finally, it was not clear if amenities such as benches or shelters were available at these bus stop locations, although we do not know if bus users in the Puget Sound Region highly value these amenities. Nevertheless, this mapping method provides initial insight into which park-and-ride lots have the most potential to serve those who drive alone to the park and ride by transit.

Concluding Remarks

Overall, this project collected and analyzed data at 17 of the busiest park-and-ride facilities in the Central Puget Sound Region to provide more detailed information on how these facilities are used. A methodology was proposed to assess the person-efficiency of parking spaces at these lots, measured as the passenger occupancy of parked vehicles. These data confirm prior expectations that most parked vehicles had just a single occupant and provides empirical justifications for the implementation of parking management strategies to improve parking efficiency. A user intercept survey confirmed that the estimates of person-efficiency from the audit was fairly accurate. The survey also revealed that the majority of users parked at these facilities for transit purposes. Fixed-route transit (such as bus or train service) was dominant, although heavy carpool/vanpool use was noted at several lots. If these flexible transit uses are not desired, then steps will have to be taken to prohibit these uses. However, these informal uses still can lead to reduced car travel (and the associated reductions in negative car-related externalities), so alternative space should be provided for carpool/vanpool formations to occur if banned at these lots.

The user survey also revealed reactions to potential parking management strategies. For example, users generally are not willing to pay to park at these (already free) lots; however, they are more willing to pay if this fee could reserve a parking space in advance, even if it was located a 10–15-minute walk away from the park-and-ride location. About a quarter of survey participants indicated that they would be willing to consider carpooling to avoid a parking fee; therefore, a targeted carpooling initiative along with pricing of SOVs could be an effective means to improve person-efficiency at these lots. The survey data suggest that providing reserved carpool spaces and allowing carpools to avoid parking fees generally would have the same impact. Thus, providing these types of prioritization strategies at overcrowded lots should significantly improve person-efficiency. Unfortunately, users did not indicate that improving bicycle and pedestrian access/facilities would significantly improve travel to the park-and-ride lots by these modes. Instead, it appears that resources to improve these facilities should be dedicated elsewhere if improved person-efficiency is the primary objective. Another way to improve efficiency is to divert SOVs to transit alternatives to access the park-and-ride. This would free-up parking spaces at these overutilized locations, which then can be dedicated to carpool vehicles to provide them with priority. As suggested by the data, there are significant fractions of single-occupant drivers who have feasible alternatives using existing transit routes.

A limitation of the survey was that respondents were asked directly about their willingness to pay for various types of parking fees. By doing so, park-and-ride users might underestimate their true willingness to pay for the already free parking spaces. Future work might instead provide respondents with a set of scenarios with different parking fee structures and amenities (including guaranteed spaces for a parking fee) to be understand their true willingness to pay for parking and park-and-ride facilities.

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Investigation of Wheeled Mobility Device Orientation and Movement on Streetcars and Light Rail Vehicles during Normal and Emergency Braking

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Abstract

Wheeled mobility devices have been accessing public transit vehicles for decades, and most new rail transit systems are accessible. This has increased ridership by people with disabilities. Side-facing orientation on rail transit vehicles often is considered an option to increase capacity for wheeled mobility devices. This paper reports findings of a study of vehicle dynamics and wheeled mobility device orientation on rail transit vehicles. The study used acceleration data and field observations to evaluate wheeled mobility devices in longitudinal and side-facing orientations on streetcar and light rail vehicles. Results from the study include recommendations for longitudinal-oriented areas for wheeled mobility devices as well as additional public outreach on best practices for passengers who use wheeled mobility devices on rail transit vehicles.

Keywords: *Wheeled mobility device, orientation, rail transit vehicle dynamics*

Introduction

Background

The braking regimes of streetcars and light rail transit vehicles are specified by the transit industry and transit agency standards (APTA 2013; German Institute for Standardization 2015). Routinely, these regimes are tested as part of the acceptance procedures of new transit vehicles. The research reported in this paper evaluated the movement of occupied wheeled mobility devices in longitudinal and side-facing orientations during normal, emergency, and panic braking regimes on new streetcar and light rail vehicles on rail test tracks.

The term “longitudinal seating” describes both forward- and rear-facing seating orientation. The research team used the same procedures used for vehicle dynamics tests of small and large transit buses (Hunter-Zaworski 2009; Hunter-Zaworski and Zaworski 2009; Zaworski et al. 2007). Several studies have related acceleration and braking as a measure of passenger ride comfort on rubber-tired vehicles but, to date, none have been reported for rail transit vehicles.

Rail transit vehicle acceleration is controlled by the vehicle’s electrical system. The acceleration regime parameters are specified by the operating transit agency during vehicle procurement. Rail transit vehicle acceleration for streetcars and street-running light rail transit (LRT) vehicles are very low and are not of concern in this study; rail transit vehicle braking is the focus of this study.

Hoberock was the first to study transit vehicle braking behavior. Braking behavior, characterized by deceleration rate and jerk, is used as a measure of ride comfort (Hoberock 1976). Jerk is the rate of change of acceleration. There are significant differences in the level of tolerance between side-facing and longitudinally-seated passengers. Recent studies by the research team on rubber-tired vehicles confirmed the observations that 1) most accidents occur under normal operations and 2) manual wheelchairs and scooters are more unstable than power chairs in rapid deceleration conditions. To mitigate some instability, wheelchair brakes always must be applied, and power wheelchairs and scooters must be powered off (Salipur et al. 2011).

This paper concentrates on streetcars and street-running LRT vehicles using the definitions from the National Transit Database (NTD) to define the modes, as shown in Table 1.

TABLE 1.
NTD Definitions of Rail
Transit Vehicles

MODE	Vehicle Type
<p>Light Rail (LR): Typically an electric railway with a light-volume traffic capacity compared to heavy rail (HR), characterized by:</p> <ul style="list-style-type: none"> • Passenger rail cars operating singly (or in short, usually two-car trains) on fixed rails-in shared or exclusive right-of-way (ROW) • Low or high platform loading • Vehicle power drawn from an overhead electric line via a trolley or a pantograph 	<p>Rail cars with:</p> <ul style="list-style-type: none"> • Motive capability • Usually driven by electric power taken from overhead lines • Configured for passenger traffic • Usually operating on exclusive ROW
<p>Streetcar Rail (SR): Rail transit systems operating entire routes predominantly on streets in mixed-traffic; typically operate with single-car trains powered by overhead catenaries and with frequent stops.</p>	<p>Rail cars with:</p> <ul style="list-style-type: none"> • Motive capability • Usually driven by electric power taken from overhead lines • Configured for passenger traffic • Often operate in shared-use corridors (shared ROW) • Typically operate with one-car trains

Source: NTD 2015

Three general classifications of wheeled mobility devices were considered and are defined as follows.

Manual Wheelchairs

Manual chairs were the most common mobility devices in the past decades. They are light, some are foldable, and they have large rear wheels and small front casters and are used mainly by people with strong arms to propel themselves. They have push bars at the rear for occupants who cannot propel themselves and are pushed by another person, typically used in hospitals, transportation terminals, and institutional places. The “common manual wheelchair,” measuring 25 inches wide and 42 inches long when occupied, was for many years used as a base for regulations and standards, with a recommended footprint of 30 x 48 inches and a turning radius of 36 inches. Securement systems were developed to secure the wheelchair to vehicles, mainly by tie-downs, to prevent forward and rearward movement (Hunter-Zaworski and Rutenberg 2014).

Power Wheelchairs

Power wheelchairs are powered by batteries and controlled by joysticks or other types of controllers. They may have special postural control systems or cushioned seats and back, a headrest, and padded armrests. These devices typically measure about 25 inches wide by 38–43 inches long and can weigh up to 300–400 pounds depending on their power pack and accessories. They are usually very nimble, have a small turning radius of about 28 inches, and usually can be accommodated on public transportation vehicles, provided the user is capable of maneuvering in and out of his/her position on-board a vehicle. Powered chairs may have added features to tilt the chair and provide extended leg and upper body supports; these additional features increase the length and weight and can easily exceed the standard footprint of 30 x 48 inches. These extra features may make transport on regular public transit vehicles more difficult due to the difficulty of using a front door ramp or lift (Hunter-Zaworski and Rutenberg 2014).

Scooters

Designed primarily for indoor use, scooters generally have 3 or 4 wheels and typically have a pedestal seat with a tiller or joystick control and small wheels. Many bases of scooters are narrow, with a width of about 20 inches, making them more prone to tipping. In addition, scooters often are procured outside the medical prescription process; many scooter riders do not receive proper training or recommendations for the correct scooter for their size and mobility level (Hunter-Zaworski and Rutenberg 2014).

This paper reports on experiments that were conducted using a standard manual wheelchair and a four-wheel scooter. Prior research conducted by the team has shown that a power-base wheeled mobility device is more stable than either a manual wheelchair or scooter.

Orientation of Wheeled Mobility Devices

Prior to the regulations associated with the Americans with Disabilities Act (ADA), sled tests showed that manual wheelchairs did not withstand side accelerations (Stewart and Reni 1981). These results contributed to the ADA regulations that specify that a wheeled mobility device (WhMD) always should be transported oriented in the longitudinal direction on rubber-tired vehicles (ADA Accessibility Specifications for Transportation 1998). Subsequent sled testing of securement systems and WhMDs has confirmed that in high acceleration (high “g”) environments, the WhMD must be in the longitudinal direction.

In many cities, rail transit systems are built to meet the increases in demand for public transit and population density. Rail transit operators are studying methods to increase vehicle capacity for WhMDs. Side-facing seating orientation for WhMDs is considered an option to increase rail vehicle capacity for WhMD. It also is widely observed that in crowded conditions, many passengers in WhMDs sit sideways in or near the vehicle vestibule because they cannot access areas designated for wheeled mobility devices. This study examined whether side-facing orientation is a viable option for rail transit based on braking studies conducted on light rail test tracks.

Vehicle Dynamics of Rail Transit Vehicles

The dynamic behavior of rail transit vehicles is significantly different from rubber-tired vehicles. The acceleration and deceleration of rubber-tired vehicles are much more variable because of the operator, tires, pavement and traffic conditions, and vehicle propulsion and transmission systems. In this study, the differences in the coefficient of friction between rubber-tire and steel-tire vehicles influenced the rate of acceleration and deceleration. In rubber-tire operations, large transit buses will experience much higher longitudinal and lateral acceleration forces than rail transit vehicles due to operating conditions and roadway geometrics.

In the United States, most streetcars and street-running LRT systems are electric, and the parameters for acceleration and braking are preset and controlled.

Scope of Study

This study examined the movement of occupied WhMDs in two different orientations during routine and emergency braking regimes of streetcars and light rail vehicles. The research questions addressed were:

- Do occupied wheeled mobility devices require securement or containment on streetcars or light rail vehicles that operate in traffic?
- Is side-facing orientation an option for occupied wheeled mobility aids on streetcars or light rail vehicles?

The focus of this study examined the orientation of WhMDs and brake testing regimes on new light rail and streetcar vehicles. The study used both video recordings of movement and an accelerometer-based data acquisition system to record vehicle dynamics. To analyze the effect of the extreme braking regimes on an occupied WhMD, a 50th percentile male anthropometric test dummy was used for all tests and to simulate a passenger with very low or no upper body strength. Two types of WhMDs were used in this study—a standard manual wheelchair and a four-wheel scooter. Both WhMDs were considered to be in used condition; however, the manual wheelchair had functional brakes, and the scooter could be powered off.

During testing, the WhMDs were oriented in either longitudinal or side-facing orientations. Most transit systems operate trains bi-directionally, and during testing they operated bi-directionally. The WhMD faced either forward or rearward when they were positioned longitudinally. Similarly, when the WhMDs were positioned in the side-facing orientation, they were exposed to braking forces on tangent, concave, and convex curved track.

Description of Testing

The streetcar and light rail vehicle were electrically-powered, and the vehicle electronic control system limited the vehicle acceleration that occurs when a train leaves a station. Full accelerations were evaluated, but the resulting movement by the test dummy and WhMDs in all orientations were insignificant.

The evaluation of braking regimes for regular, full, and emergency braking was included in this study. To evaluate the impact of not applying brakes on the manual wheelchair, a member of the research team occupied it and did not set the brakes; it was necessary for the researcher to manually restrain the wheelchair chair to prevent excessive motion.

Testing occurred at two locations. The streetcar was evaluated on the United Streetcar test track in Clackamas, Oregon, and the light rail vehicle was evaluated on the TriMet test track in Gresham, Oregon.

Braking Regimes

The three braking regimes included in this study for both streetcar and light rail vehicles were 1) normal braking from 25 miles per hour (mph) to full stop at a station, 2) emergency stops, and 3) panic stops (only on tangent sections). For the TriMet light rail tests, the braking regime specification depended on whether the bogies or trucks have power. There were three bogies per vehicle—two powered with electric motors and one without power, located in the articulated or middle section of the vehicle. The powered bogies had both electrodynamic braking systems with a back-up friction brake system. The unpowered bogie had only a friction brake system. The control of the braking was independent on speed except for in some modes of friction-only braking. The braking regime depended upon requested and actual achieved braking rates and were dependent on passenger loads and rail adhesion levels. The powered bogies provided

most of the braking force, primarily by electrodynamic braking. The unpowered bogie assisted in braking only if there was a high passenger load or the vehicle was not reaching the commanded brake rate. Normal service braking or deceleration rates are:

- Normal service braking—ranges from 0.426 ft/s² to 4.4 ft/s² (0.13 m/s² to 1.34 m/s²)
- Emergency and safety braking rates—7.67 ft/s² (2.34 m/s²) minimum

The characteristics of the streetcar and light rail test tracks limited the scope of testing. Both test tracks are level track. The TriMet test track has a short tangent section of track that limits the maximum speed to 25 mph. The test track allowed for low-speed braking on the highly-curved sections. Due to the risk of damage to both the rail and vehicle wheels, panic brake regime tests were completed only once per site.

During the light rail vehicle tests, the manual wheelchair and four-wheel scooter were occupied by a male test dummy. The wheelchair had brakes applied and was occupied by the test dummy, and the scooter had its power turned off and was occupied by the test dummy.

Streetcar (United Streetcar Test Track)

United Streetcar manufactures the streetcars used by the City of Portland and other cities. The manufacturing facility has a test track with both tangent and highly-curved sections of track. During testing, the tracks were wet due to rain, but no excessive skidding was observed. Trains operated bi-directionally on the track. In the tests, the male test dummy occupied the manual wheelchair. The wheelchair brakes were applied during most of the tests, and the wheelchair was oriented in the longitudinal position, with the arm of the dummy over the fold-up seat.

Streetcar Testing and Observations

The testing at United Streetcar included the male test dummy occupying a manual wheelchair. The standard regular and emergency braking regimes were tested. Testing occurred with the wheelchair brakes engaged and oriented longitudinally. When the wheelchair was oriented in the side-facing direction, it encroached into the travel path of passengers. During the brake tests, when the dummy's arm was on the back of the side-facing folded-up seats, there was no significant movement. There was a little more movement, but none of concern, when the dummy's arm was resting in the lap of the dummy. This showed that a person holding onto a seat back prevents movement even in an emergency braking regime, similar to a passenger holding onto a stanchion.

Observations showed that a side-facing orientation of a WhMD severely affects interior circulation in the aisle and other spaces. A side-facing orientation of an WhMD during braking was not evaluated on the streetcar due to the restricted interior circulation.

Light Rail (TriMet Test Track)

Conducted in May 2015, primary testing took place at TriMet's light rail maintenance facility in Gresham, Oregon. The test track was dry. The test track is primarily a flat tangent section, although low-speed brake tests were conducted on a sharply-curved section of track. There were negligible elevation changes in the track. The light rail vehicles were coupled as a married pair and operated bi-directionally. The bi-directional operation permitted both forward and rear-facing orientation for the wheeled mobility devices, and the side-facing orientation permitted the use of a side barrier in one direction only. Regular and emergency brake tests were conducted on the curve section. No panic stops were conducted on curve sections.

Light Rail Testing and Observations

Data collection involved the use of accelerometer data, video recording, and visual observations. The three-dimensional accelerometers used were Gulf Coast Data Concepts Data USB X2-2 data loggers that included high-sensitivity, low-noise, three-axis +/-2g accelerometer sensors. Each was calibrated and collected data at 100 hz.

The accelerometers were placed on the floor of the vehicle and were orientated longitudinally or in line with the direction of travel. To ensure data collection, two accelerometers collected data, which was transferred to Microsoft Excel for further analysis. During testing, a hand-held video camera recorded the WhMD movement. A researcher recorded all videos from the same point in the vehicle. Visual observations by the remaining researchers and agency staff also were recorded for other points in the vehicle. The test dummy was side-facing for all the tests except the first panic stop when the test dummy was in the longitudinal orientation.

Testing Results

The results showed that during regular braking, the deceleration observed was in the 0.15 g range. During panic stops, the maximum observed deceleration was 0.41 g. These were within the specified range for the vehicles.

The following tables describe the tests and the observed motion of each test and maximum deceleration. The description of the tests includes the restraint of the test dummy and the track geometry. The driving regime section includes the different movements testing. The observed movement section includes the information on the different types of movement of the WhMD encountered during the test. It is important to note that the accelerations recorded and presented were for vehicle acceleration and not for the WhMD or test dummy.

One operator drove the train for testing on the tangent track. The manual chair occupied by the test dummy was tested first; the test dummy then was moved to the scooter, and the tests were repeated. A different vehicle operator drove the train on the curved track tests, and only the scooter was tested with the test dummy.

Tables 2 and 3 show the test plan and observed accelerations of the occupied manual wheelchair. The tests used both tangent and curved track at the TriMet testing facilities. Testing included a control test with regular acceleration and deceleration before each test group. Illustrated are the performance of the control tests prior to the experimental braking tests. For the curved track test, only rapid decelerations were tested. On the tangent track, tests of rapid acceleration and panic stops were conducted. The variables that changed during this testing were the track geometry, upper body restraint, and test deceleration.

TABLE 2.
Straight Track Test
Description, Results, and
Observations for Manual
Wheelchair

Test #	Description		Driving Regime		Max Acceleration Observed	Observed Movement
	Upper body used for restraint	Track type	Control movement	Test movement		
1	YES	Straight track	Control movement	Normal acceleration/ deceleration	0.12 g	None
	Track type		Test movement	Rapid acceleration	0.15 g	None
			Test movement	Panic stop	0.39 g	None
2	NO	Straight track	Control movement	Normal acceleration/ deceleration	0.15 g	None
	Track type		Test movement	Rapid acceleration	0.147 g	None
			Test movement	Panic stop	0.398 g	Slight movement; casters moved, device moved within designated area

TABLE 3.
Curved Track Test Description,
Results, and Observations for
Manual Wheelchair

Test #	Description		Driving Regime		Max Acceleration Observed	Observed Movement
	Upper body used for restraint	Track type	Control movement	Test movement		
3	YES	Curve track	Control movement	Normal acceleration/ deceleration	0.09 g	None
	Track type		Test movement	Rapid acceleration	0.12 g	None
4	NO	Curve track	Control movement	Normal acceleration/ deceleration	0.08 g	None
	Track type		Test movement	Rapid acceleration	0.15 g	None

Scooter testing followed a testing sequence similar to manual chair testing. Control movements and test movements were tested. The scooter testing included testing on tangent and curved track. The scooter was tested in a side-facing orientation in the same securement location as the manual chair that was used for the tangent section. Tables 4 and 5 shows the test plan and observations for the scooter.

TABLE 4.
Straight Track Test
Description, Results and
Observations for Scooter

Test #	Description		Driving Regime		Max Acceleration Observed	Observed Movement
1	Upper body used for restraint	YES	Control movement	Normal acceleration/ deceleration	0.14 g	None
	Track Type	Straight track	Test movement	Rapid acceleration	0.15 g	None
			Test movement	Panic stop	0.41 g	None
2	Upper body used for restraint	NO	Control movement	Normal acceleration/ deceleration	0.13 g	None
	Track Type	Straight track	Test movement	Rapid acceleration	0.15 g	None
			Test movement	Panic stop	0.27 g	Slight movement of upper body

TABLE 5.
Curved Track Test Description,
Results, and Observations
for Scooter

Test #	Description		Driving Regime		Max Acceleration Observed	Observed Movement
3	Upper body used for restraint	YES	Control movement	Normal acceleration/ deceleration	0.06 g	None
	Track Type	Curve track	Test movement	Rapid acceleration	0.11 g	None
4	Upper body used for restraint	NO	Control movement	Normal acceleration/ deceleration	0.02 g	None
	Track Type	Curve track	Test movement	Rapid acceleration	0.08 g	None

The only tests that showed movement of the WhMD were the panic stops. If the upper body of the test dummy was propped on the seat back, there was no observed movement. This confirms observations that when passengers hold onto stanchions or the back of a seat, their movement is limited.

The third part of the testing included a researcher sitting in the manual chair without any brakes or upper body restraint while the train traveled on the tangent and curved track sections; this was included to illustrate the effectiveness of the WhMD brakes. The performance of this test illustrates the effectiveness of the WhMD on-board braking system. Test performance did not occur during any rapid acceleration or deceleration tests because of safety concerns.

The largest change in acceleration was in the longitudinal direction for all tests. The largest accelerations occurred during panic stops or rapid decelerations. Figures 1 and 2 show plots of the test segments when the rail vehicle went into a panic stop. Note that the vertical scale in the two diagrams is not the same. The graphs show the constant velocity phase (zero acceleration) that preceded the application of the brakes, followed by rapid decelerations, followed by the application of the track brake that produces a significant “jerk” reaction. The last segment shows the “damping” effect of the vehicle

suspension system. Jerk is the rate of change of acceleration and, often, the jerk causes standing passengers to lose their balance and seated passengers to reach for a stanchion or armrest. Observable “jerk” occurred in all braking tests. The panic braking tests were the only tests in which all researchers reached for stanchions and arm rests for stability. In Figure 2, the “jerk” on the street car is larger than the “jerk” on the light rail vehicle and this is attributable to the difference in mass and suspension systems of the two vehicles.

FIGURE 1.
Panic brake longitudinal acceleration (light rail vehicle)

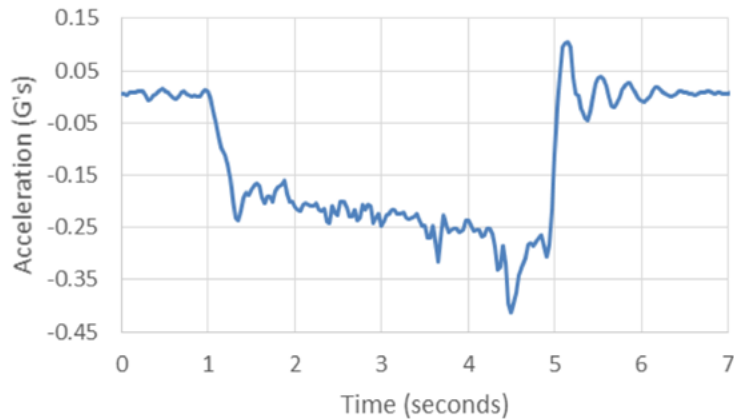
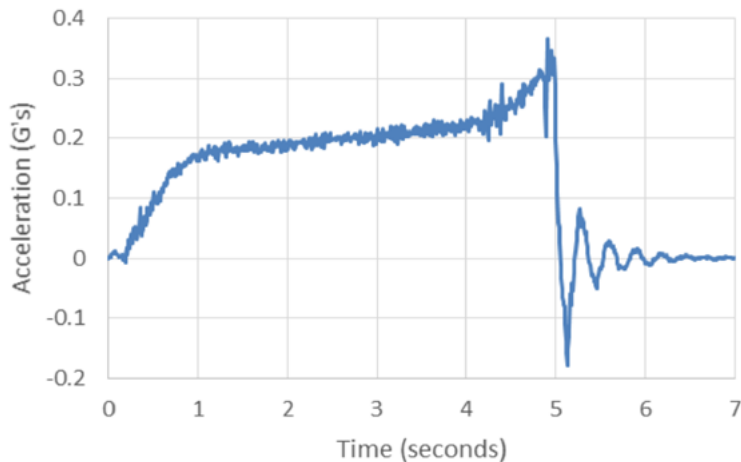


FIGURE 2.
Longitudinal acceleration panic stop (streetcar)



The data collected by the accelerometers was independent of the securement type, WhMD, and direction of securement. The placement of the accelerometers was on the vehicle and not on the WhMD. The sign of the acceleration also was dependent on vehicle direction. The accelerometer directions were not changed when the train reversed direction. The change in magnitude of acceleration response is of interest when reporting acceleration.

All testing was within the parameters for TriMet, with the overall maximum acceleration of 0.41 g in the longitudinal direction for light rail. For streetcar data, the maximum acceleration was recorded at 0.36 g. Table 6 summarizes these results. Note the large difference in maximum acceleration for different movements. The panic stop resulted in much larger accelerations than rapid acceleration.

TABLE 6.
Summary of Maximum Accelerations

Vehicle	Movement	Max Acceleration
Light rail	Rapid acceleration	0.15 g
Light rail	Panic stop	0.41 g
Streetcar	Panic stop	0.36 g

Discussion of Results

Side-facing Orientation

During the light rail testing at TriMet, the side-facing orientation of the scooter and the manual wheelchair did not show significant movement during the regular or emergency braking regimes when the brakes were applied on the manual wheelchair or when the scooter was powered off. Active control by the occupant was needed during occupied side-facing testing when the brakes were not set. It was observed that the toes and footplates of the manual wheelchair and the front of the scooter both encroached into the aisle of the rail vehicle, impacting the interior circulation of passengers standing or moving through the aisle. This resulted in a reduced flow of passengers passing the securement areas. Figure 3 shows the side-facing test dummy. It is important to note that the right arm of the test dummy in the photo is resting on the top of the flipped-up seat, and the front casters are rotated, which can increase instability. The wheelchair brakes were engaged in this photo.

FIGURE 3.
Side-facing occupied manual wheelchair on light rail vehicle



Containment Type

In both streetcar and light rail vehicle testing, it was observed that when the dummy's arm was put on the flipped seat back for forward and rearward orientation or on a modesty panel for side-facing, there was almost no motion of the WhMD during all braking regimes. This is analogous to passengers holding onto stanchions or bracing

against a seat. Figure 4 shows a manual wheelchair in the longitudinal orientation with the dummy's arm resting on a horizontal bar. Slight movement of the WhMD occurred when the dummy's arm was not restrained. The movement did not result in movement outside the securement area or any tipping.

FIGURE 4.
Occupied manual
wheelchair—longitudinal
orientation



The brakes on the WhMD were applied during all brake tests that when the dummy was used. To evaluate the effectiveness of the brakes on the wheelchair, a researcher occupied the manual wheelchair without applying the brakes. During normal braking conditions on tangent and curved sections of the track, the wheelchair moved around the vehicle and the researcher had to control the motion of the wheelchair actively. The wheelchair moved outside the designated area, but it did not tip, and all four wheels stayed in contact with the floor of the vehicle during the test.

Conclusions and Recommendations

The results showed that most people would not experience large movements during emergency braking in any of the orientations of the WhMDs when the WhMDs either are powered off or have functioning brakes. The tests on the light rail vehicles showed that side-facing and longitudinal orientations are options. Although both orientations are viable, the longitudinal orientation of the WhMD avoided incursions into the aisle space and reduced the impact on other passenger moving through the vehicle. This is especially important for crowded vehicles. The movement in either orientation was very small, even in the lightweight mobility aids.

During the side-facing testing on the light rail vehicle, it was difficult for standing passengers to move around the WhMD and access other parts of the vehicle. Train operators expressed concern about the need for a clear aisle during regular and emergency operations.

All the testing procedures showed the importance of WhMDs applying brakes or powering off and the impact on movement of the WhMD during regular and

emergency braking regimes. Active control of the wheelchair was necessary to prevent it from moving around the vehicle when the brakes were not used on the manual wheelchair.

The tests also showed that all passengers should hold onto a stanchion or seatback to minimize movement during braking. Recommendations include developing and placing placards onboard the vehicle to indicate to WhMD passengers the location of safe areas to hold on for those who are able. In addition, placards should remind WhMD passengers to use their brakes or power off.

In summary, longitudinal orientation is recommended for all transit vehicles. Side-facing orientation does not pose a significant safety risk on rail transit vehicles, as it does on bus transit during braking. Side-facing orientation may be convenient during short trip segments when it is difficult for WhMD passengers to access the space assigned to passengers with disabilities. It should be noted that large WhMDs might influence internal circulation for other passengers.

Recommendations for Future Testing

The tests performed did not measure the impact of vertical curvature. The research team recommends the need for further testing on tracks with vertical curves. Whereas track vertical curvatures are much lower than on roadways, there are elevation changes. A positive or negative vertical grade change could impact the stability of the wheeled mobility devices, which is likely to be especially important during side-facing orientation.

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How Intermediate Capacity Modes Provide Accessibility and Resilience in Metropolitan Transit Networks: Insights from a Global Study of 19 Cities

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Abstract

Drawing on the Spatial Network Analysis of Multimodal Urban Transport Systems (SNAMUTS) accessibility tool, this paper introduces comparative results of public transport network performance measures in 19 metropolitan regions in developed countries. These results are assessed typologically and functionally to highlight the contribution of each common public transport mode to maximize (or not) the integration of transport networks with the urban structure to optimize accessibility outcomes. It is shown that the capacity and performance spectrum embodied by each mode represents a gradual scale that allocates a specific niche to intermediate modes, particularly trams that are present in half the cities studied and absent from the others.

In a comparison of Munich, Germany, where a full spectrum of public transport modes is present, and Hamburg, Germany, where there is a performance gap between heavy rail and buses, accessibility outcomes are discussed. Alongside “alternative history” scenarios concerning the hypothetical retention of trams in Hamburg and full closure of the system in Munich, it is shown that the absence of an intermediate mode in Hamburg’s actual network has a significant detrimental effect on the resilience of the public transport system compared to its Bavarian counterpart as well as to other international cities.

Key words: Accessibility, land use-transport integration, network analysis, trams

Introduction

Public transport networks in Western cities have developed over time under varying regimes of city building traditions, infrastructure provision, governance arrangements, and policy priorities regarding the importance afforded to collective modes of

transport. One of the results of this historically-grown divergence in policy and practice is that different cities now find themselves with differing ranges of modes making up their public transport systems. In a spatial accessibility study on a sample of 23 cities on 4 continents, 19 of which are discussed in this paper, it was found that the provision of rail modes, in particular, follows no uniform template. Many cities abandoned at least part of their tram operations in the early post-WWII period, but there are notable exceptions as well as examples where the mode was reintroduced some decades later. A majority of North American cities gave up on rail-based public transport altogether for a period after 1945. Elsewhere, many cities made a concerted effort to adapt their mainline rail networks to the needs of suburban passenger travel, although the outcomes vary greatly in terms of network density and service levels. Some cities introduced new underground metro systems or upgraded and expanded existing operations, and others rejected such a move as not worth the substantial investment required in the face of leaner and perhaps more effective alternatives for improving public transport. Although buses represent a ubiquitous transport mode that can be found in each of the 19 case study cities, the configuration of their networks and the deployment of services once again illustrate a raft of differing priorities between the cities in the sample.

The varying technical and economic performance characteristics of the different public transport modes have been widely documented in the literature and in practice reviews (for a thorough discussion, see, for example, Hass-Klau et al. 2003; Griffin 2005; Vuchic 2005; Van der Bijl and Van Oort 2014). In contrast, this paper explores and attempts to categorize such differences with a view to investigating their impact on accessibility outcomes. For this purpose, a limited range of comparative accessibility indicators from the Spatial Network Analysis for Multimodal Urban Transport Systems (SNAMUTS) toolbox is introduced (Scheurer and Curtis 2016), namely the operational input into the sub-networks of each transport mode in each city (service intensity), the proportional importance of each mode in facilitating travel opportunities across the network (betweenness centrality), and the occurrence of under- or over-utilization of a mode's potential as expressed by its ability to meet this level of importance (network resilience). Essentially, we are interested in whether public transport networks with modes of intermediate capacity and performance, particularly trams, as the most widespread such mode in the sample, have been able to optimize accessibility outcomes for public transport networks as a whole and enhance their capacity to absorb current or future growth in passenger numbers.

The first part of this paper provides an overview of the differences and similarities between cities in providing (or not) each of the key modes suburban rail, metro/light rail (LRT), tram, and bus and the roles that these modes take up in the transport mix of their host city. In the second part, the accessibility and network resilience effects of a hypothetically-modified modal balance in two case study cities, Hamburg and Munich, Germany, are tested. A brief reflection on the circumstances in which cities can address the shortfalls identified in the analysis and on the role that accessibility tools such as SNAMUTS can play in assisting this process, follows in conclusion.

Modal Range of Public Transport Systems—An Overview

Table 1 provides an overview of the public transport modes available in each of 19 Australasian, North American, and European case study cities. For the rail modes, it also provides a rough categorization of the degree of network consolidation: does the mode consist only of a starter line (single route), does it consist of more than one route but covers only a minority of a city's key transport corridors (selected corridors), does it cover a majority of them while leaving some gaps (multiple corridors), or does it cover practically all of them (mature expansion)? In the North American case study cities, suburban rail systems are characterized by limited operation spans, in some cases only during weekday peak hours in the peak direction. Elsewhere, "low frequency" should be understood as typical weekday daytime frequencies of 30 minutes, "medium frequency" as 15 or 20 minutes, and "high frequency" as 10 minutes or better. Metro and light rail systems generally fall into the medium- to high-frequency category everywhere, for which reason their service frequencies are not explicitly specified. In some cities, notably Portland, Seattle, Oporto, and (partially) Amsterdam, light rail networks have been listed under the "metro" category since these systems share many performance characteristics (multiple-unit vehicles and segregated, prioritized alignments) with heavy rail. However, these systems also contain some on-street running, and it is acknowledged that this circumstance reduces their average speed in some instances and, thus, limits their performance compared to fully grade-separated urban rail technology.

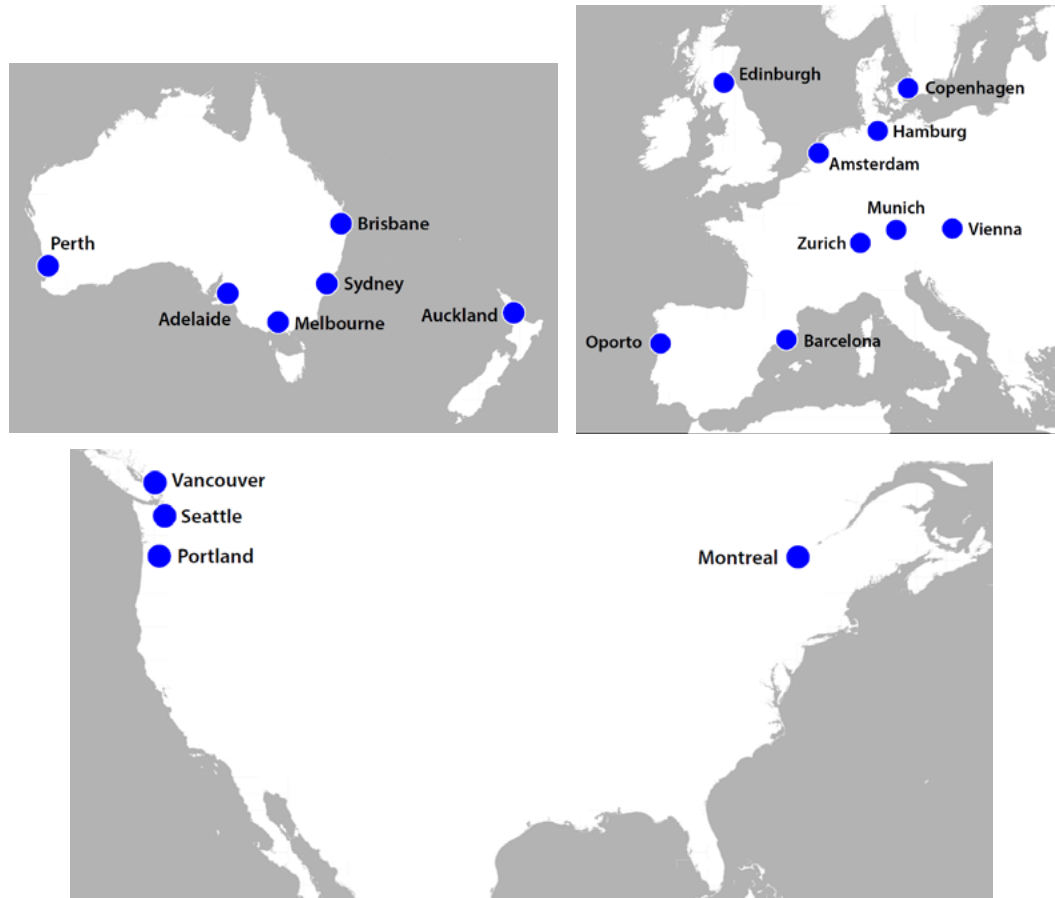
Tram networks are categorized by "first generation" and "second generation," with the former term depicting systems that have been in operation continuously since their inception in the era before mass motorization (generally in the late 19th or early 20th centuries), and the latter term describing systems that have been reintroduced to their host cities more recently (1980s or later) after a period when trams were absent. In Seattle and Portland, the term "tram" is applied to these cities' streetcar systems, built during the 2000s primarily to access and attract property investment to inner city redevelopment areas. In other cities, first generation tram systems have survived only as heritage operations on specific lines (Barcelona, Oporto) or were reintroduced as such (Vancouver, Auckland), using historic vehicles. These systems are not further discussed in this analysis, since they usually cater exclusively to the tourist and recreational market and do not form an integral part of or accept the fares of the regular public transport network.

TABLE 1. Overview of Presence and Key Characteristics of Public Transport Modes in 19 Case Study Cities

City	Suburban Rail	Metro	Tram	Bus	Other
Adelaide	Selected corridors; low frequency	None	First generation; single corridor	Radial core city coverage; single BRT corridor	
Auckland	Selected corridors; low frequency	None	Heritage only	Selected radial core city coverage; single BRT corridor	Ferry routes
Brisbane	Selected corridors; low frequency	None	None	Selected radial core city coverage; selected BRT corridors	Ferry routes
Melbourne	Multiple corridors; medium frequency	None	First generation; mature expansion	Selected corridors, mostly orbital	
Perth	Multiple corridors; medium frequency	None	None	Selected radial core city coverage; selected suburban corridors	Ferry route
Sydney	Multiple corridors; medium frequency	None	Second generation; single corridor	Mature core city coverage; selected suburban corridors, some BRT	Ferry routes
Montreal	Selected corridors; low frequency, limited span	Multiple corridors	None	Mature core city coverage	
Portland	Marginal	Multiple corridors (LRT)	Second generation; selected inner urban redevelopment areas	Mature core city coverage	
Seattle	Marginal	Single corridor (LRT)	Second generation; single inner urban redevelopment area	Selected core city coverage and corridors; some trolleybus lines	
Vancouver	Marginal	Multiple corridors; driverless	Heritage only	Mature core city coverage and suburban corridors; some trolleybus lines	Ferry route
Amsterdam	Multiple corridors; medium frequency	Selected corridors	First generation Mature expansion	Mature core city and suburban coverage in conjunction with trams; selected BRT corridors	Ferry routes
Barcelona	Multiple corridors; medium frequency	Mature expansion	Second generation Selected corridors	Mature core city coverage; selected suburban coverage	Cable cars
Edinburgh	Selected corridors; medium to low frequency	Single corridor (LRT) opened 2014 (post-analysis)	None	Mature core city coverage; selected suburban corridors	
Hamburg	Multiple corridors; high frequency	Multiple corridors	None	Mature core city coverage; selected suburban corridors	Ferry routes
Copenhagen	Mature expansion; high frequency	Selected corridors; driverless	None	Mature core city and suburban coverage	Ferry route
Munich	Mature expansion; medium frequency	Mature expansion	First generation Multiple corridors	Mature core city coverage in conjunction with trams	
Oporto	Selected corridors; medium to low frequency	Multiple corridors (LRT)	Heritage only	Mature core city coverage; selected suburban corridors	Cable car
Vienna	Multiple corridors; high to medium frequency	Mature expansion	First generation; mature expansion	Mature core city coverage in conjunction with trams	
Zurich	Mature expansion; medium frequency	None	First generation; mature expansion	Mature core city and suburban coverage in conjunction with trams; some trolleybus lines	Ferry routes, cable cars

For buses, the categorization is limited to those parts of the networks that meet the SNAMUTS minimum service standard, which requires a weekday daytime service frequency of 20 minutes or better and a weekend daytime service frequency of 30 minutes or better. In many cities, this procedure focuses our attention on a cohort of core routes. Do these form a predominantly or exclusively radial network? If so, are the radial corridors spaced in a way that enables walkable access to at least one corridor within a maximum 400-meter distance from anywhere (full coverage), or are there spatial gaps between these walkable catchments (selected coverage)? Does the network consist of lines in different directions—radial, orbital, and perhaps diagonal (mature expansion)? Do these characteristics apply only to the core city (in most European and North American cities, the central municipality; in others, roughly the outline of the pre-1945 city expansion), or do they extend further into suburban areas? In some cities, notably Amsterdam, Munich, Vienna, and Zurich, a mature surface network structure is achieved primarily through the interplay of bus and tram routes; this is also noted. Last, in some cities, specific (segregated and prioritized) bus rapid transit (BRT) infrastructure has been provided to some corridors to boost performance and capacity. The most expansive such network among our 19 case study cities can be found in Brisbane, but BRT lines also are present in Auckland, Adelaide, Sydney, and Amsterdam.

FIGURE 1.
Geographical location
of case study cities in
Australasia, Europe,
and North America



Role of Trams in Case Study Cities

This section highlights the role of trams as an intermediate-capacity transport mode that is present in approximately half the case study cities in the sample. As mentioned above, the characteristics of tram systems differ across these cities. Our focus is on operations that are predominantly aligned at surface level within public road reserves (with or without track reservation) and largely operated by single-unit contemporary vehicles. This applies to the systems in Europe and Melbourne and the streetcar lines in Seattle and Portland. It partially applies to the tram operations in Sydney and Adelaide, which feature similar characteristics in terms of vehicle capacity but have a greater-than-50% share of off-street reservations.

Qualitative correlations are drawn between the presence, expansion, and configuration of tram networks in each of these cities, identifying some key parameters of accessibility performance. For this purpose, we draw on three SNAMUTS measures. For more detail on the origins and methodology of the tool, readers are advised to consult Curtin and Scheurer (2016) or the project website at www.snamuts.com.

Service intensity depicts the number of vehicles or train sets in simultaneous revenue service during the weekday inter-peak period that are required to operate the

proportion of the network that meets the SNAMUTS minimum service standard (30-minute frequencies or better for suburban rail, metro/LRT, or ferries; 20-minute frequencies or better for trams and buses), expressed relative to metropolitan population (vehicles per 100,000 residents). It is an indicator for the level of operational input that a city's decisionmakers appear willing and capable of supplying towards its public transport service. High figures can be read as a measure of largesse in this context; however, particularly for surface modes, they can also speak of inefficiencies accrued in the operation of smaller than necessary vehicles at slower than desirable speeds.

Service intensity deliberately does not differentiate between modes of different passenger capacity, as it is interested primarily in quantifying movement opportunities from the perspective of the user (e.g., a six-car train can carry a multiple of the passengers of a standard bus, but both modes provide one movement opportunity per departure in space and time).

Segmental betweenness counts the proportion of travel opportunities created by a city's land use-transport system that are attracted to the mode in question. Travel opportunities are defined as potential trip relations between concentrations of residents and jobs in a metropolitan area, moderated by their spatial separation or travel impediment, which, in turn, is composed of travel time and service frequency on public transport. Each trip relation between a matrix of activity nodes is allocated a preferred network path (by taking in the factors of travel impediment, transfer intensity, and travel time), and these network paths are traced to route segments of each mode. The figures can tell us how important a particular transport mode is in facilitating movement between activities in a metropolitan area and whether or not this level of importance appears commensurate with the network characteristics assessed qualitatively in the previous section or to the position of the mode in the transport mix of the city in question.

The concept of betweenness centrality as a network measure first appeared in the literature in Freeman (1977) and is discussed in detail by Koschützki et al. (2005) and Porta et al. (2006). It has been modified specifically to suit the purpose of analysing public transport networks (Scheurer et al. 2007).

Network resilience utilizes the segmental betweenness results on each network element and extracts their ratio with the actual passenger capacity offered, which varies by service frequency, transport mode, and operational practice (e.g., how many carriages a suburban train has, on average). It can provide us with an idea whether or not a transport mode is equipped to handle the tasks allocated to it by the configuration of the land use-transport system and to what extent it is in a position to absorb further patronage growth as land uses increase and consolidate and/or as public transport's role in the urban mobility market strengthens. This measure picks up on the concept of stress centrality first mentioned in the literature by Shimbel (1953). In this adaptation, positive figures indicate resilience, and negative figures depict mounting stress/vulnerability. Generally, the measure has been calibrated to mark a cause for concern for levels below zero, and a crisis point for levels below -30. Note, however, that poor

network resilience does not necessarily equate to actual overcrowding of a service; it can just as well be indicative of a degree of “latent demand” across the network or along particular corridors that public transport, for a variety of reasons, fails to pick up.

Table 2 shows that the tram systems in the sample differ quite significantly in character and history. In some cases, this is due to periods of uncertainty over their future associated with partial closure (Adelaide and Munich) or the recent reintroduction of the mode to what does not yet amount to a coherent network (Barcelona and Sydney). Only in Melbourne, Amsterdam, Vienna, and Zurich can there be talk of a mature, first-generation network that largely retained its significance for urban movement throughout the city. In segmental betweenness terms, this characteristic becomes manifest in double-digit percentage figures, whereas in terms of service intensity, it positions these four cities at a multiple of the operational input elsewhere. Thus, with the possible exception of Melbourne, network consolidation, service intensity and the modal share of segmental betweenness behave roughly proportionally to each other.

TABLE 2.
SNAMUTS Indicators for
Tram Systems in 10
Case Study Cities

City	Tram	Service Intensity	Proportion of Segmental Betweenness	Average Network Resilience
Adelaide	First generation; single corridor	0.8	5.0%	+10.6
Sydney	Second generation; single corridor	0.1	0.8%	+1.2
Portland	Second generation; selected inner urban redevelopment areas	0.5	2.5%	+14.3
Seattle	Second generation; single inner urban redevelopment area	<0.1	0.5%	+2.1
Barcelona	Second generation; selected corridors	0.5	1.1%	+19.8
Munich	First generation; multiple corridors	2.1	7.8%	+17.3
Melbourne	First generation; mature expansion	6.7	30.0%	+10.4
Amsterdam	First generation; mature expansion	6.3	16.6%	+18.1
Vienna	First generation; mature expansion	10.0	27.8%	+17.8
Zurich	First generation; mature expansion	9.0	21.7%	+21.7

The network resilience index, however, reveals a more differentiated picture. It is conceded that aggregate measures across entire networks conceal the localized resilience performance of specific routes and corridors (see the next section for an example of a more-detailed geographical representation of this index in Hamburg) and, for the same reason, limit the scope for a meaningful comparative interpretation of results in the very small tram systems of Seattle, Portland, and Sydney. However, it becomes obvious that at a system-wide scale, the next least-resilient tram networks in the sample can be found in Australia, namely Adelaide and Melbourne. In both cities, but of particular relevance for Melbourne, trams ply some primary radial corridors which, in Munich and Vienna, would have been supplied with a metro line at some stage during the past half century. Thus, in the Bavarian and Austrian capitals, the role of trams in the modal mix has shifted as their metro networks grew, to focus more on secondary and, increasingly, orbital corridors. In Zurich, plans to build a metro did not

come to fruition when they were rejected in favor of surface network improvements in local referenda during the 1970s (Ott 1995). However, the relatively small and compact size of the settlement area, enforced by its mountainous topography and protective spatial planning regime, ensures that the limited spatial reach of on-street tram operation remains sufficient to optimize accessibility within the core city. A higher service input in combination with a similar degree of network significance in Vienna, and a similar service input in combination with a lower degree of network significance in Amsterdam, lead to the tram systems in the Austrian and Dutch cities appearing substantially less vulnerable to the effects of current overcrowding, and capable of absorbing future patronage growth, than that of Melbourne.

Case Studies: Hamburg and Munich—What If?

To examine the impact on the resilience and vulnerability of a public transport network to potential congestion effects and its ability to accommodate further growth in patronage, the two existing public transport networks of Hamburg and Munich are assessed under scenarios that would have steered their historic evolution in a different direction. In 1958, Hamburg's city-state government decided to gradually close down the city's expansive tram network and, despite mounting public protests in the final phases of the program, followed through with it over a 20-year period (Kähler 2012). During the same period, Munich also toyed with the idea of eventually phasing out the mode and, roughly between the 1970s and 1990s, complemented the rapid growth of its metro system with widespread withdrawals of tram lines in the catchment of newly opened metro extensions. However, in 1986, the city council decided in favor of retaining the surviving tram routes for the long term and, since the late 1990s, embarked on a trajectory of modest network expansion (Cervero 1998). Still, as we have seen in the previous sections, Munich's much-diminished current tram network has a relatively minor role in facilitating travel opportunities around the metropolitan region compared to its larger counterparts in Amsterdam, Melbourne, Vienna, or Zurich.

This section assesses the impact on network resilience under the assumption that the two German cities' policy decisions had been reversed: What if Hamburg had retained its tram system, give or take the closure of some routes parallel to new metro lines, as well as expanded the network to access major urban development areas of the past half century? And what if Munich had, instead, decided to convert its tram network entirely to bus operation and followed through with it?

For this purpose, a hypothetical tram network was constructed for Hamburg based on the city's current network of high-frequency bus routes (Metrobus, Schnellbus, and some others) and assuming that those sections of current bus lines that follow historic tram routes were still operated by trams. In total, 14 hypothetical tram lines were identified, replicating 12 actual Metrobus lines, three Schnellbus branches, 7 regular bus lines, and fragments of several others. For service levels and capacity, it is assumed that each tram line is operated by single contemporary units (150 passengers) and at a standard 10-minute weekday inter-peak frequency (except between Lokstedt and the city center, where 5-minute intervals prevail as on the actual bus route). Further,

the same travel times as shown in the current bus timetable are utilized, which is a conservative assumption since it is likely that continued tram operation would have resulted in the creation or retention of a greater share of tracks on reservation, as well as traffic priority measures, than is the case along the actual bus network. All other parameters—the current expansion and configuration of the rapid rail network, service levels on other bus routes, and the distribution of land uses across the metropolitan region—are held constant. This occurs to avoid further contamination of the analysis with peripheral factors, although it stands to reason that a retained tram network in Hamburg likely would have influenced land use trends as well as rapid rail investment decisions in ways that differ from actual developments during the past six decades. A further exploration of this context would be of interest, but exceeds the scope of this paper.

In this scenario, total service intensity remains nearly identical over the status quo. As shown in Figure 2, the operational input for Hamburg's hypothetical retained tram network would be 4.8 vehicles per 100,000 population—more than twice as many than in present-day Munich, but fewer than in Amsterdam, Melbourne, Vienna, and Zurich. The number of buses, accordingly, would be reduced by a similar amount.

In terms of attracting travel opportunities generated by the land use-transport system (segmental betweenness), Hamburg's hypothetical retained tram network would absorb just under 20% of the potential transport task—far greater than in more heavy-rail dominated Munich and also eclipsing Amsterdam, but trailing behind Vienna, Den Haag, and Rotterdam (Zuid Holland) as well as the metro-free agglomerations of Melbourne and Zurich.

The assumptions for this scenario, thus, do not appear out of bounds within the context of the policy directions other, comparable cities have taken. Yet, it does not represent a blueprint for the future, in the sense that the tram network constructed here was intended as a viable template for the possible reintroduction of the mode in Hamburg: it should more accurately be described as an “alternative history” scenario.

FIGURE 2.

Service intensity on tram network in 11 case study cities in vehicles per 100,000 population in simultaneous weekday inter-peak revenue service, highlighting Hamburg's hypothetical retained tram operation

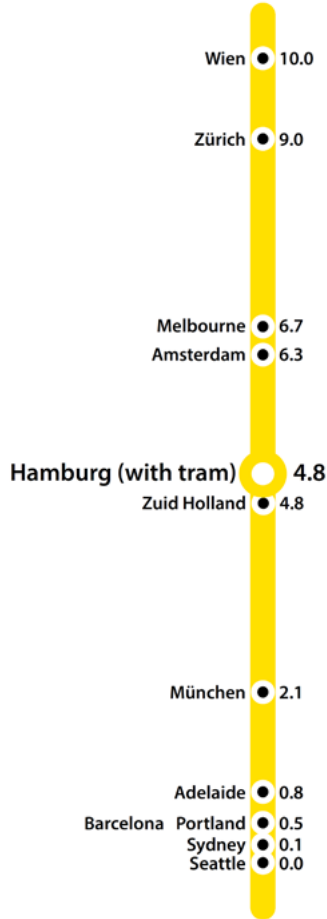
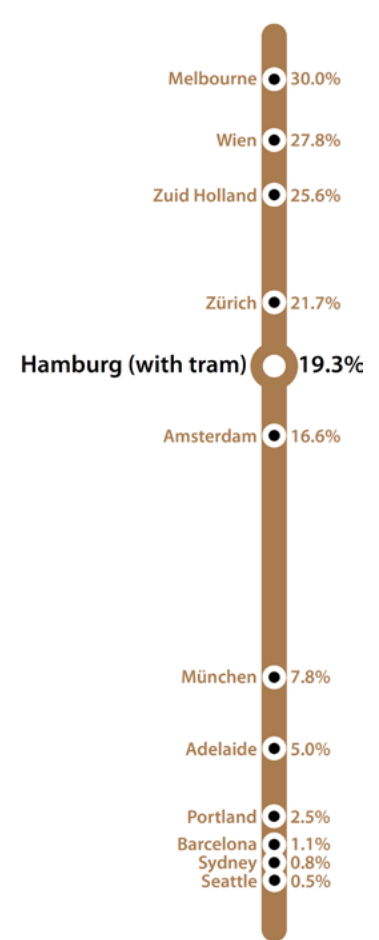


FIGURE 3.

Proportion of metropolitan-wide segmental betweenness values (travel opportunities) attracted to tram routes in 12 case study cities and city-regions, highlighting Hamburg's hypothetical retained tram operation



In the absence of travel time reductions through priority measures or frequency improvements compared to the actual bus lines, the main benefit of the hypothetical tram network in SNAMUTS terms will become visible in the network resilience index. This is because trams are capable of moving a significantly greater number of passengers per vehicle than buses¹ and, hence, are capable of withstanding overcrowding effects and maintaining operational reliability up until a higher level of network significance, as expressed by the segmental betweenness index.

¹ In the Hamburg case study, we assume the comfortable passenger load per vehicle to be 150 per tram and 60 per bus, the latter representing an average across the actual fleet composition of standard, single-articulated, and double-articulated vehicles in the Hanseatic city. It is true that there is a greater likelihood for larger buses to be operated on busy routes, including some of those assumed for tram retention in this scenario. SNAMUTS does not make such differentiation (since it is not possible to obtain robust fleet deployment details on a route-by-route basis in most cities) and, thus, is likely to understate segmental resilience in some cases for the actual 2013 bus network. However, in the comparison to the tram retention scenario, the assumption of 150 passengers per tram is also relatively conservative, since larger vehicles and the practice of coupling two units into train sets are available (where the infrastructure permits) and would improve the resilience count accordingly.

Figures 4 and 5 depict the distribution of network resilience performance across the Hamburg network in the 2013 status quo and in the hypothetical tram retention

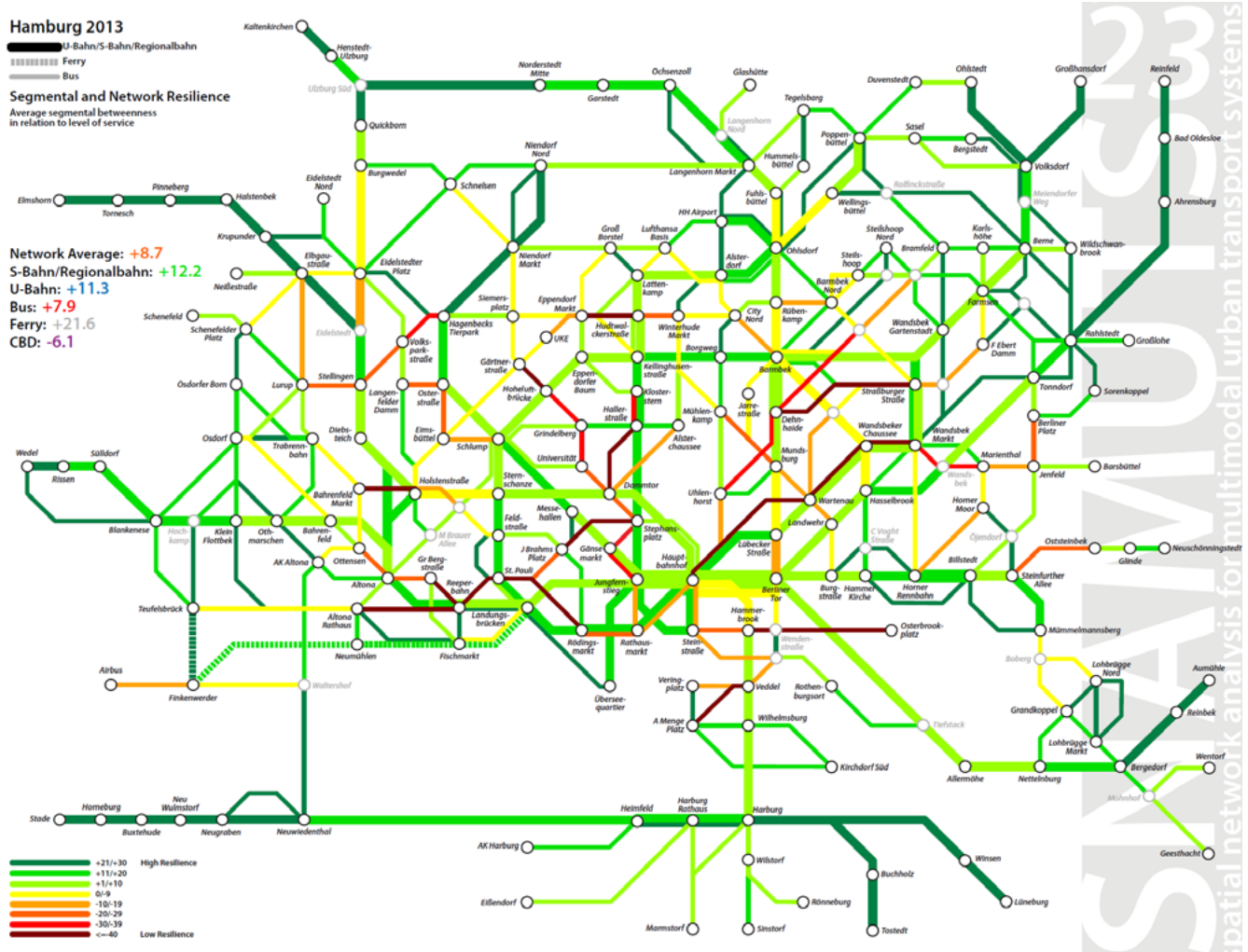


FIGURE 4. Segmental and network resilience diagram for Hamburg network in 2013

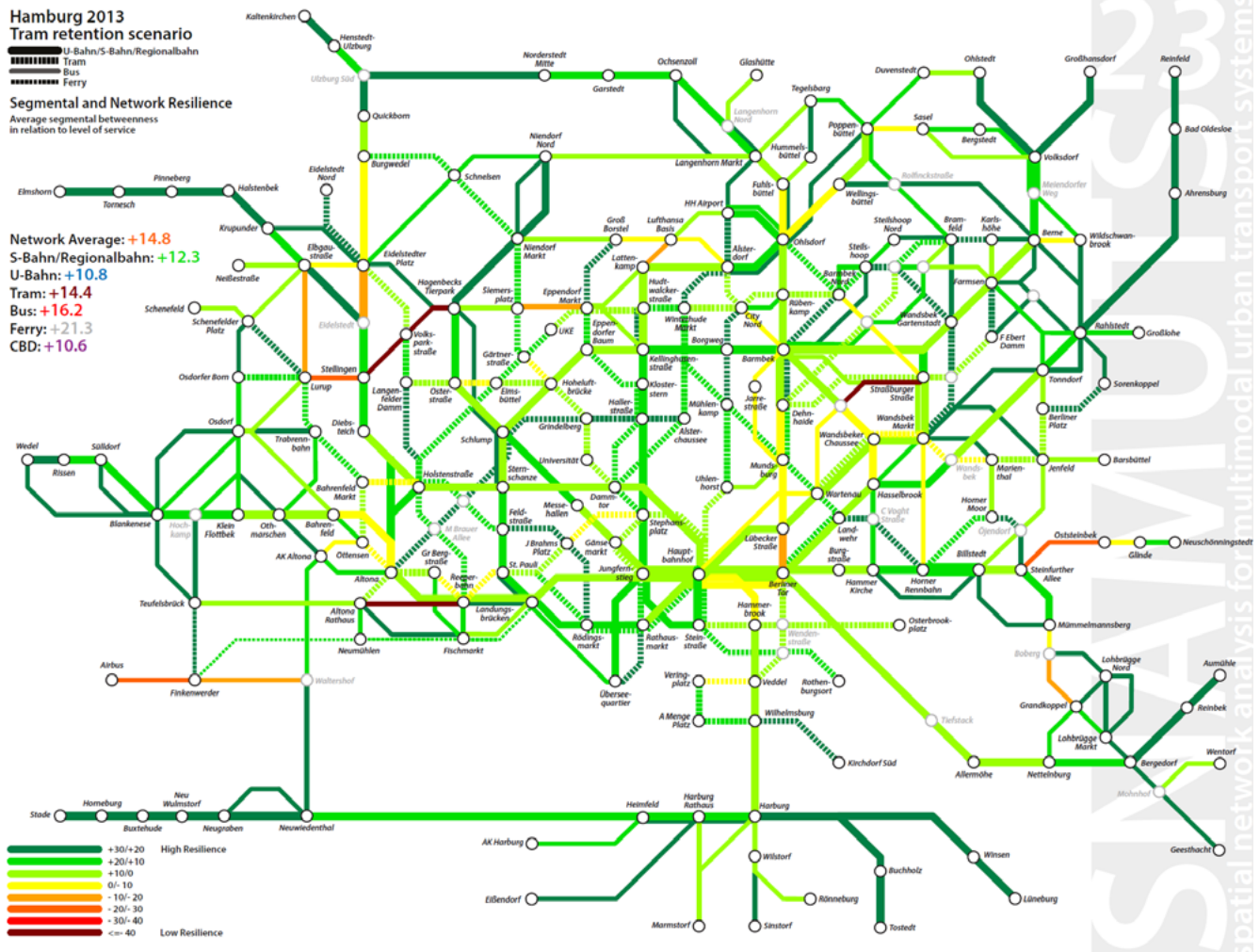


FIGURE 5. Segmental and network resilience diagram for Hamburg network in hypothetical tram retention scenario

Average network resilience in Hamburg improves from an actual 2013 level of +8.7 to +14.8 in the tram retention scenario, similar to present-day Munich or Copenhagen and among the best performers across the SNAMUTS sample. In the CBD, whose surface public transport network is dominated by trams in the retention scenario, the average resilience value increases to +10.6 from a concerning -6.1 in the 2013 status quo network, the second poorest such value in the sample before Sydney. Figures 6 and 7 show these results in the context of the international cohort of case study cities.

FIGURE 6.

Average network-wide resilience values on public transport networks of 21 case study cities, highlighting Hamburg in 2013 status quo and tram retention scenario

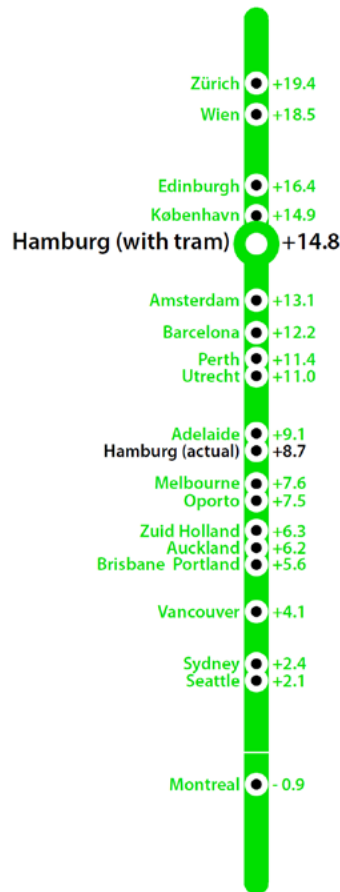
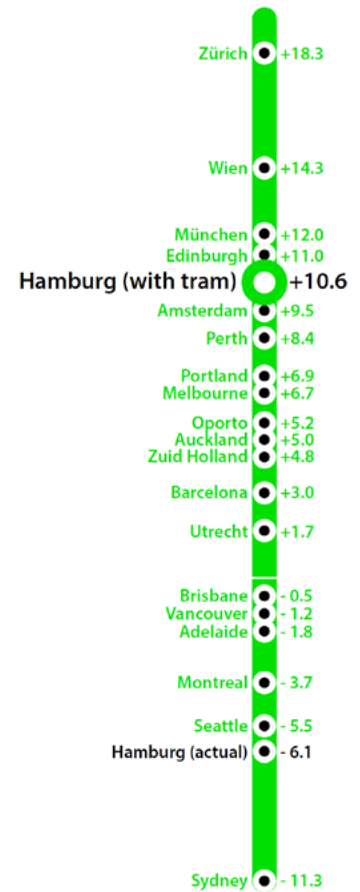


FIGURE 7.

Average resilience values on CBD proportions of public transport networks of 21 case study cities, highlighting Hamburg in 2013 status quo and tram retention scenario



Conversely, the assessment of Munich in the hypothetical scenario of an implemented closure of the tram system (replacing the existing tram lines one-on-one by buses, with service frequencies and travel times unchanged) delivers an expected drop in resilience performance, although it is not quite as drastic as that experienced by Hamburg in real life (Figures 8 and 9). On the network-wide assessment, Munich would slip into the lower mid-field among its European peers, whereas in the CBD-specific assessment, a tram-free Bavarian capital would be exposed to greater average vulnerability when it comes to catering for travel opportunities by public transport than all other European case study cities bar Utrecht and Hamburg.

FIGURE 8.

Average network-wide resilience values on public transport networks of 21 case study cities, highlighting Munich in 2011 status quo and tram closure scenario

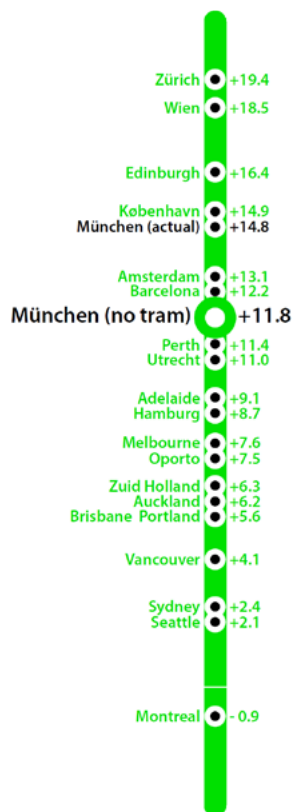
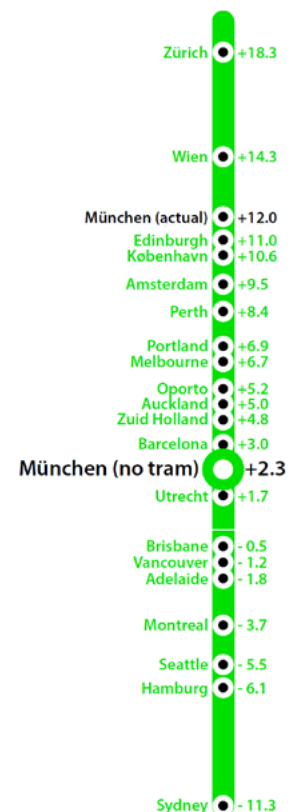


FIGURE 9.

Average resilience values on CBD proportions of public transport networks of 21 case study cities, highlighting Munich in 2011 status quo and tram closure scenario



Thus, provided the resilience index itself offers the analytic robustness required for making such a statement, we can conclude that Hamburg's current precarious position in making its public transport network absorb growing passenger numbers and a growing mode share can be traced, to a significant part, to its post-war decision to replace its tram system with buses. Furthermore, this circumstance leads to a particular performance deficit in the central area where the main bus trunk routes are timetabled to saturation levels and where there is limited scope, and road space, to increase capacity by further boosting bus service frequencies. Conversely, it appears as though Munich has averted a similar crisis through its decision to preserve and modernize at least a lean core of its once-extensive tram network, and that these benefits play themselves out most impressively in the inner area where a much larger deployment of buses would be necessary to achieve a level of passenger convenience and network resilience comparable to the status quo.

Discussion and Conclusions

The intention of SNAMUTS as an accessibility tool is to assist decisionmakers in identifying visible as well as less visible shortfalls in the interplay of land use patterns and transport network performance to devise strategic interventions to enhance the position of public transport in the mobility mix of a city. In this context, the interplay of different public transport modes with varying inherent passenger capacity and operational characteristics is often a factor that is not at the forefront of public debates in each city, given that the modal distribution of transport tasks tends to be subject to a gradual, city-specific evolutionary process that is usually "taken for granted" by most stakeholders. It is also associated with the notion that the introduction of an additional transport mode and its development beyond a niche role generally represents a "generational project," requiring a vast allocation of resources as well as concerted efforts in terms of political vision, championship, and consensus-building to come to fruition. This is how Montreal, Munich, and Vienna established their metro systems at the peak of post-war modernism (Pucher and Kurth 1996; Paulhiac and Kaufmann 2006), and how Perth, Portland, and Vancouver embarked on developing leaner forms of urban rail in the emerging sustainability era (Newman and Kenworthy 1999; Schiller et al. 2010), in all cases driven by the desirability of shifting a greater share of urban transport onto rail on the grounds of city-building, efficiency, and environmental protection. It is also how Zurich, aided by the Swiss regime of direct democracy, went against the grain of conventional transport planning wisdom in the 1970s and delivered an alternative, highly-effective, and locally-adapted mix of regional and urban transport modes (Cervero 1998; Mees 2010) without resorting to the introduction of an underground metro (while building several inner-city tunnels for the regional rail system).

But such a coincidence of supportive factors towards public transport investment and modal diversification is not a global standard; in other cities, it simply failed to materialize. Hamburg is looking back on two failed attempts to reintroduce light rail since 2000 after the debate had descended into political partisanship, and the plans did

not survive subsequent changes of government. Edinburgh opened a light rail starter line in 2014, but its further expansion has been mired in similar public controversy and remains uncertain (Karou and Hull 2014). Montreal's metro system, for all its demonstrable improvements to public transport accessibility in the core city, has expanded at a much slower than desirable rate over the past quarter century because it is technologically unsuited to operate on cheaper-to-build above-ground alignments in the harsh Québec winter. Vancouver's SkyTrain is on track to become a victim of its own success in instilling a "public transport culture" in the British Columbian city, likely necessitating expensive retrofits to increase its passenger capacity in the future (Curtis and Scheurer 2016). In each of these examples, we can detect patterns of path dependency that inhibit or slow down efforts to further enhance public transport, whether for reasons of transport technology or for factors to do with the course of political debates specific to each city (Curtis and Low 2012).

Against this background, is it even practically helpful to make comparisons between public transport performance in cities that have, for many decades, embarked on different trajectories that cannot be modified easily or within the time frames that determine the horizons of political decisionmakers?

The analysis undertaken in this paper asserts that there is a role for a benchmarking process that can point out what constitutes international best practice in public transport accessibility and serve as a guide for cities to inform their transport and land use planning practice with the aid of quantification tools such as SNAMUTS. The purpose of such a process is not to merely lament—to use our case study example—the standard of accessibility performance that Hamburg failed to achieve but could have achieved had it followed the public transport development policies of Amsterdam, Munich, or Vienna over the past half-century. Rather, it is about unleashing the creativity of policymaking as demonstrated, for instance, by Zurich since the 1970s in exploring alternative futures that lead to comparable or superior outcomes in accessibility terms than what the conventional strategies of cities with greater resources or less political contention are able to deliver.

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Public Transit Equity Analysis at Metropolitan and Local Scales: A Focus on Nine Large Cities in the US

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Texas A&M Transportation Institute

Abstract

Recent studies on transit service through an equity lens have captured broad trends from the literature and national-level data or analyzed disaggregate data at the local level. This study integrates these methods by employing a geostatistical analysis of new transit access and income data compilations from the Environmental Protection Agency. By using a national data set, this study demonstrates a method for income-based transit equity analysis and provides results spanning nine large auto-oriented cities in the US. Results demonstrate variability among cities' transit services to low-income populations, with differing results when viewed at the regional and local levels. Regional-level analysis of transit service hides significant variation through spatial averaging, whereas the new data employed in this study demonstrates a block-group scale equity analysis that can be used on a national-scale data set. The methods used can be adapted for evaluation of transit and other modes' transportation service in areas to evaluate equity at the regional level and at the neighborhood scale while controlling for spatial autocorrelation. Transit service equity planning can be enhanced by employing local Moran's I to improve local analysis.

Keywords: Transit; equity; local Moran's I

Introduction

Public transportation serves the important role of providing affordable mobility across the social and economic spectrum, particularly for the largest cities in the United States (Forkenbrock and Sheeley 2004; Pucher 2004). Transit planners need analysis methods that balance practicality and precision to evaluate how well proposed improvements meet the needs of riders, especially those who may have limited options due to income. This study deploys a consistent data and techniques that can evaluate the relative quality of transit service to employment opportunities at a variety of geographic scales.

The recent federal emphasis on evaluating transportation investments with performance measures provides an opportunity for transportation agencies to employ new data sources and methods to evaluate transit service (United States Congress 2012). Since this responsibility for measuring performance is most often attributed to individual transportation agencies (Fabish and Haas 2011; Ramani et al. 2011), most previous studies of transit service equity approach the problem as either a qualitative overview within a region, or as case studies with notable methodological advancements (Beyazit 2011; Delbosc and Currie 2011; Duthie, Cervenka, and Waller 2007; Forkenbrock and Schweitzer 1999; Forkenbrock and Sheeley 2004; Foth, Manaugh, and El-Geneidy 2013; Golub 2014), rather than comparing service equity details among peer agencies. Transportation agencies can analyze equity from multiple perspectives and time frames, and additional methods help improve planning for a range of equity perspectives (Duthie et al. 2007; Hay 1993; Kaplan et al. 2014; Welch and Mishra 2013).

Accessible transit service is an equity issue because buses, trains, and other transit services provide the motorized transport necessary for social inclusion and for access to jobs needed for social mobility (Boschmann and Kwan 2010; Clark and Wang 2010; Lucas 2012; Phillips and Edwards 2002; Sanchez, Stolz, and Ma 2004). This study focuses on transit equity regarding access to service, rather than including costs to individuals. This approach does not account for individual mobility needs or personal costs. This is aligned with the concept of horizontal equity, where fairness of services across income groups is considered; however, it does not consider vertical equity in the sense that disadvantaged households would pay a smaller share or receive greater services than others (Litman 2007, p. 51). Low-income populations that may not have access to a car are put at a disadvantage in competing for jobs located more than a few blocks from home, even if they are fully qualified. Slower transit services also compound challenges on low-income families who need to chain trips to stores with work and transporting children to school and other activities (Bricka 2008; Christie et al. 2011; Jain, Line, and Lyons 2011; Jiao, Moudon, and Drewnowski 2011; Sanchez et al. 2004). Transit systems are planned at the geographic scale of the region or city, but the benefits and costs of transit provision is felt at the local level. Individual routing of bus or rail service in, or around, neighborhoods of differing income status has accordingly different effects on the residents' access to jobs, goods, and services (Delbosc and Currie 2011; Foth et al. 2013; Jiao et al. 2011).

This study contributes to the literature on transit equity by reviewing a relatively standard, region-level descriptive statistic of access to transit service, with a novel application of a geostatistic (through local Moran's I) that identifies significant clusters and outliers of high and low transit service access by differing populations. In addition, using a nation-wide dataset allows comparison of transit equity by region and by neighborhood. This method has the potential to identify equity issues with existing transit service early in a planning process, to help guide further analysis of potential transit infrastructure and service. Transit access can have many implications on the geography of opportunities for jobs, healthy food, cultural resources, and other human needs documented elsewhere in the urban geography literature. Access to transit affects broad aspects of people's lives, particularly those whose mobility options may

be limited by circumstance. Improved transit data and analysis methods are valuable to help address the equity of urban transit provision, and improve the discourse of transportation planning by evaluating equity at multiple scales.

The paper begins with a brief review of the challenges of transportation equity in the United States. We then position the study in the context of our focus on large cities in the United States. Finally, we propose a geostatistical method to provide a stronger methodological bridge between the understanding of geodemographics and transit services, offering conclusions linking this study for use at the sub-national level and in other countries.

Evaluating Transportation Equity

There is little debate on the role of transportation planners and governments to provide infrastructure enabling mobility to as many people as possible, but the challenges involve the decisions involved with equitable distribution of transport resources over a finite population geography (Boarnet 2009; Litman and Brenman 2012; Martens, Golub, and Robinson 2012).

Some recent research has identified that the scale of evaluation is important. In the United States, authority for major transportation investments are frequently at the state level (Plotnick et al. 2011), yet the everyday impact of transportation on peoples' lives occurs at the regional and local levels (Bond and Kramer 2010; Bullard 2008). Appleyard and others have suggested that wealth and social status play a major role in guiding decisions concerning who's community is made more livable through certain transportation investments, suggesting normative principles based on supporting pursuit of quality of life, and care for society's most vulnerable citizens (Appleyard et al. 2014).

Transportation access is a multimodal challenge. Although transit is considered a key mode for equitable mobility, access to an automobile has been shown to significantly increase opportunities for employment (Clark and Wang 2010). However, other factors such as demographics, geographic factors, and access to multiple transportation modes affect access to employment in complicated ways, so improving the roadway network alone cannot be expected to fix all employment access problems for all people (Boschmann and Kwan 2010). The adequacy of sidewalks, affordable bike sharing systems, and other modes all play a significant role in accessing transit service (Ehrenfeucht and Loukaitou-Sideris 2010; Goodman and Cheshire 2014; Griffin and Sener 2016).

In theory, effective transportation planning that integrates social equity as a core value should help direct urban regions towards a more just transportation system. In practice, a recent review of equity objectives and measures in North American transportation plans suggests these values are not clearly integrated in the planning process (Manauh, Badami, and El-Geneidy 2015).

Local and regional planning bodies often face challenging choices on which aspects to focus on given resource and time constraints (Duthie et al. 2007), and the reality that adequate information may not be readily available (McCray 2009). Information needed for these analyses often comes from modeling, geographic information systems, and qualitative methods.

Evaluation of transportation user effects include methods to evaluate the ability to reach desired destinations and choices in terms of quantity and quality of transportation options, typically involving geographic information systems (GIS) and travel demand forecasting. GIS has become instrumental to integrate existing socio-demographic community data with planning scenarios developed in a modeling framework. GIS-based platforms have the particular strengths to geographically organize data for analysis of numerical data, and more recently for information gleaned from affected persons of a qualitative nature (Jones and Evans 2012; McCray and Brais 2007).

Many of these methods were developed by researchers and planners with their peers in mind, rather than providing tools understandable or usable by a wider population (Bailey and Grossardt 2009; Hanna 2000). One recent advancement to make transportation equity analysis more accessible involved the development of a proof-of-concept website that arrays various regional transportation scenarios in a planning effort, *vis-à-vis* demographic groups such as income and race (Golub, Robinson, and Nee 2013). Although this effort provides a new method to expand the availability of information to the public with an environmental justice perspective, the authors noted it may be complicated for some users, and lead to misinterpretation. Recent research shows that advancements in transport policies regarding equity have had limited effect on equity of transit service (Golub, Marcantonio, and Sanchez 2013). This study proposes a step back from case studies, to a larger perspective of multiple large cities.

United States Transit Context

Though transportation equity is a concern over all populations and places, this study focused on the challenges of transit service in large, auto-centric cities in the United States. This emphasis combines an interest in both the unique challenges of more auto-oriented growing cities and the presence of newly-developed data. The availability of the Environmental Protection Agency's (EPA's) new Access to Jobs and Workers via Transit promotes efficient geographic analysis, while covering 88% of all transit ridership in the United States (Ramsey and Bell 2014). This emphasis seizes an opportunity to leverage new data to support equity analysis in cities with expanding and changing transit systems.

United States Legal Planning Requirements

Federal actions on civil rights began broad changes in transportation planning in the United States, but many issues related to both policy frameworks and the role of staff-level decisions regarding equity continue (Karner and Niemeier 2013; United States

Department of Justice 1964). In 1994, Executive Order 12898, Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations (Clinton 1994), updated earlier guidance on Environmental Justice (United States Department of Transportation 2012). The new guidance advised transportation planners to avoid disproportionate adverse impacts on minority and low-income groups, and the research community responded with diverse solutions for improving transportation equity. However, most of the methods address only automobile traffic, either regarding network efficiency (Duthie and Waller 2008), tolling impacts (Plotnick et al. 2011; Ungemah 2007), or negative impacts such as air and noise pollution (Forkenbrock and Schweitzer 1999). Metropolitan planning organizations (e.g., Capital Area Metropolitan Planning Organization 2010) and states (e.g., Cambridge Systematics and Akin, Gump, Strauss, Hauer and Field 2002) have considered environmental justice criteria as part of the multimodal project prioritization, but no known studies have systematically analyzed transit services offered in the United States from an environmental justice perspective.

Focus on Nine Large Cities in the United States

This study focuses on large cities in the US that have not retained a robust transit system over several generations. New York City, Boston, Massachusetts, and, to some extent, Washington, DC, were largely developed before popularization of the automobile, and built out rail and bus transit systems concurrently with development. In terms of equity, more challenges are anticipated in cities developing in the midst of the challenges of suburban dispersal, limited transit funding, and growth in population and employment. An additional requirement for this study is the availability of transit operation data combined with income data for equity analysis, which is described later. The following nine cities meet these criteria, and their regions comprise the focus of this study: Atlanta, GA; Austin, TX; Dallas, TX; Denver, CO; Houston, TX; Indianapolis, IN; Los Angeles, CA; Seattle, WA; and San Diego, CA. Whereas the aim of the present research is focused on an empirical and methodological approach to equity, the cultural and political contexts of these cities and their states vary widely and are expected to be among the drivers of transit planning and service outcomes (Grenge 2002). The known similarities and contextual differences between the cities motivates our multiple case study approach, which facilitates understanding of the differences in local issues, but also supports the validity and generalizability of this study's conclusions (Chmiliar 2010; Schlossberg 2001).

Each of these large cities of focus in this study varies in its size, density, and transit service. Table 1 includes their basic characteristics based on the 2012 National Transit Database (NTD) (Federal Transit Administration 2014), with calculations performed by the authors. Whereas Atlanta is similar to the other cities in terms of its service area and population, it has a 96-mile heavy rail system with almost double the annual passenger miles of its bus system. Indianapolis has the lowest passenger kilometers per capita, with a straightforward bus system. Service area population densities vary from that of the urbanized area because transit services for the primary transit agency may extend well past municipal boundaries or can also be shared with multiple agencies.

TABLE 1. Primary City Transit Service Area Characteristics

Primary City	Primary Transit Agency	Service Area (sq. km)	Service Area Pop. (Census 2010)	Annual Passenger km per Capita	Pop. Density of Service Area (sq. km)	Fixed-Route Modes (Annual Operating Expenses, in millions)
Atlanta, GA	Metropolitan Atlanta Rapid Transit Authority	1,290	1,574,600	1,150	1,221	Bus (\$220), Heavy Rail (\$208)
Austin, TX	Capital Metropolitan Transportation Authority	1,352	1,023,135	405	757	Bus (\$111), Hybrid Rail (\$14), Commuter Bus (\$8)
Dallas, TX	Dallas Area Rapid Transit	1,803	2,423,480	505	1,344	Bus (\$249), Light Rail (\$151)
Denver, CO	Denver Regional Transportation District	6,024	2,619,000	583	435	Bus (\$313), Light Rail (\$87)
Houston, TX	Metropolitan Transit Authority of Harris County	3,328	3,527,625	392	1,060	Bus (\$305), Commuter Bus (\$47), Light Rail (\$18)
Indianapolis, IN	Indianapolis and Marion County Public Transportation	1,026	911,296	130	889	Bus (\$51)
Los Angeles, CA	Los Angeles County Metropolitan Transportation Authority	3,919	8,626,817	681	2,201	Bus (\$931), Heavy Rail (\$117), Light Rail (\$234), Bus Rapid Transit (\$24)
Seattle, WA	King County Metro	5,527	1,957,000	763	354	Bus (\$440), Trolleybus (\$61), Street Car Rail (\$3)
San Diego, CA	San Diego Association of Governments	1,834	2,813,833	355	1,534	Bus (\$143), Light Rail (\$66), Commuter Bus (\$3)

Source: Federal Transit Administration 2014

Data: Description and Processing

The EPA’s new Access to Jobs and Workers via Transit database combines transit service and selected demographic variables to allow evaluation of the performance of neighborhoods in regard to their accessibility to destinations via public transit service (Ramsey and Bell 2014). This dataset includes information on a range of transit and population-related statistics, both at the US Census Bureau’s Core Based Statistical Area (CBSA), which is a large metropolitan region, and block group geographies, which generally include multiple blocks, but smaller than most neighborhoods. CBSAs include one or more counties with a core area containing at least one core of 10,000 population or more, together with adjacent communities having a high degree of economic and social integration with that core (US Census Bureau 2012).

This study uses a small portion of the variables available related to transit access and income to evaluate equity across nine aforementioned large cities in United States. To evaluate relative equity of transit service, we focused on access to transit, using data related to the percentage of low-wage workers with transit access and the percentage of all workers with transit access. The first variable referring to transit accessibility is defined as the “employed population able to access the block group within a 45-minute transit commute from their home location as a percentage of total regional employed population” (Ramsey and Bell 2014, p. 4). The low-wage classification for the second attribute is defined as workers earning \$1,250 per month or less. The prevalence of

low-wage workers in a block group is the focus in this study, but we also note that this statistic does not replace other key variables in understanding equity at the local level, such as the availability of jobs, and cultural relationships that may help support some low wage workers.

Transit service information includes calculations of travel time from each census block group to all other census block groups accessible via transit. Census 2010 data were integrated to tabulate how many people live and work in those accessible block groups, using a 45-minute travel time limit that includes wait times, transfers, and walking to and from transit stops. The 45-minute transit travel time restriction included with the EPA data source may not represent all trips well, since the 2009 National Household Travel Survey (NHTS) reports an average commute time of 53 minutes (Santos et al. 2011). This could be expected to restrict destination accessibility represented in these data more in suburban areas than city centers, but any bias in this regard is applied equally among the cities through these data. Each city's proportion of population living in urban and suburban areas varies, which is also affecting the efficiency of transit service. However, density variables predict less of the variability in transit use than diversity of land uses, street design, and distance to transit stops, on average (Ewing and Cervero 2010). The data cover only metropolitan regions and counties served by transit agencies that provide their service data using a standard data format called General Transit Feed Specification (GTFS), which includes stops, routes, trips, and other schedule data (Google 2012). Although sidewalk coverage is also related to increased transit use (Ewing and Cervero 2010), neither sidewalk quantity nor quality data are currently available for any of the cities in a comparable format.

Methods

This study demonstrates a method for analyzing spatial variation in transit access by income. Improvements to transit accessibility such as increases of geographic service and frequency are well-documented, but are restricted by funding available to transit agencies for improvements. This method contributes to evaluation of transit service at multiple scales, using publicly-available data described in the previous section. The next section describes our use of descriptive statistics and block group level geostatistics for identifying local variation, clusters and outliers in transit access.

Descriptive Analysis

We evaluated transit service equity by first understanding the level of accessibility experienced by low-income classification versus the accessibility level experienced by the remainder of the population, following EPA's Access to Jobs and Workers via Transit database definitions. For each block group in each of the nine CBSAs, equity was evaluated as the arithmetic difference between the percent of low-wage, transit-accessible workers and the total of transit-accessible workers. Next, we aggregated the differences in transit accessibility by income level at the CBSA level and calculated the average, minimum, maximum, and standard deviations of those differences.

Spatial Analysis

In his article describing simulation of urban growth over time, Tobler invoked the first law of geography: "... everything is related to everything else, but near things are more related than distant things" (Tobler 1970). The degree to which each block group is influenced by its neighbor can be described with spatial statistics. Anselin developed a local Moran's I statistic to describe this relationship:

$$I_i = z_i \sum_j w_{ij} z_j \quad (1)$$

where "the observations z_i, z_j are in deviations from the mean, and the summation over j is such that only neighboring values $j \in J_i$ are included" (Anselin 1995). The local analysis of clustering of each block group with its neighbors prevents global statistics' tendency to hide issues of significance when averaged as a whole. Since we are interested in understanding the effects of transit service levels in different locations, the local Moran's I helps explain the likelihood of transit service being similar in locations close to each other.

Variances in transit access by income are expected to follow Tobler's Law, in that observations in one location are more likely influenced by their geographic neighbors than other locations. Therefore, local Moran's I is calculated using an inverse distance weighted conceptualization of spatial relationships. We used a Euclidean distance calculation on data with coordinates in the Albers equidistant geographic projection, which minimizes distortions in area and distance on a national scale. Like other local indicators of spatial autocorrelation, the local Moran's I "... gives an indication of the extent of *significant* spatial clustering of similar values around that observation" (Anselin 1995). Cluster and outlier analysis with Moran's I with the same transit service level datasets and income data across each of the regions allowed localized comparisons within each region, and between each other, in addition to p-values to evaluate statistical significance.

Results

Each of the nine large cities varies in the difference between workers' transit access by income class. Table 2 depicts the differences in transit service between low-wage and all transit-accessible workers in each of the nine study regions. Observed at the core based statistical area level, the Atlanta region has the least average difference between the percentage of low-wage workers and all transit-accessible workers, and the Austin region has the greatest discrepancy. Again, we define transit-accessible workers following the Access to Jobs and Workers via Transit database, as "employed population able to access the block group within a 45-minute transit commute from their home location as a percentage of total regional employed population" (Ramsey and Bell 2014).

The differences between the cities in terms of equity of transit service are significant ($t = -3.954$, two-tailed $p = 0.004$) The minimum, maximum, and standard deviation indicate the lowest variation between block groups in the Atlanta region as well, with the greatest deviation in the Denver region. Though the Denver region provided the

highest percentage of low-wage workers able to reach work destinations from their home location, it also had the highest standard deviation of block groups within the region, indicating disparity in local service. Such a regional view provides the first known analysis of these cities in terms of the income equity of transit service, helping answer questions of difference in transit accessibility between large cities and within neighborhoods.

TABLE 2.
Percent Difference in Transit Service between Low-Wage and All Transit-Accessible Workers

CBSA	Average Percent Difference	Minimum Percent Difference	Maximum Percent Difference	Standard Deviation Percent Difference
Atlanta-Sandy Springs-Marietta, GA	-0.55	-1.19	8.35	1.36
Los Angeles-Long Beach-Santa Ana, CA	-0.97	-4.55	14.03	3.09
Dallas-Fort Worth-Arlington, TX	-1.11	-2.29	10.69	1.74
San Diego-Carlsbad-San Marcos, CA	-1.27	-6.19	22.68	4.97
Houston-Sugar Land-Baytown, TX	-1.61	-3.60	13.32	2.83
Indianapolis-Carmel, IN	-2.16	-5.47	15.75	4.70
Denver-Aurora-Broomfield, CO	-3.25	-10.72	23.84	6.34
Seattle-Tacoma-Bellevue, WA	-4.41	-8.23	24.40	5.25
Austin-Round Rock-San Marcos, TX	-5.80	-10.04	11.82	5.95

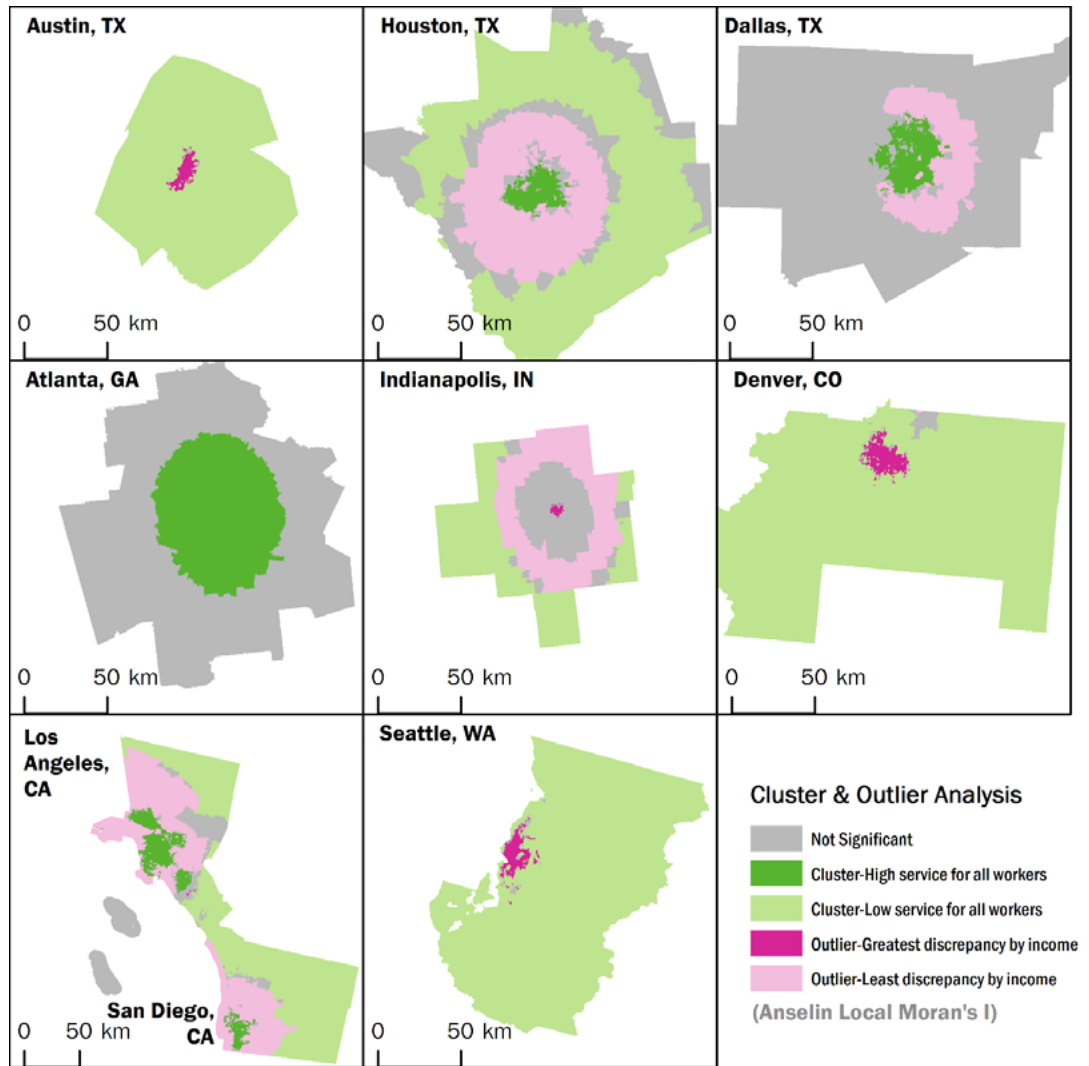
Transit equity can be evaluated at multiple geographic scales, and doing so reveals different results. The minimum percent difference of transit service by income in Table 2 refers to the individual block group in each region, with Atlanta again leading in terms of equity. However, there are local communities in the San Diego, Denver, and Seattle regions with a difference in the percent of population transit access by more than 20%. The presence of rail transit in concert with fixed-route bus service is associated with the regions with the least variance in transit access by income class. This is likely due to the higher average speed associated with rail transit as compared to most bus transit, in addition to the larger overall transit investments of all modes found in Atlanta, Los Angeles, and Dallas. This snapshot of transit equity at the regional average and at the extremes in each region provides a first-level of screening analysis to help identify areas of concern. Future research would benefit from more detailed spatial analysis to determine where transit equity might need further review.

Analysis at the regional level reveals variances in access to transit service by income class, but these results must be reviewed with caution. Though the regions with the least apparent variance are well-served by at least fixed-route bus and rail transit, the location of low-income groups is not necessarily static, and transit agencies are challenged to coordinate their services in an efficient manner while serving the riders with the most need. However, global statistics can hide the relationships and clustering of transit access within and between neighborhoods, which is addressed by analysis of local spatial clustering.

Cluster and outlier analysis of local Moran's *I* unpacks the relationships between low-income and all transit-accessible workers at the block group level. Each of the maps

in Figure 1 displays this relationship classified into either clusters indicating similarity between block groups, or outliers indicating dissimilarity. Each grouping is significant ($p < 0.05$), or it is designated as Not Significant. Significant clusters of transit service levels and all income levels are indicated in green—high service in dark green, and low service in light green. The outliers are in purple—the darker area has the greatest discrepancy of transit service level by income, and the lighter shades indicate outliers with the least discrepancy in transit access by income.

FIGURE 1.
Transit service cluster
and outlier analysis



Regional analysis of spatial autocorrelation reveals neighborhood effects between transit access by income group. Each region reviewed is characterized by a different relationship between low income and all transit-accessible worker communities, but no region has a cluster of both low transit accessibility and low-income workers near its urban core. The radial patterns of the cluster and outlier analysis in Houston, Dallas, Atlanta, and, to a lesser degree, Indianapolis are partly due to the spatial pattern of the

transit network, but may generally indicate that the transit services do not have major spatial omissions across the region. Conversely, Austin, Denver, and Seattle have large areas including their downtowns with a significant difference between transit access among low and all income groups. This finding aligns with local analysis, such as a recent case study of Denver's Southeast Light Rail Line, which demonstrated a growth in predominantly high-income jobs following completion of the service in 2006 (Sadler and Wampler 2013). In addition to the potential for transit service equity variance, this could be associated with constraints in the cost of service extensions, clustering of low-income neighborhoods, or other factors. Generally, Los Angeles and San Diego do not share the previous cities' spatial clustering of low and high transit access discrepancies by income at the neighborhood level.

The results of the cluster and outlier analysis in Figure 1 are consistent with the descriptive analysis in Table 2, identifying the greatest variation in transit access by income in the Austin, Denver, and Seattle regions and the least variation in Atlanta, Los Angeles, and Dallas. These differences can be due to a combination of factors relating to both transit services and the distribution of populations by income. Though all of these major cities receive Federal Transit Administration grants, each city deploys its own combination of local funding to support its system, which limits the comparability of systems with a singular method such as this one. The literature demonstrates that both of these issues are addressable by transportation and housing policies, planning, and implementation that seek to improve access to the supply of residential choices and mobility options that connect people of a range of incomes to jobs and services needed for a high quality of life. The methods described in this study could be useful for more in-depth, better-coordinated, and interactive policy analysis regarding transportation and housing, since cities in the US have varying governance and planning practices regarding transportation and housing.

Conclusions

Transit service changes in large, auto-oriented cities provide uneven access and mobility benefits, and, to date, US metropolitan planning organizations (MPOs) have accomplished little in terms of achieving spatial justice or social equity through transportation planning (Manauagh et al. 2015; Martens et al. 2012). Some cities, such as Los Angeles, rank highly in others' transit accessibility rankings (e.g., Owen and Levinson 2014), in addition to this study's analysis of equity by income. Other cities, such as Atlanta, may rank low on overall accessibility (e.g., Owen and Levinson 2014) while doing well in terms of equity by income. Additional methods are needed to leverage advanced data sources for more spatially disaggregate analysis of transit equity. Despite the recent emphases on performance measurement in federal guidance (Clinton 1994; United States Congress 2012), few spatial methods have been articulated to evaluate transportation equity. Confounding this challenge is the fact that changes in both transit provision and locations of low income demographic groups make equity analysis a moving target. The same challenges that affect travel demand modeling regarding demographics, mode choice, issues of temporal and spatial precision, and accuracy are

present in similar quantitative analyses (Karner and Niemeier 2013). The application of recent advancements in spatial modeling, on the other hand, can help control for effects such as spatial autocorrelation, resulting in better understanding of the local nuances of transit service.

This study adds to the literature by employing a new data set integrating transit service, worker locations, and income, allowing standard comparisons of nine large cities as a whole, and a neighborhood scale as well. Regional summaries of differences in transit service for income classes provide a broad-scale analysis of income-based equity, while analysis of the same data with local Moran's I geostatistics provide a nuanced view of equity that controls for spatial autocorrelation. The method developed in this study is not aimed to be a substitute for local analysis including specific proposed transportation changes or land use effects, but can be considered a spatial screening tool to identify prospective equity issues at geographic areas larger than the more typical corridor analysis. The provision of transit modes beyond traditional bus service, such as rail, was found to have a positive relationship with transit equity at both the regional and neighborhood levels in this study. Increased numbers of routes and speeds may serve to increase mobility and access for all income levels, promoting job access, and in turn, economic mobility.

The methods used in this study point to policy and planning implications of not only the location of service, but speed and frequency having impacts on job access and economic mobility. To demonstrate competency in equitable service, planners and policy makers need standardized comparisons of locations that consider income. Transit investments represent a faith that allocation of projects serve existing and future needs, and efficient and accurate equity analyses support rational communication between the public and transit agencies if shared in open forums of discussion. This method can be adapted to scenario planning techniques by adjusting the transit service metrics by block group as an output of other planning processes involving public participation and modeling. Accessibility by income also could be used as input in comprehensive growth models for evaluation of policy and planning decisions.

In addition to growth in rail and bus transit, the increasing prevalence of bus rapid transit (BRT) may cause significant changes in transit accessibility, but this will be limited to the extent that low-income communities are conveniently served by this mode and its connectivity to destinations for these groups (Weinstock et al. 2011). In the cases that BRT can take advantage of managed lanes and other features designed to increase speed, it can reduce the time needed to reach more jobs within a reasonable time frame and can add job accessibility to the communities it serves. However, when transit services are added to improve mobility, retaining local access to the existing stops is crucial to many communities, including low-income neighborhoods.

After all of the preliminary analysis is done, the primary conduit for implementing transit policies and funding is through an urban area's transportation plan. The best analysis will likely be implemented when supported by robust public involvement with engaged public officials (Evans-Cowley and Griffin 2012; Slotterback 2010), and staff

that work to explicitly incorporate social equity into the objectives and measures of transportation plans (Manaugh et al. 2015).

While examining the relationship between transit accessibility and worker income, this study does not address the root causes of discrepancies in this relationship. Future studies would benefit from adding to the literature in this area by integrating spatial analysis of urban form, housing affordability, other demographic variables associated with equity, and transit-based access to social services. The effect of multi-modal transit trips on accessibility and justice also need to be explored. Finally, future transit services could be modeled with local spatial analysis for equity using similar methods, which will help evaluate existing or proposed service levels to improve the equity of transit systems.

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Passenger Satisfaction and Mental Adaptation under Adverse Conditions: Case Study in Manila

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Abstract

Public transportation systems in several developing cities face congestion, air pollution, and safety problems, yet many passengers use them regularly. This study examines the structure of passenger satisfaction and the role of mental adaptation under such conditions. Metro Manila MRT-3 was analyzed as a case study.

The actual and perceived conditions at the MRT-3 were assessed using surveys. Results of the waiting time and PM_{2.5} monitoring surveys revealed that passengers queue for 30 minutes, on average, while being exposed to unsafe levels of PM_{2.5}. The questionnaire survey results show some discrepancies between actual and perceived values, suggesting a perception gap.

Passenger satisfaction in MRT-3 was then modeled using ordered logit, with actual and perceived conditions (waiting time, in-vehicle time, fare levels, risk perception, and air quality perception) as significant explanatory variables. Mental adaptation was found to moderate passenger satisfaction, which may explain why some passengers are satisfied despite MRT-3's shortcomings.

Keywords: Commute satisfaction, waiting time, mental adaptation, PM_{2.5} exposure, risk perception, air quality perception

Introduction

Efficient mass public transportation systems in developing cities are essential to address increasing mobility needs. However, their level of service is typically characterized by chronic congestion, unreliability and safety problems (National Research Council 1996), which result from various factors such as insufficient and outdated infrastructure, inadequate planning, and lack of safety measures. Moreover, rapid urbanization and

inadequate environmental measures in many developing cities have led to the increase of air pollutant emissions and deteriorating urban air quality (Kim Oanh et al. 2006). In line with this, air pollution in public transportation systems is an increasing cause of concern and air pollutant exposure depends on the travel mode used (e.g., Chan et al. 2002, Niewenhuisen et al. 2007).

These conditions likely could lead to lost productivity and opportunity costs, stress and anxiety, health impacts, and accidents. However, in spite of these negative physiological and psychological effects, many commuters still endure this situation daily. One possible explanation is lack of choice, so physical adaptation (e.g., changing departure time or mode) would no longer be feasible. Another possible explanation is a psychological phenomenon called mental adaptation, which refers to the desensitization to a negative stressor with repeated exposure over time. It is similar to hedonic adaptation in psychology, which is defined as the psychological process by which people become accustomed to a positive or negative stimulus, such that the emotional effects of that stimulus are attenuated over time (Frederick and Loewenstein 1999). In this context, it would imply that commuters may have become accustomed to commuting in such conditions due to repeated exposure and have changed their way of thinking about their commute, which helps reduce its negative psychological effects. In the same vein, some researchers have found that travel mode choice also depends on psychological factors rather than just the objective service level of the transportation system (Fujii and Kitamura 2003).

Moreover, the traditional way of evaluating passenger satisfaction may not suffice for such systems, as it focuses on conventional level-of-service attributes such as comfort, convenience, and accessibility that are more relevant to the developed world, where transportation systems usually have better service quality and commuters are used to higher standards. In the case of severe commuting conditions, it may be more appropriate to employ a vaster approach that considers the distinct problems faced.

Several studies have focused on commute satisfaction in developing countries, which typically have inadequate infrastructure and are more polluted than developed ones. Rahaman and Rahaman (2009) found that overall service satisfaction in a railway section in Bangladesh depends on factors including waiting time, crowding, and security. Ngatia et al. (2010) noted that commute satisfaction in Nairobi is significantly influenced by travel cost, service quality, and safety. Tangphansankun et al. (2010) found that fare, comfort, convenience, safety, and security are the main explanatory variables for commute satisfaction on Bangkok's paratransit modes.

Taking these into consideration, this paper investigates the structure of passenger satisfaction considering actual and perceived conditions. Specifically, it includes pollution exposure, waiting time, risk perception, fare levels, in-vehicle travel time, and adaptation as predictors of passenger satisfaction using Metro Manila MRT-3 as a case study. Various data collection methods are used to establish the extent of the congestion, air pollution, and safety problems, then a passenger satisfaction model that tests the significance of the above-mentioned predictors is developed. The perception-based approach in this paper is deemed to be more appropriate given the situation

wherein commuters have physically adapted to their situation and that their only option left is to change their way of thinking about their commute (Mijares et al. 2016).

Case Study: Metro Manila MRT-3

Metro Manila is the chief metropolitan area in the Philippines. It has a daytime population of 14.5 million in a 638.6 km² (246.6 mi²) area, yet its rail network is underdeveloped. Among its rail lines, Metro Rail Transit Line 3 (blue line in Figure 1), or MRT-3, has the highest ridership and is generally considered as the most critical. The 16.7-km (10.4-mi) line runs along EDSA, which is Metro Manila's main thoroughfare that connects major central business districts and other landmarks. However, its level of service has been deteriorating since 2005 when its ridership exceeded its design capacity. The only other public transportation options along EDSA are air-conditioned and ordinary buses, which are slow due to frequent stopping and heavy traffic congestion and are more expensive, especially for longer trips. Jeepneys, which are the most heavily-used public transportation mode in Metro Manila, are not permitted to ply along EDSA, but they are essentially smaller versions of ordinary buses as they are also diesel-run and open-air.

FIGURE 1.
Existing rail network in
Metro Manila



This problem is multi-faceted and encompasses financial, political, and institutional barriers, but it is mostly attributed to insufficient capacity relative to passenger demand. Significant changes in infrastructure and operations to increase its capacity have not been implemented since its full operations began in 2000. Urban rail fares also had been kept constant from 2000 to 2014 amid inflation and increases in non-rail public transportation fares, which made urban rail travel relatively cheaper, contributing to the increase of rail demand and deteriorating level of service.

As a result of the discrepancy between passenger demand and MRT-3 supply, many passengers spend a long time waiting at several stations during morning rush hours. Also, there have been several safety incidents in the past few years, with the most severe being a derailment accident in August 2014. Moreover, exposure to particulate air pollution is also a matter of concern for Metro Manila dwellers, especially regular commuters. Whereas coarse particle (PM_{10}) concentration levels in Metro Manila are monitored daily by the government and are generally within the 24-hour guideline values, such monitoring is not yet fully implemented for fine particles ($PM_{2.5}$) even though they have worse health effects. Moreover, previous studies suggest that $PM_{2.5}$ concentration levels in Metro Manila are much higher than the guideline values especially in high traffic areas (Kim Oanh et al. 2006), and at the roadside and platform of an MRT-3 station (Simpas et al. 2011). As such, commuters may be exposed to unhealthy $PM_{2.5}$ levels for a prolonged period while waiting at the roadside and platform of the MRT-3.

Despite these problems, ridership is still high because the MRT-3's level of service is relatively superior to other modes in terms of affordability, travel time, safety, and accessibility, which, in a sense, leaves commuters with no choice but to continue using MRT-3 daily. Another reason is mental adaptation, which was confirmed to moderate commuting stress for some passengers when using MRT-3 (Mijares et al. 2016); however, its effect on overall passenger satisfaction has not been studied.

Data Collection

Three different types of surveys were conducted to establish the conditions at the MRT-3: (1) waiting time and in-vehicle travel time surveys, (2) $PM_{2.5}$ particle count monitoring survey, and (3) a questionnaire survey.

Waiting Time and In-vehicle Travel Time Surveys

An observation survey was conducted on October 1, 2014 (Wednesday) to determine the extent of passenger waiting time, which is the time spent waiting from the end of the queue into the station up to getting on the train. A surveyor was deployed as an MRT-3 passenger at every 15-minute interval from 6:45–8:00 AM at North Avenue and Cubao stations, and the time spent completing each stage of queuing was recorded. Meanwhile, an in-vehicle travel time survey was performed on 20 regular weekdays between February–March 2015 for MRT-3 as well as ordinary and air-conditioned buses for intermodal comparison.

PM_{2.5} Particle Count Monitoring Survey

This survey aimed to quantify the PM_{2.5} exposure while waiting at the roadside and platform of MRT-3 stations and while inside the train, as well as to compare the results with those of buses along EDSA. The survey was divided into two components: intra-modal and intermodal. Intra-modal comparison focused on the roadside, ticketing area and platform of five out of 13 MRT-3 stations, which were selected according to their morning peak ridership and characteristics. Intermodal comparison was conducted by measuring the PM_{2.5} levels while inside the train or bus.

PM_{2.5} levels were measured using particle count using a portable particle counter that measures the number of particles detected through light scattering and produces instantaneous results. Particle count is an equally important indicator of air quality as mass concentration, especially in investigating associations between air pollution and adverse health outcomes (Ruuskanen et al. 2001). It is even suggested to be more closely correlated to adverse health effects than mass concentration (Wichmann et al. 2000). That said, the typically-used mass concentration would have also been appropriate as PM_{2.5} count includes the more harmful ultra-fine particles (>1 micrometer), but it is costlier and more time-consuming to measure.

PM_{2.5} particle count was measured at every one-minute interval during the morning peak period on 20 regular weekdays from February to March 2015 using the portable particle counter. Measurements were not done simultaneously for different MRT-3 stations and travel modes due to equipment availability issues. Measurements were done at each travel mode or station at least four times throughout the survey period.

Questionnaire Survey

A questionnaire survey was used to assess the commute characteristics of MRT-3 passengers and their perception on air quality, risk and adaptation. It mainly targeted commuters who use the MRT-3 during the morning peak period on a daily basis to travel from their home to the workplace. Data collection was conducted in September 2014 in cooperation with the University of the Philippines National Center for Transportation Studies (UP NCTS) using online and on-site interviews. The profile of the sample data (age and gender) was found to adequately represent that of the general population of Metro Manila. Data screening was also performed to eliminate unengaged respondents and outliers, reducing the sample size from 225 to 211.

Among the 211 respondents, 119 (56.4%) were females, 84 (39.8%) had a monthly income of PhP20,000, and 130 (61.6%) were below age 30. In total, 55 (26.1%) respondents had been using the MRT-3 for their everyday morning commute for more than five years, and 48 (22.7%) had been using it for less than two years.

Actual and Perceived Conditions at MRT-3

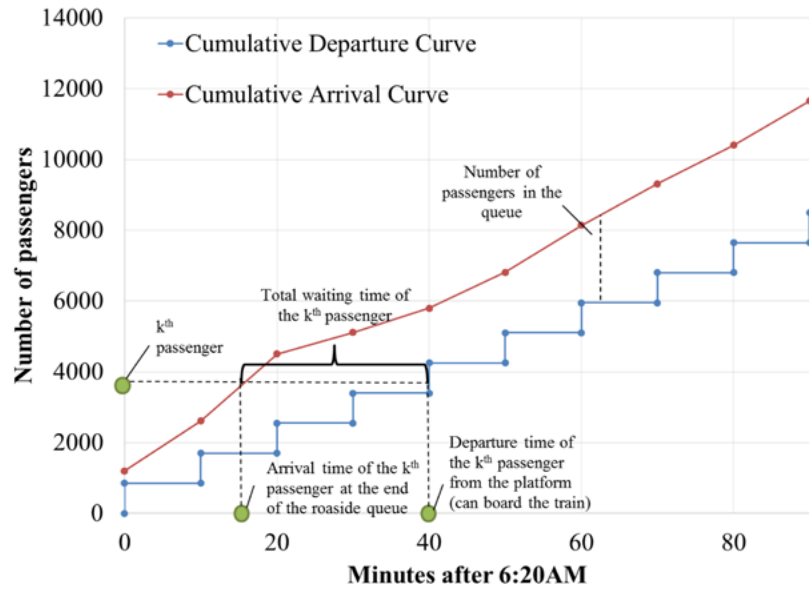
This section establishes the extent of the congestion problem in Metro Manila MRT-3 in terms of waiting time, in-vehicle time, fare, PM_{2.5} exposure, and passengers' commute characteristics and perception about risk, air quality, and adaptation, which are hypothesized to be the explanatory variables that influence passengers' satisfaction with their MRT-3 commute. Comparisons with buses that run parallel to the MRT-3 alignment were also made.

Passenger Waiting Time

Passenger waiting time refers to the time spent from arriving at the end of the queue at the station until getting on the train and is the sum of station access time and platform waiting time. Platform waiting time at the MRT-3 has been studied and shown to be disproportionately high in the middle stations (Mijares et al. 2013, 2014). Station access time is also a critical part of total waiting time as ocular surveys have shown that queues into the station frequently spill out onto the roadside. Furthermore, MRT-3 passengers are not provided real-time information by the operator about their estimated waiting time.

The results of the waiting time survey in October 2014 indicated that passengers experience long and variable waiting times at certain stations as a result of the O-D patterns and operations policies. These include the "stop entry" policy, which limits the number of passengers on the platform to 500 at a time, and the "skip train" policy, which deploys empty trains to the third and fourth stations to provide capacity to boarding passengers (refer to Mijares et al. 2015 for more details). It was found that morning peak period passengers at North Avenue Station (northern terminal) wait for an average of 35.6 minutes, with majority of the time spent queuing at the roadside and at the stairways. Figure 2 shows the estimated cumulative arrival and departure curves at North Avenue Station, which indicates that the queue length had reached up to around 3,500 passengers during the 90-minute interval. Meanwhile, passengers at Cubao Station (fourth station southbound) spent an average of 50.2 minutes queuing both at the roadside and platform. In general, the first five stations in the southbound (peak) direction, experience such severe waiting conditions.

FIGURE 2.
Estimated cumulative roadside arrival and platform departure curves at North Avenue Station



The results of the questionnaire survey are also consistent with these findings. Respondents were found to spend an average total waiting time of 30.0 minutes (Table 1). Waiting time variability at the MRT-3 was also an issue largely as a result of the operations policies, with 33.6% of respondents stating that their waiting time varied by 10–20 minutes on average and 48.3% reporting that it varied by more than 20 minutes on average.

TABLE 1.
MRT-3 Commute Characteristics of Respondents

Variable	Min.	Max.	Mean	Std. Dev.
Total waiting time at MRT-3	5 min	60 min	30.0 min	15.2 min
Feeder time (access and egress)	3 min	180 min	41.4 min	26.7 min
In-vehicle travel time at MRT-3	4.5 min	40 min	28.1 min	10.9 min
Total trip time	30 min	240 min	118.4 min	41.3 min
MRT-3 fare	PhP10.0	PhP15.0	PhP12.7	PhP1.5
Feeder fare (access and egress)	PhP0.0	PhP90.0	PhP33.8	PhP15.0
Total fare	PhP11.0	PhP102.0	PhP45.5	PhP13.5

In-Vehicle Travel Time and Feeder Travel Time

The results of the in-vehicle travel time survey show that MRT-3 had an average speed of 23.5 kph considering running and dwell times, but dropped to around 16.1 kph when waiting time was included. In comparison, ordinary and air-conditioned buses along the same route had average speeds of 10.9 kph and 11.2 kph, respectively, due to road congestion and frequent stops.

However, MRT-3 commuters typically have to use feeder modes as well, which are commonly road-based. The questionnaire survey revealed that while in-vehicle travel time using the MRT-3 is at an average of 28.1 minutes, the average feeder access time

is 41.4 minutes (Table 1), with an average of 2.7 transfers, bringing the average total morning commute time to almost two hours (Table 1). Overall, this indicates that MRT-3 commuters spend a long time commuting and that a substantial part of it is spent on waiting at the MRT-3 and feeder modes.

Fare Levels

When the survey was conducted in 2014, fare levels in MRT-3 ranged from PhP10 for the first three stations (~4 km) and PhP15 for an end-to-end trip (~17 km). In contrast, road-based transportation modes had higher fares, with bus fares almost double the MRT-3 fares for longer trips. The fare structure is distance-based but not integrated (i.e., need to pay base fare for every transfer), making the whole trip cost higher especially for people who live or work far from the MRT-3 line.

Air Quality

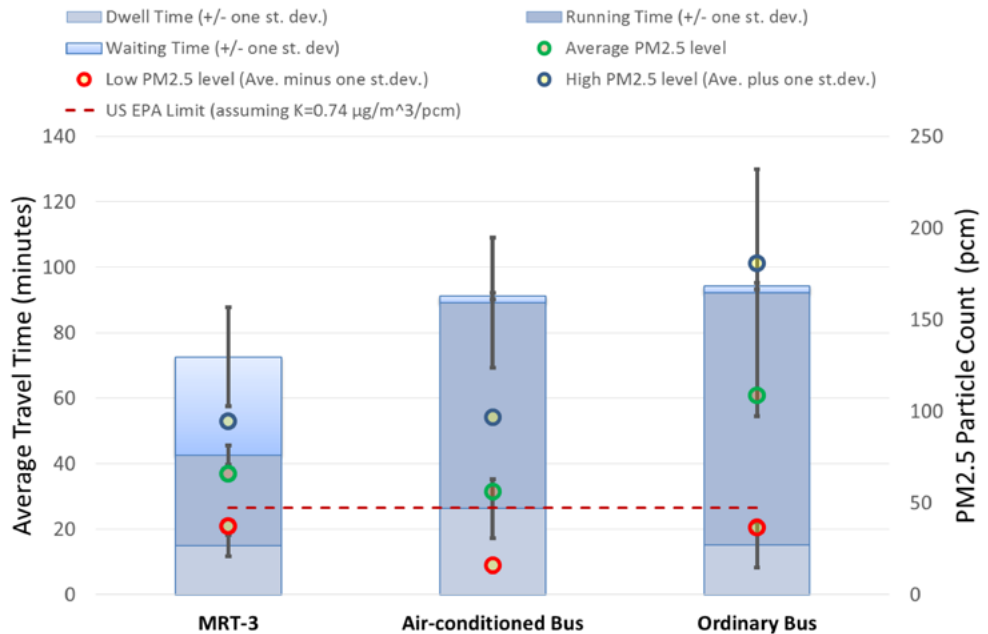
The analysis of air quality in MRT-3 is limited to $PM_{2.5}$ particle count, which may pose health risks, and passengers' perception on air quality.

PM_{2.5} Particle Count Measurement. Intra-modal comparison was conducted at roadside, stairways, ticketing areas, and platform of five out of 13 MRT-3 stations (Figure 1). The average particle count per minute (pcm) are as follows: (1) North Avenue – 78.9 pcm (sd =32.5 pcm); (2) Quezon Avenue – 82.1 pcm (sd =34.4 pcm); (3) Cubao – 79.7 pcm (sd =27.2 pcm), (4) Ayala – 70.5 pcm (sd =22.9 pcm); and (5) Taft Avenue – 106.8 pcm (sd =45.8 pcm). Taft Avenue, which is located near provincial bus terminals, has significantly higher pcm than the other stations.

Intermodal comparison between MRT-3, ordinary bus and air-conditioned bus entailed measurements of $PM_{2.5}$ particle counts inside the vehicles and exposure time (equivalent to running time and dwell time). Ordinary buses had the highest $PM_{2.5}$ levels (mean=108.7 pcm, sd=71.9 pcm), and the longest in-vehicle travel time for a 16.7-km trip (mean running time=77.1 min, mean dwell time=15.1 min), making it the worst mode among the three in terms of $PM_{2.5}$ exposure. Air-conditioned buses ranked second, with $PM_{2.5}$ levels (mean=56.3 pcm, sd=40.4 pcm) that are considerably lower than that of ordinary buses but slightly higher and more variable than that of MRT-3 (mean=53.7 pcm, sd=23.9 pcm). In-vehicle travel time of air-conditioned buses was almost similar to that of ordinary buses (mean running time=63.0 min, mean dwell time=26.3 min), thus exposure time was also around 90 minutes for a one-way trip.

When additional exposure when waiting is considered, exposure time is equivalent to the sum of waiting, running and dwell times. Even in this case, ordinary buses still had the highest $PM_{2.5}$ levels and longest exposure time among the three modes, as seen in Figure 3. However, the ranking between air-conditioned bus and MRT-3 switched because the $PM_{2.5}$ levels while waiting at the roadside, ticketing area, and platforms drove up the overall exposure levels for MRT-3 (mean=65.9 pcm, sd=28.6 pcm). In contrast, $PM_{2.5}$ exposure for bus passengers mostly occurred while inside the vehicles given that buses ran frequently along EDSA so waiting time was significantly lower.

FIGURE 3.
Intermodal comparison of
PM_{2.5} exposure (travel time
and particle count)



To allow a comparison with the US EPA limit in Figure 3, a conversion factor that converts particle count to mass concentration was calculated based on fine particle characteristics in Metro Manila (Simpas et al. 2011) and particle density. Using this conversion factor, the USA EPA limit of 35 $\mu\text{g}/\text{m}^3$ would be equivalent to 47 pcm.

A comparison with PM_{2.5} measurements in some sites was also made for reference. At a rural town outside Metro Manila called Gabaldon, Nueva Ecija, the average PM_{2.5} concentration was 11 $\mu\text{g}/\text{m}^3$ (~14.8 pcm) (Simpas et al. 2011), which is way below the US EPA limit and the EDSA values. Measurements were also made by the survey team using the same equipment at Laurel Avenue in Metro Manila, which is along a jeepney route and has moderate to heavy vehicle traffic. The average value is 103.1 pcm, which is similar to the level in ordinary buses and roadside of MRT-3. Jeepneys are popular MRT-3 feeder modes, so the findings suggest that MRT-3 commuters are exposed to unhealthy PM_{2.5} levels in other aspects of their commute.

Air Quality Perception. Perceived air quality pertains to passengers' rating on the air quality at the MRT-3, and represents their awareness and concern about their exposure to air pollution during their commute. PM_{2.5} exposure is substantial for MRT-3 commuters as established in the PM_{2.5} monitoring survey.

PM_{2.5} particle count and waiting time were correlated against air quality perception, which is measured by the reverse of the statement, "I am exposed to air pollution while waiting to ride the MRT-3 at the roadside, ticketing area and platform" using a 7-point Likert scale (mean=5.3; sd=1.8); however, no significant relationships were found. The lack of statistically significant correlations implies that air quality perception is linked to other individual differences rather than exposure-related measurable data. This finding is consistent with previous studies which show that the visual and olfactory characteristics of air have a significant impact on perceived air quality, so the absence of

black exhaust fumes (like $PM_{2.5}$, which is invisible to the naked eye) may lead to a better rating of air quality (Saksena 2011).

Safety and Risk Perception

Risk perception is characterized as the intuitive judgment of individuals and groups of risks in the context of limited and uncertain information (Slovic et al. 1985). It is difficult for non-experts to correctly perceive objective safety, so there may be a gap between the two.

Respondents were asked to rate risk perception in the questionnaire survey using the reverse of the statement, "I feel that MRT-3 is a safe transport mode" using a 7-point Likert scale (mean=4.2, sd=1.5; not reversed). The results imply that respondents have moderate ratings of perceived risk.

Adaptation

There are two types of adaptation in commuting: (1) physical (or behavioral) adaptation, which means changing their behavior or the situation itself; and (2) mental adaptation, which refers to changing their way of thinking about it (Punpuing and Ross 2001).

The questionnaire survey results confirmed that passengers had already physically adapted to the situation by changing their travel behavior in one or more ways—90% had switched to an earlier departure time, 19% had changed their boarding station to a less crowded one, 19% had moved to another residence, and 5% had moved to another workplace.

As MRT-3 commuters had already exhausted physical adaptation options, mental adaptation may set in as a coping mechanism in dealing with this unsatisfactory situation daily. Mental adaptation was measured using the statement, "I have completely adapted to commuting in this situation" (mean=3.9, sd=1.7) and "I have become used to this everyday situation" (mean=4.0; sd=1.7) using a 7-point Likert scale. Both statements were found to be internally consistent, but the first statement was used to represent mental adaptation for the purpose of analysis. Results indicate that mental adaptation had not set in for many respondents. Contrary to intuition, there was no correlation between adaptation and the length of experience with using MRT-3 daily, implying that adaptation may be due to individual characteristics.

Passenger Satisfaction Model

This section investigates the structure of passenger satisfaction in MRT-3 considering the actual and perceived conditions discussed in the previous section. Fare, in-vehicle travel time, waiting time and its variability, perception on risk and air quality, and mental adaptation are hypothesized to influence passengers' satisfaction with their MRT-3 commute (Table 2).

TABLE 2. Proposed Explanatory Variables and Expected Results

Explanatory Variable	Variable Name	Variable Type	Expected Results	
			General	Differences between Income Groups
Total fare in Philippine pesos (MRT-3 and feeder modes)	C	Continuous	Lower fare → Higher satisfaction rating	Low income → higher effect
Total in-vehicle travel time in minutes (MRT-3 and feeder modes)	T	Continuous	Lower in-vehicle travel time → Higher satisfaction rating	Medium/High income → higher effect
Average waiting time at the MRT-3 in minutes	W	Continuous	Lower waiting time → Higher satisfaction rating	Medium/High income → higher effect
Waiting time variability (1 –always the same; 5 – more than 30 minutes)	V	Ordinal (1-5 scale)	Lower variability → Higher satisfaction rating	Medium/High income → higher effect
Air quality perception	Q	Ordinal (1-7 scale)	Higher air quality perception → Higher satisfaction rating	Medium/High income → higher effect
Risk perception	R	Ordinal (1-7 scale)	Lower risk perception → Higher satisfaction rating	Medium/High income → higher effect
Mental Adaptation Level	A	Ordinal (1-7 scale)	Higher mental adaptation level → Higher satisfaction rating	No difference

The ordered logit model was chosen to represent passenger satisfaction because it is more appropriate for ordered data and has been used in general satisfaction studies (e.g., Theodossiou, 1998). Passenger satisfaction was measured by the statement, “I am satisfied with the service provided by MRT-3” using a 7-point Likert scale. This was reduced to a 4-point scale to reduce the skewness of the data, where 1-strongly dissatisfied, 2-dissatisfied, 3-neutral, and 4-satisfied.

The passenger satisfaction model has the proposed form:

$$y_i^* = \beta_c C_i + \beta_t T_i + \beta_w W_i + \beta_v V_i + \beta_Q Q_i + \beta_r R_i + \beta_a A_i + \varepsilon_i \quad (1)$$

For all $i = 1, \dots, N$; in which the continuous latent utility, y_i^* , (passenger satisfaction) is observed in discrete form through a censoring mechanism. The expected results are shown in Table 2.

Data from the questionnaire survey was used to estimate the model. Income segmentation was done: low income (monthly salary ≤ PhP20,000) and medium- to high-income (monthly salary > PhP20,000). Low-income respondents had higher satisfaction levels than their counterparts, probably because MRT-3 is relatively affordable. More adapted commuters were also more satisfied, confirming that mental adaptation plays a role in improving satisfaction.

The model estimates for the different models are provided in Table 3. All relevant tests (e.g., chi-square, test of parallel lines) were acceptable for all models. The results in Table 3 are similar to the expected results in Table 2, except for waiting time variability which was insignificant. Skip train service might also have a role in explaining its insignificance, as passengers may have become habituated to the day-to-day variability of waiting time

resulting from this policy (Mijares et al. 2014). Total fare was also valued more by low-income passengers as higher travel costs would mean less monetary resources for other needs.

TABLE 3. Parameter Estimates for Passenger Satisfaction Model

Model	-2Log-Likelihood (Final)	Model Fit/ Test of Parallel Lines	Parameter Estimates, (Level of Significance)						
			Predictor Variables						
			Total Fare	Total In-Vehicle Travel Time	Waiting Time	Waiting Time Variability	Air Quality Perception	Risk Perception	Mental Adaptation
Full model (N=211)	401.3	OK	-0.062 (1%)	-0.018 (1%)	-0.072 (1%)	0.19 (NS)	0.23 (1%)	-0.37 (1%)	0.40 (1%)
Low-income group (N=84)	150.2	OK	-0.13 (1%)	-0.013 (5%)	-0.070 (5%)	0.23 (NS)	0.33 (5%)	-0.31 (10%)	0.20 (5%)
Medium-/ high-income group (N=127)	233.7	OK	-0.032 (5%)	-0.019 (1%)	-0.079 (5%)	0.26 (NS)	0.21 (5%)	-0.39 (1%)	0.47 (1%)

NS – non-significance

The values of in-vehicle time and waiting time were calculated by dividing the coefficients of in-vehicle time and waiting time by that of the total fare. Table 4 shows that waiting time was valued around four times larger than in-vehicle travel time for all groups, implying a strong aversion to waiting. This estimate is slightly higher than those in previous studies (e.g., Mohring et al. 1987, Mishalani et al. 2006) wherein waiting time was valued 1.5–3 times higher than in-vehicle travel time, probably because the waiting time at the MRT-3 is typically longer and the waiting environment is generally more unfavorable. As expected, higher income passengers valued in-vehicle time and waiting time several times more than their low-income counterparts.

TABLE 4. Values of In-vehicle and Waiting Time

Model	“I am satisfied with the service provided by MRT-3”	
	Value of in-vehicle travel time (PhP/min)	Value of waiting time (PhP/min)
Full model (N=211)	0.29 (1%)	1.16 (1%)
Low-income group only (N=84)	0.10 (5%)	0.59 (5%)
Medium-/high-income group only (N=127)	0.59 (1%)	2.18 (1%)

PhP – Philippine pesos (1 USD ≈ 45 PHP)

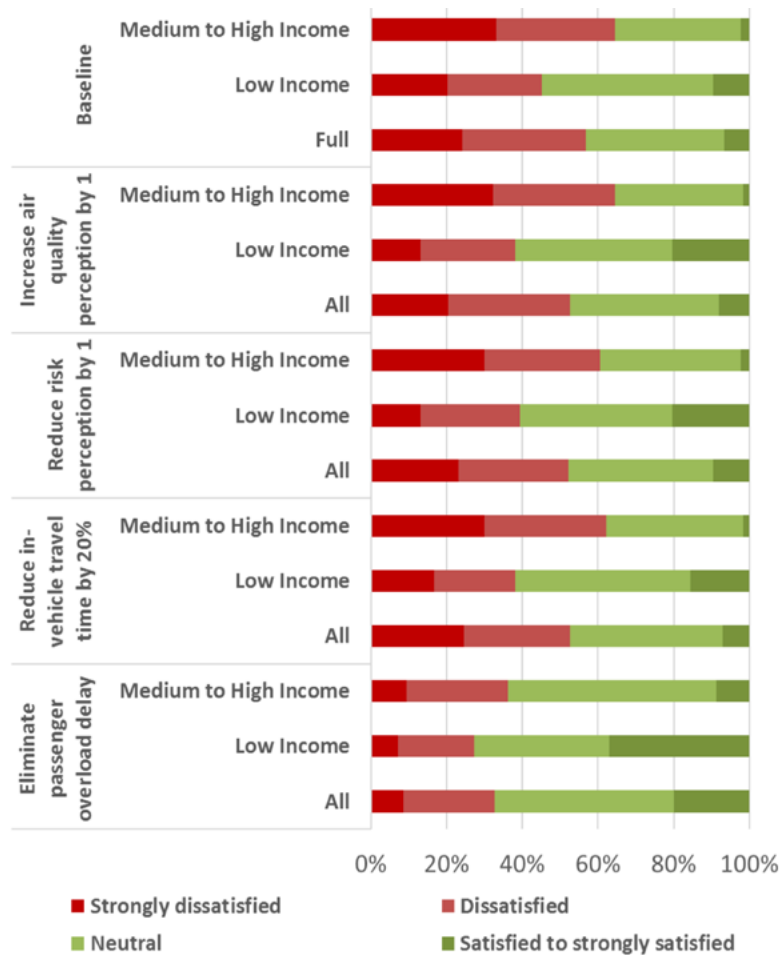
The passenger satisfaction model was also used to estimate the changes in satisfaction levels as a result of a change in the level of the attributes, for example, due to a countermeasure. These are computed using the predicted probability equation for ordered logit model:

$$P(Y_i > j) = \frac{\exp(X_i\beta - \kappa_j)}{1 + [\exp(X_i\beta - \kappa_j)]}, j = 1, 2, 3 \tag{2}$$

Where κ_j refers to the threshold values for each category, and j is the category of the passenger satisfaction level.

A cumulative probability threshold of 55% was used to classify respondents into “strongly dissatisfied,” “dissatisfied,” “neutral,” and “satisfied.” Figure 4 shows the results of the sensitivity analysis, which illustrates the effects of an attribute change to passenger satisfaction levels compared to the baseline levels.

FIGURE 4.
Sensitivity analysis of passenger satisfaction levels



A comparison between income groups shows that low-income people generally have higher satisfaction levels than higher-income ones given that they have lower values of time.

It was found that improving perception-related variables such as air quality and risk perception would only have a minimal effect on satisfaction levels. Moreover, reducing in-vehicle travel time by 20% also yields to small changes in satisfaction levels. However, reducing waiting time by eliminating passenger overload delay (i.e., delay due to insufficient capacity) would yield the highest improvement in satisfaction, almost doubling the satisfaction levels for all groups. This implies that countermeasures that increase capacity and subsequently reduce waiting time and PM_{2.5} exposure should be prioritized over those that improve other variables. Some ideas for increasing capacity include adding train cars, reducing headway, and doubling the number of rail tracks. Further study needs to be done to evaluate the detailed impacts of such countermeasures.

Summary and Conclusions

This paper examined the structure of passenger satisfaction and the role of mental adaptation in severe conditions, with MRT-3 in Metro Manila as a case study. First, it established the actual and perceived conditions at the MRT-3 in terms of waiting time, in-vehicle travel time, fare, air quality, risk perception, and adaptation using several data collection methods. Then, it developed a passenger satisfaction model that incorporates the said variables.

Passenger waiting time was found to be long and variable at the roadside and platform largely due to excessive demand and operations policies, which exposes passengers to $PM_{2.5}$ for an extended period of time. The overall $PM_{2.5}$ exposure level at the MRT-3 was found to be similar to that of an air-conditioned bus due to long exposure times while waiting at the roadside and platform.

In addition, the estimation of the passenger satisfaction model using ordered logit showed that actual conditions (fare, waiting time, in-vehicle travel time) and perceived conditions (risk and air quality) predict passenger satisfaction with MRT-3. Mental adaptation tends to increase passenger satisfaction, which can be both beneficial and detrimental. On a positive note, it helps reduce the negative effects of an unfavorable commute. However, it may lower expectations and keep commuters complacent, thus they do not demand for better services from the operator, and it may also expose them to actual physiological harm.

This study would help draft appropriate countermeasures and evaluate them by extending the results of the sensitivity analysis. The results of the preliminary analysis showed that eliminating waiting time due to passenger overload delay would double passenger satisfaction levels, which suggests that increasing the capacity of MRT-3 would be an effective countermeasure.

The results also suggest that public transportation in Metro Manila should be improved in general. Even in its poor state, MRT-3 is still preferred by many commuters because of lack of appealing options. Bus services should also be improved to provide a reasonable alternative for traveling along EDSA and other parts of Metro Manila. Improving public transportation would also discourage the modal shift to private cars. Given that vehicular traffic is the main contributing factor to fine particulate matter pollution in Metro Manila (Villarín et al. 2014), reversing the rapid motorization trend by improving public transportation could contribute in improving air quality. However, solving the air pollution problem in Metro Manila would require a wider effort on a regional scale to address natural and anthropogenic sources of pollution.

Although this study specifically focuses on Metro Manila MRT-3, the methodology and evaluation framework used may also be applicable and contextualized to other public transportation systems experiencing congestion, air pollution, and safety problems especially in developing cities.

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Regularity of Public Transport Usage: A Case Study of Bus Rides in Lisbon, Portugal

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Abstract

This paper presents an analysis of regularity in public transport usage based on a large-scale bus transportation data of Lisbon, Portugal. By exploring the combined information from the bus boarding history of riders and bus arrivals at each bus stop, an analysis of individual bus usage was performed. Daily and weekly patterns were extracted, from which it was observed that a rider takes, on average, 2 trips, visits 1.93 distinct stops, and uses 1.55 distinct bus lines daily. Inter-trip time analysis revealed a daily cycle, and a study of the interaction between riders and bus infrastructure explored how usage was concentrated on particular bus lines and stops.

Keywords: *Public transit; bus data mining; smart card data; urban computing; transport usage patterns.*

Introduction

With fast-growing urbanization, collective transportation systems (such as buses, trains, and subway systems) become significantly important, as they enable continuous movement of a large quantity of inhabitants while also saving energy and reducing carbon emissions. In addition, public transportation information can provide useful data that reflect citizen needs and their daily patterns. Therefore, urban planners should pay close attention to these transportation modalities to learn from the information about a city's pulses of activities and improve the existing systems to meet passenger demands. If the public transportation infrastructure fails to evolve and adapt to user

behavior, the use of the public transportation may drop, and the increase of individual vehicles may occur, causing more traffic congestion, energy consumption, and pollution.

The development and adoption of new technologies such as smart card systems provide an exceptional opportunity to collect relevant information regarding the use of transportation systems. Several studies have taken advantage of the available information, most commonly to provide online information about bus scheduling or an estimation of waiting time according to timetable charts. Previous research has tackled data-centric problems in the public transport domain, but has focused predominantly on the performance metrics of the transport system itself, not on how individual users rely on public transport systems as part of their daily routines.

By combining large-scale data collected by Automated Fare Collection (AFC) and Automated Vehicle Location (AVL), we analyzed the regularity of bus usage, focusing on rider patterns and choices when using the public bus transport system. First, we uncovered typical daily and weekly transport behaviors according to the frequency of usage of bus lines and stops. Then, by quantifying the similarity of travel across different days of a week, we discovered characteristic temporal structures. Finally, by analyzing sequential travel decisions, we inferred typical periodicities of the bus ride behavior and identified temporal dependencies between bus boardings.

Related Work

The development of novel public transport information systems has been the focus of active research over recent years. Mobile transport applications such as OneBusWay (Ferris et al. 2010b), Tiramisu (Zimmerman et al. 2011), PATH2GO (Zhang et al. 2011) or MOVE-ME (Cunha and Galvão 2014) have been proposed to give smartphone users access to travel information from virtually anywhere. Other applications provide the best travel information according to user location (Weigang et al. 2005) or using social networks to provide feedback and improve the user experience (Nunes et al. 2011). More recently, researchers have proposed personalized transport information that proactively recommends transport updates to individual travelers ahead of time and without requiring active user intervention (Ferris et al. 2010a).

However, personalization concepts that are based on an understanding of transport usage routines are not incorporated into these applications. With the unprecedented availability of large amounts of digital data produced by sensors integrated into public transport systems, novel opportunities have emerged to mine transport behavior patterns that could make these applications behave more intelligently.

Traditionally, data mining in the area of public transport systems focuses primarily on ridership demand estimation and optimization of public transport management and operation. For instance, Ceapa et al. (2012) used AFC data to estimate crowd levels at London Underground stations and predict events of overcrowding. To estimate intra-city travel flows, Smith et al. (2012) employed a gravity model to approximate the variance in travel demand between two underground stations in London. To study the accessibility of the London Underground system for persons with disabilities, Ferrari et

al. (2013) combined information from journey planning with a demand model gained from transport usage data. To establish a low-cost solution for congestion detection and traffic flow analysis, Bejan et al. (2010) leveraged on-bus probe data to analyze journey times experienced by road users. To improve reliability of public transportation Matias et al. (2010) studied the optimum number of schedules. The authors applied the Dynamic Time Warping distance with a k-means clustering and were able to identify different profiles between weekends and weekdays in non-scholar periods.

Recently, the focus of data mining studies has expanded to the analysis of individual transport usage. Instead of characterizing aggregate demand or travel flows, this direction of research seeks to improve the understanding of transport usage patterns linked with individual users. For instance, Lathia et al. (2012) demonstrated that travel histories can be exploited to improve journey planning information. By incorporating variances in transport behavior among individual users, travel times can be estimated that are more accurate than those provided by official schedules. Further, Lathia et al. (2011) proposed a ticket recommendation system to help travelers make the best ticket purchase decision. Analysis reveals that significant monetary savings potentially could be achieved when recommending tickets that match the user's travel needs. Foell et al. (2013) proposed a machine learning approach to predict travel intentions of riders. Based on features that characterize temporal usage pattern, a prediction was made if a user will be an active rider on a future day or not.

In this work, we expand previous works (Foell et al. 2015) by analyzing specific aspects of individual bus usage. In particular, we investigated behaviors of daily bus usage of individual riders, looking at both bus stop and bus line access patterns, uncovering pattern similarities on daily and weekly use and inter-trip time behaviors.

Dataset Description

Study Area

Lisbon, Portugal, as of 2010, consisted of 53 parishes, an area of around 110 km², and a population of 800,000 habitants, as represented in Figure 1.

The city's downtown is the central area, which includes the oldest and smallest parishes with the greatest population density (red); touristic, historic, and commercial areas; and the interface for several public transportation services (bus, subway, train, and ferry). Encircling the city center are residential areas surrounding business areas with lower population density (yellow). Major infrastructures (e.g., airport, industrial facilities) are located on the city's outskirts. The public transportation system consists on bus, subway, train, and ferry.

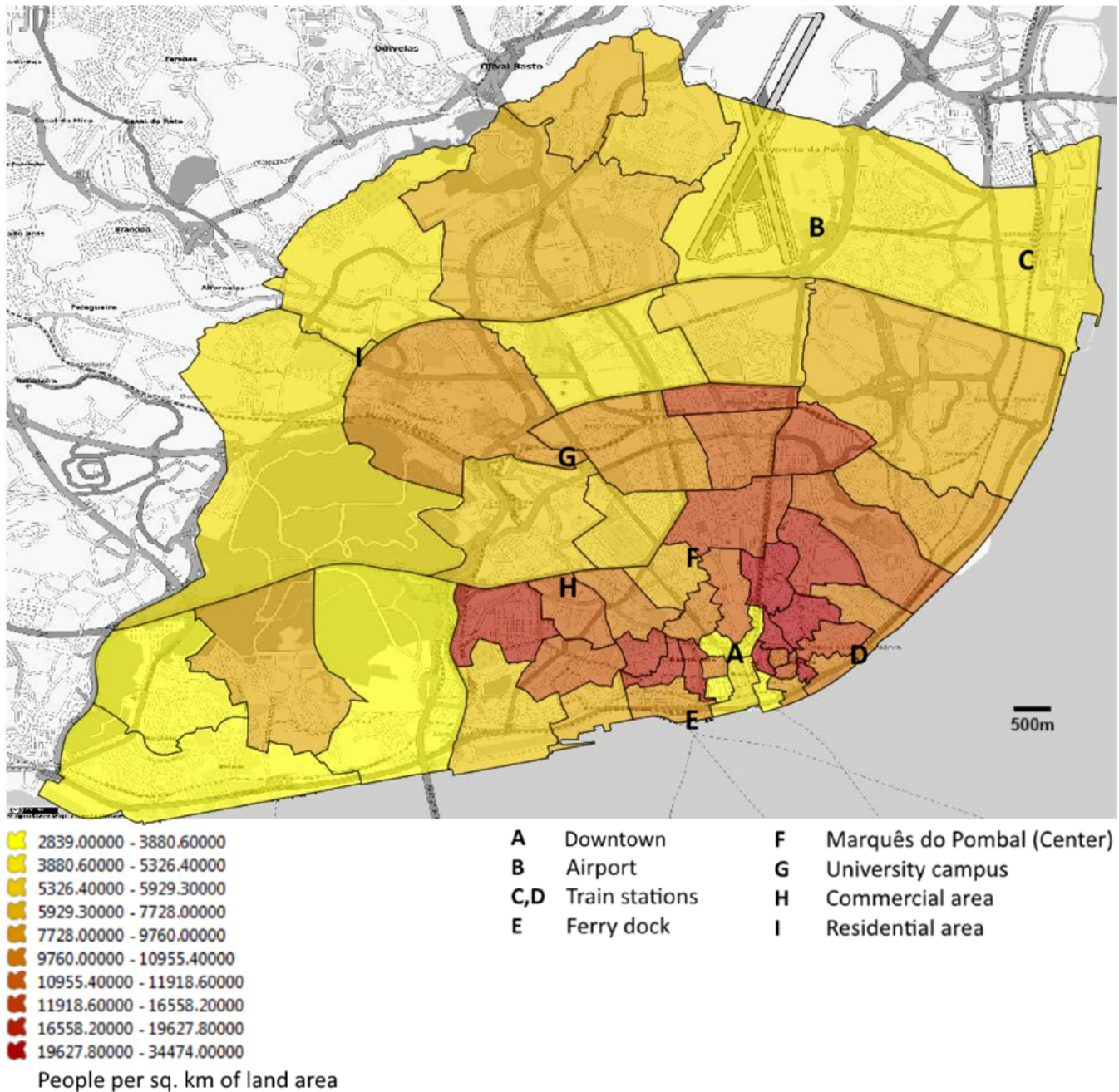


FIGURE 1. Lisbon municipality and population density

All transportation systems (train, subway, bus and taxi) provide station hubs in the city center, enabling a multimodal transportation system. However, the train system has routes only near the riverside, connecting the city to other districts. The main public transportation is bus and subway, with 235 million and 180 million passengers, respectively, in 2010,¹ using a radial route. These two transportation systems were

¹ INE, Instituto Nacional de Estatística, Statistics Portugal, <https://www.ine.pt/>.

developed independently and overlap in some routes. However, the subway system is limited to the city of Lisbon, and the bus system provides connections with the outskirts. Passengers usually use either the bus or subway system, not both, in the same commute.

Bus Data

Large-scale data of bus transportation was provided by Carris,² the largest bus operator in Lisbon. The bus system comprises 2,328 bus stops and 105 bus lines, operated by 773 vehicles. Each bus line has vehicles moving in opposing directions, and 56.7% of bus stops are shared by different bus lines. From the top 5 bus stops shared by more than 10 bus lines, 4 are located downtown. Figure 2 shows the location of bus stops and the corresponding number of rides started at each stop, represented by the radius.

FIGURE 2.
Lisbon map, showing popularity of bus stops



Radius scaled according to number of rides that started at the stop.

The data were collected from April 1–May 30, 2010, resulting in almost 9 weeks of bus usage tracking (61 days). For the purpose of the study, we investigated two different datasets, A and B, where A refers to a record of AFC data and B entails AVL data. Dataset A provides the bus boarding history of passengers identified by the IDs of their smart cards, without any personal information from the user. Dataset B supplies bus probe data that contain entries of recorded bus arrivals for each stop along the bus route, but no user-related travel data.

² Carris, <http://www.transporteslisboa.pt/>.

To analyze the transport behavior of bus riders, we combined both datasets into ride histories, which include spatio-temporal ridership information. Whereas dataset A gives an insight into the buses taken by riders, no information is given about the departure bus stops. Using the bus probe data from dataset B, we linked the start of each bus ride to the closest matching bus arrival. More precisely, to identify the correct departure stop, we looked for the smallest time difference between a rider's bus boarding event and the arrival of the same bus at any stop. As part of this procedure, we removed rides that could not be linked due to inconsistencies—i.e., for some boardings, no matching record of the same bus was present, the time gap was too large, or duplicate entries were observed in which smart cards were logged twice or more times upon bus boarding.

This process produced a cleaned dataset of complete bus ride information. Even though the data were associated with individual riders, only anonymous user data were provided. Formally, the dataset consisted of bus rides $\langle u, t, s, l \rangle \in H$, where H represents the entire ride history, $u \in U$ is the individual rider, $t \in T$ indicates the bus boarding time, $s \in S$ is the ride's departure location (bus stop), and $l \in L$ is the bus line taken by the user. In total, we obtained $|H| = 24,257,353$ bus rides taken by $|U| = 809,758$ users over the observation period of two months. The rides started at $|S| = 2110$ distinct bus stations and were taken with $|L| = 96$ distinct bus lines. For each individual bus user u , H_u denotes the user's bus ride history, S_u is the set of bus stops, and L_u is the set of lines used by u .

Regularity of Bus Ridership

The main goal of this work was to explore patterns of bus ridership. This section analyzes different viewpoints in travel behaviors, from the rider perspective as well as the bus infrastructure. In the following sections, we explore the temporal distribution of travels, the usage of distinct bus lines and stops, how the bus infrastructure is used, the similarity of travel patterns on consecutive days, and rider behavior between trips.

Daily and Weekly Distribution of Ridership

The study began with the exploration of the average weekly distribution of bus rides, plotted in Figure 3 (daily) and Figure 4 (weekly). As expected, bus is used predominantly on weekdays. Daily activity is characterized by two peaks of travel movements (morning and evening), which correspond to inbound and outbound commuting on weekdays and a small increase of activity during lunch time. In the morning, 21% of travel activity takes place between 7:30 and 10:00 AM, and in the evening, 21% of all weekday travels are taken between 4:30 and 7:00 PM.

FIGURE 3.
Daily distribution of average
ridership demand

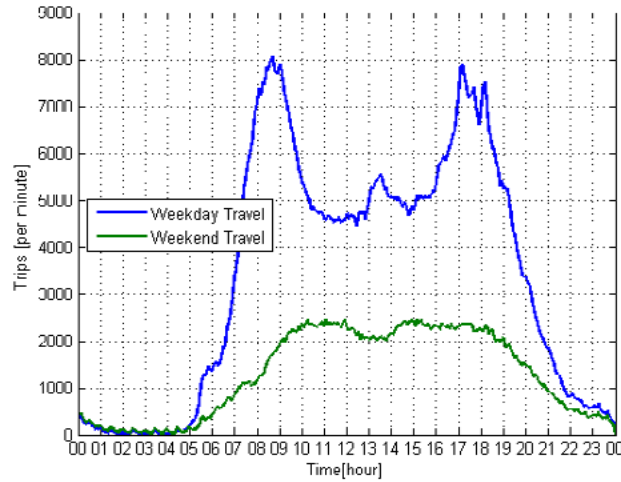
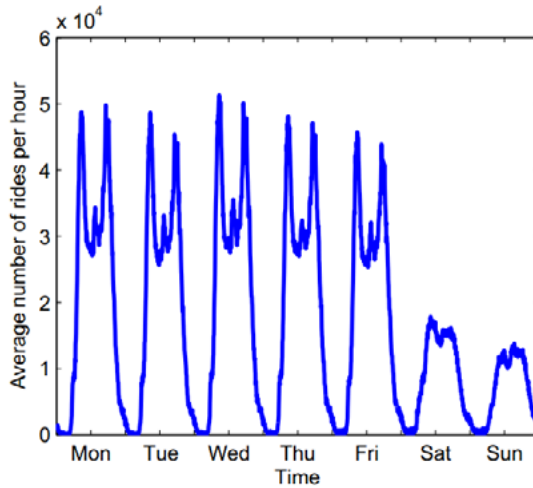


FIGURE 4.
Weekly distribution of
average ridership demand
(Mon–Sun). Significant peaks
of high volume ride activity
on weekdays and lower and
more uniformly-distributed
ridership on weekends.



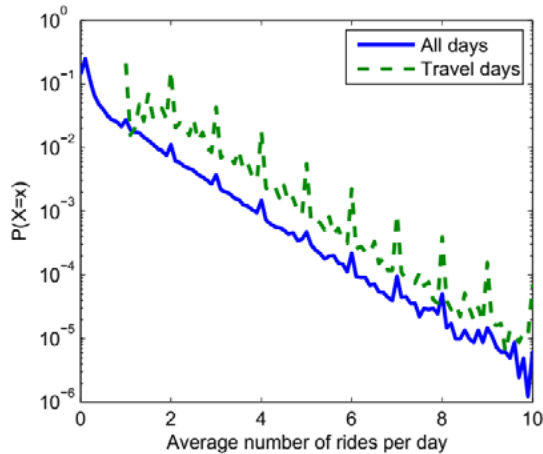
On weekends, the number of rides is more equally distributed across the days. After the morning increase, around 10:00 AM, the decrease of rides takes place only in the evening. However, a distinctive characteristic of the rides allows the differentiation of Saturdays from Sundays: for the former, the bulk of the rides takes place before 12:00 noon; for the latter, the highest demand falls into the afternoon hours. Moreover, when compared to weekdays, the increase in trips tends to start later in the day on weekends, from 10:00 AM onwards. Interestingly, the daily temporal pattern of bus ridership shares similar characteristics with other urban transportation system, i.e., taxi service (Phithakkitnukoon et al. 2010).

Distribution of Individual Ridership

Each individual passenger has a specific travel pattern. To determine those patterns, we computed the probability distribution of individual ridership demand (Figure 5). We used two measures for analyzing individual ridership demand: f_u is the average number of rides taken per day, including non-travel days (starting with the user's first ride), and f'_u is the average number of bus rides per actual travel day.

FIGURE 5.

Probability distribution of individual ridership demand. Two measures of ridership shown: average number of rides per day (all days, blue) and average number of rides per day when buses actually used (travel days, green).



We observed that 78% of passengers traveled by bus less than one time per day. On average, f_u is 0.61 rides per day, corresponding to 4.4 bus rides per week. This result was significantly affected by two groups of passengers: for 12.9% of riders, only one ride was recorded, and 12.8% of the users took two rides). Nonetheless, 50% of the most active riders had an average of 1.12 rides per day, whereas for the top 10%, 2.65 rides per day was observed. However, as noted, these results include non-travel days.

Exploring another scenario, we computed the number of bus rides per actual travel day (f'_u). On average, each passenger took two daily trips, which is intuitive (i.e., commutes, traveling from home to work and vice-versa). As Figure 5 shows, the distribution of f'_u is characterized by visible peaks around integer (whole-number) frequencies. These patterns still hold for larger ride frequencies, even though the probability of occurrence decreases exponentially. As a consequence, we can conclude that bus ride demand is heterogeneously distributed across the population.

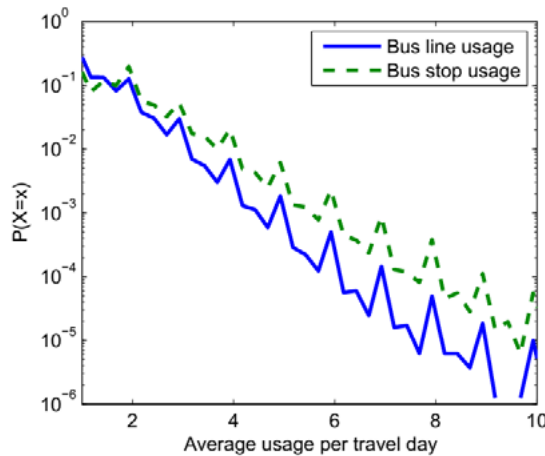
Bus Stop and Line Usage

To investigate the adequacy of the bus service to passenger needs and general mobility patterns, we examined rider interactions with the bus infrastructure—more specifically, where passengers boarded the bus and what lines were taken. On average, passengers visited 1.93 distinct stops each day and used 1.55 distinct bus lines.

To determine individual mobility patterns, we computed the probability distribution of a passenger's average daily usage (Figure 6). We observed that a larger fraction of passengers visited a higher number of bus stops than bus lines. Moreover, although passengers rarely visited the same bus stop on the same day, the same bus line was seen more often in a user's daily ride history repeatedly, e.g., for taking return trips.

FIGURE 6.

Probability distribution of rider average daily usage, differentiating between stops (green) and lines (blue) used. Distribution of bus stop usage more skewed than bus line usage.



To further investigate the relationship of travel frequency and the usage of bus infrastructure (distinct bus stops and bus lines), we used a linear regression. For the case of bus stop visits, the data can be fitted with a linear equation $s_u = 0.9449 * f'_u + 0.0115$. Based on the fitted slope, we can conclude that there is almost a one-to-one correspondence between the number of bus rides and the number of distinct bus stops observed on the same day—i.e., every time a passenger takes a bus ride on the same day, a distinct bus stop is used. This relationship holds for all users, as most of the variation in observed bus stop visits can be explained by the travel activity ($R^2 = 0.9944$).

In case of bus lines, the relationship can be fitted with a linear equation $l_u = 0.6096 * f'_u + 0.3507$, with more variation in the data ($R^2 = 0.7656$) when compared with the bus stops visited. This can be explained by the fact that the decision whether a certain bus line is suitable depends on the origin and destination of a ride. The fitted slope implies that there is a 40% chance that a ride is taken with the bus line used before on the same day.

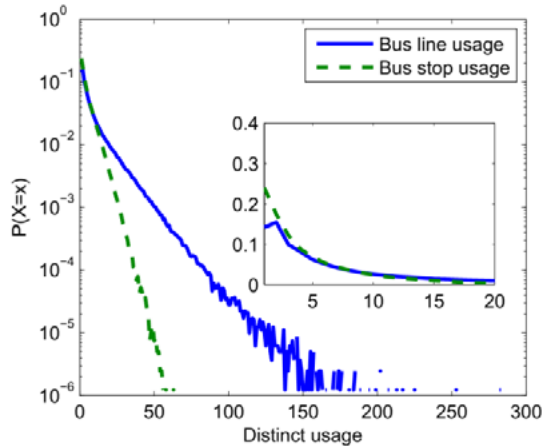
Travel Scope

In the previous section, we analyzed the daily interaction between passengers and the bus infrastructure (bus stops and bus lines) to understand the daily patterns of the riders. In this section, we analyze the subsets of the transport infrastructure that are relevant for the rider's mobility requirements, termed "travel scope."

We are interested in exploring the quantity of bus lines and bus stops used by distinct passengers to identify limits in transportation activities of different users. Figure 7 shows the proportion of distinct bus lines ($|L_u|$) and bus stops ($|S_u|$) used by the rider. Most passengers use a small part of the bus infrastructure. In the case of bus lines, 70% of riders use only 1–5 lines, and 20% of riders use 5–8 lines (from a total of 2,110 possible bus lines). In the case of bus stops, the scope is larger and varied: 70% of all riders visit 1–9 stops, and 20% are seen at 10–23 different stops (from a total of 96 bus stops).

FIGURE 7.

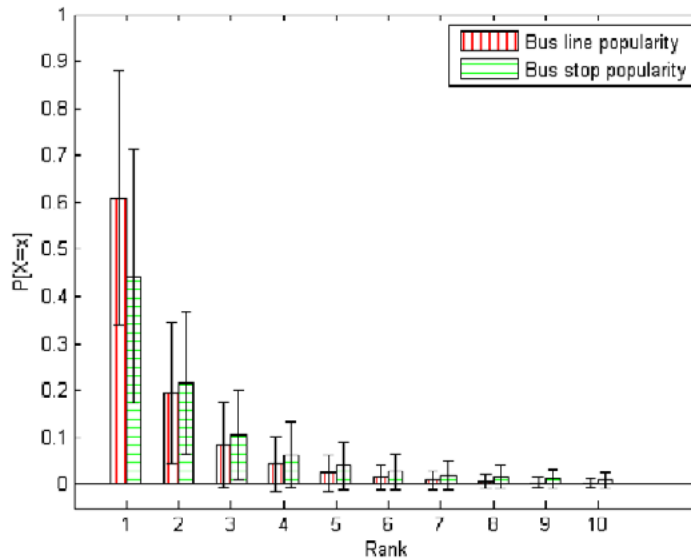
Characterization of scope of rider bus usage—probability distribution that certain number of distinct lines and stops used by any rider.



It is also important to understand if the full range of bus lines and stops are used equally or if some elements of that network are used only occasionally. To analyze if there is any skew in the usage, we computed a ranked distribution of the average popularity of the top 10 most frequently-used stops and lines in a user’s ride history, as depicted in Figure 8.

FIGURE 8.

Ranked average popularity of top 10 most frequently-used bus lines (red) and stops (green) in user ride history. For each rank, mean and standard deviation of popularity are shown.



To achieve this outcome, we first created, for each user u , an ordered vector $r_u = [p_1, p_2, \dots, p_n]$ of usage probabilities p_i , that measure the fraction of rides associated with the user’s i -th most frequently-used bus stop/line, and then averaged the result across all users. As shown on 0, the usage popularity quickly drops after higher ranks. We can conclude that, on average, the use of the bus infrastructure is concentrated on a limited number of bus lines and stops. Whereas the most popular bus line is accessed with a probability of 0.61 on average, the second most popular line has a probability of only 0.19 (third rank 0.08, fourth rank 0.04). In contrast, for bus stops, the popularities decrease at a slower rate, which means that a larger number of different stops is relevant: the most popular bus stop is visited with a probability of 0.44 on average, and

the second ranked bus stop 0.2 (third rank 0.1, fourth rank 0.06). This is in line with our previous analysis, where we emphasized that more distinct bus stops are involved in rides than distinct lines, on average.

Similarity of Travel across Week

Previous sections have shown an apparent temporal pattern. Therefore, we examined the similarity of passenger behavior on different days for which we used the cosine similarity to compare vectorized representations of a rider's bus usage on different days.

For the similarity coefficient, it should be relevant to consider which same bus stops and lines have been taken on different days, and their usage count should be in a comparable order on those days. We transformed the bus line usage patterns on a specific day in a vector space model (VSM). A similar procedure was applied to bus stops visits.

For given two days $d_i, d_j \in D, d_i \neq d_j$ and the set of all used bus lines $L_u(d_i, d_j) = L_u(d_i) \cup L_u(d_j)$ on these days, we derive a travel vector $tr_{u,i,j}(d_i) = \langle n_1, n_2, \dots, n_{|L_u(d_i, d_j)|} \rangle$, which encodes the number of rides of u taken with various lines. More precisely, the i -th entry, $n_i \in \mathbb{N}, 1 \leq i \leq |L_u(d_i, d_j)|$, of the travel vector denotes the number of rides taken with bus line $l_i \in L_u$ on the selected day, d_i . For each pair of days $d_i, d_j \in D, d_i \neq d_j$, we can then compute the similarity, defined as:

$$C_u(d_i, d_j) = 1 - \frac{tr_{u,i,j}(d_i) \cdot tr_{u,i,j}(d_j)}{\|tr_{u,i,j}(d_i)\| \cdot \|tr_{u,i,j}(d_j)\|} \quad (1)$$

which corresponds to the cosine distance.

Note that we subtracted the cosine similarity (right) from 1 to produce values in the interval [0,1] to obtain a ranking in ascending order, where 1 represents the highest and 0 is the lowest similarity score. Based on individual users' similarity scores, we constructed a population-wide similarity matrix S_c of size $|D| \times |D|$. Each entry $(i, j), i \neq j$, of matrix S_m , stores the average similarity value:

$$S_c(i, j) = \frac{\sum_{u \in U_{i,j}} C_u(d_i, d_j)}{|U_{i,j}|} \quad (2)$$

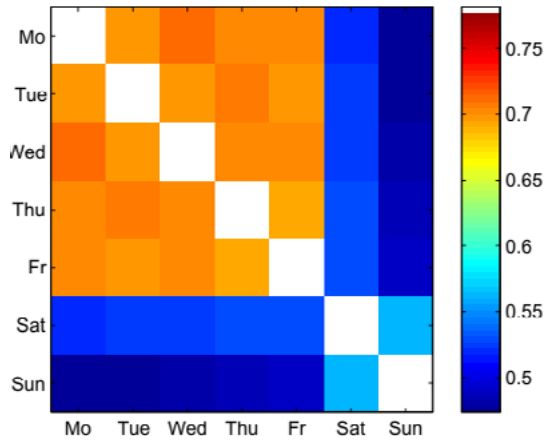
among the days $d_i, d_j \in D, d_i \neq d_j$, across all users $u \in U_{i,j} \subset U$, who have taken at least one ride on both days (note that S_c is symmetric across all day pairs, i.e., $S_c(i, j) = S_c(j, i)$).

The heatmap in Figure 9 displays the similarity matrix between different days of the week; the color denotes the intensity of the similarity. Clearly, two distinct groups arise, with stronger (weekdays) and weaker (weekends) travel similarities among their elements. On weekdays, travel behavior follows a regular pattern, explaining the similarity between days. The similarity of the Monday/Wednesday pair and the Tuesday/Thursday pair appear to be relatively high, suggesting a stronger link between these pairs, which are two days apart. In contrast, weekend bus rides are highly distinctive

from weekdays rides, especially on Sunday, which significantly deviates from the bus usage pattern observed on other days.

FIGURE 9.

Similarity matrix for weekly bus line usage. Similarity of ride behavior among different weekdays measured using cosine distance over vector of observed bus line boardings.

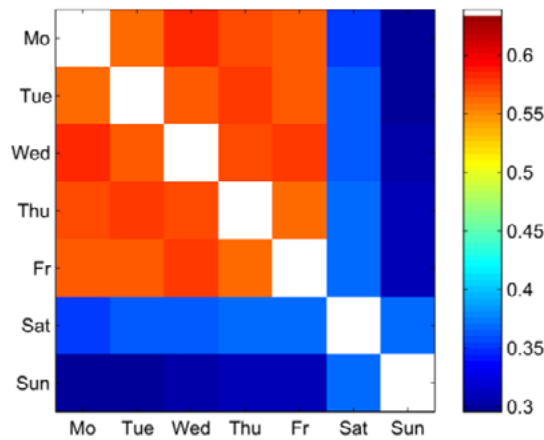


These observations are in line with empirical observations: usually, on weekdays, passengers tend to have a more rigorous schedule (e.g., work, school), which generates a more regular pattern. On the other hand, on weekends, passengers have a more diverse and less restrict schedule of activities (e.g., shopping, attending cultural or sporting events), creating a more random pattern.

A similar approach was applied to bus stop visits, and a similar outcome was obtained. The heatmap in Figure 10 displays the similarity matrix between different days of the week for bus stop visits. The similarity patterns follow the same trend observed for bus line usage. However, the absolute similarities values prove to be lower since bus stop visits exhibit a less certain usage signature, as shown previously.

FIGURE 10.

Similarity matrix for weekly bus stop visits. Analogous to 9, similarity scores represent values of cosine distance, but in this case applied to bus stop usage vectors.



To summarize the findings, we aggregated the computed cosine distances in Table 1. Days are grouped in different categories with the correspondent intra-group (all days, weekdays, weekends) and inter-group (between weekdays and weekends) average similarities.

TABLE 1.
Similarities of Bus Usage over
Different Parts of a Week

Day Subset	Bus Line Usage Similarity	Bus Stop Visit Similarity
All days	0.60	0.48
Weekdays only	0.70	0.57
Weekends only	0.56	0.37
Weekdays/weekends	0.50	0.33

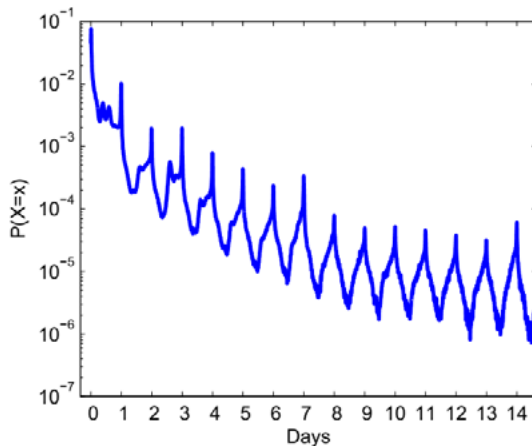
Values indicate average cosine distance

Periodicity of Travel Behavior

In addition to passenger patterns of using bus infrastructure, we explored their travel behavior between bus trips, i.e., the riders’ inter-trip times (elapsed time between two consecutive bus boardings). Note that this time period does not correspond to bus waiting times, but to a temporal measure, characterizing public transit access periods, and, hence, a measure for regularity of travel.

The distribution of the inter-trip times is shown on Figure 11 (from 23,447,595 consecutive buses, considering all individual rides) and indicates that inter-trip times are frequently short (12% of all observations fall within the interval $t \leq 20$ minutes, and inter-trip times are within $t \leq 30$ which account for 18%). This can be explained by the change between bus lines in a single journey. Previously, we observed that, on average, each passenger used 1.55 distinct bus lines daily. Since each passenger visits, on average, 1.93 distinct stops each day, this can also be an indication that the observed inter-trip time could include additional waiting time and short walk to a different bus stop.

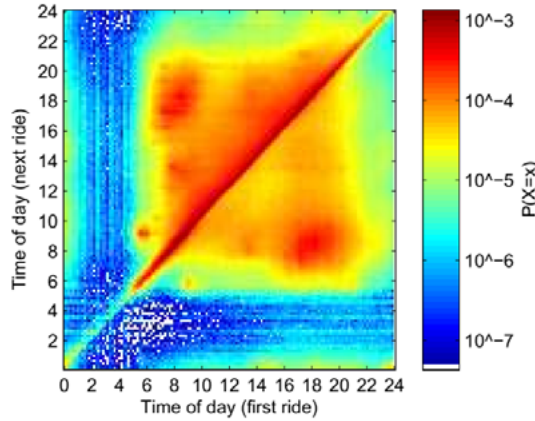
FIGURE 11.
PDF of inter-trip times across
all trips. Distribution reveals
high number of interchanges
with short inter-trip times and
characteristic daily cycles of
consecutive bus boardings



Considering the inter-trip times taking place on the same day, we can observe two (daily) peaks, at 9.5 hours and 14.5 hours after the last trip. The former is consistent with a typical daily commute, taking place when a passenger returns home after a working day (e.g., first trip to work at 9:00 AM, second trip returning home at 6:00 PM). The latter is complementary to the first peak and covers the following overnight period (e.g., 6:30PM– 9:00AM).

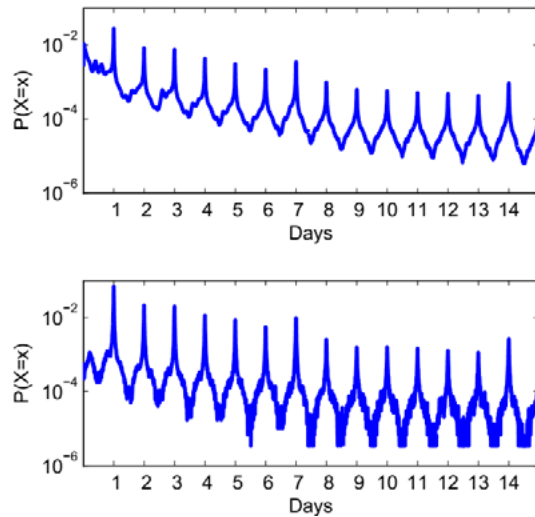
By observing the distribution over a wider time window, we can identify that one-day cycles have the largest probability of occurrence. Surprisingly, this suggests that the usual commuting pattern (home–work–home) was not observed, as only one bus ride was observed daily. To further explore this finding, we examined the joint distribution of the trip starting times of consecutive bus rides (Figure 12). The probability density is at the highest around the diagonal, which demonstrates that subsequent bus rides often are conducted at the same time of the day. This is especially true for the morning and evening periods of a day, when most rides take place.

FIGURE 12. PDF of timings of consecutive bus rides. High probability density on diagonal demonstrates that subsequent bus rides often taken at same time of day.



Since passengers, on average, board at the same hour on consecutive days, one can hypothesize that bus riders take the same route daily with a certain purpose. To test this, we computed the probability distributions of inter-trip times of rides taken with the same lines and rides boarded at the same stops, shown on Figure 13. A clear cyclic pattern of travel is observed, supporting the idea that bus rides that involve the same lines and stops often are connected to a specific and regular trip purpose (e.g., commuting to work or school).

FIGURE 13. PDF of inter-trip times with strong cyclic patterns for bus rides taken with same bus lines (top) and departing from same stop (bottom).



Conclusions

In this work, we studied the regularity of bus usage in Lisbon, Portugal. By mining two months' bus ride data, we were able to reveal some usage behavioral patterns, as follows.

There are more rides on weekdays than on weekends, most possibly due to the usual commutes, and, on average, a user takes 2 daily trips, visits 1.93 distinct stops, and uses 1.55 distinct bus lines. Weekdays travel patterns hold a strong similarity, whereas weekends (especially Sundays) reveal a very distinctive pattern. These behaviors are a strong evidence of the usual commutes.

Inter-trip times are mostly short (18% of observations fell within the interval $t \leq 30$ minutes). The second trip of the day usually takes place at 9.5 hours and 14.5 hours after the last trip. Subsequent bus rides often are taken at the same time of day (especially in the morning and evening periods).

On average, the use of the bus infrastructure is concentrated on a particular number of bus lines and stops. In the case of bus lines, 70% of riders use between 1–5 lines, and 20% use 5–8 lines (a maximum of 3.8% of the lines available), whereas in the case of bus stops, 70% of all riders visit 1–9 stops, and 20% were seen at 10–23 different stops (up to 23% of bus stops available).

This work has leveraged on the availability of bus ride histories for better understanding the regularity in bus usage behavior. In contrast to existing data mining studies of transport usage that are mostly concerned with aggregate travel characteristics, e.g., travel demand estimation, we analyzed travel behavior patterns of individual bus riders. Understanding individual travel behavior patterns is important for the development of novel personalized transport information systems that can provide proactive assistance to transport users. Our results provide a basis to develop a robust predictive algorithm, which is part of our future work.

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Optimal Limited-stop Bus Routes Selection Using a Genetic Algorithm and Smart Card Data

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Young-Jae Lee, Ph.D., Morgan State University

Abstract

In recent years, express bus service has come into the spotlight by overcoming slow bus operating speeds while maintaining its accessibility when it operates with local bus services. This study developed an optimal limited-stop bus routes selection (LSBRS) guideline as a scenario-based analysis and compared it with case study results. Smart card data and a genetic algorithm (GA) were used to develop the model with different scenarios. Then, total travel time savings as a result of implementing limited-stop bus service generated by the GA model were computed. The effectiveness of each factor was verified by multiple regression analysis, and the LSBRS methodology was determined. This methodology was applied to Suwon, Korea, as a case study. As a result, travel time savings were estimated to be 9.0–19.0%. The ranking of the total travel time savings proposed by the LSBRS methodology presented a similar tendency with that of the case-study analysis.

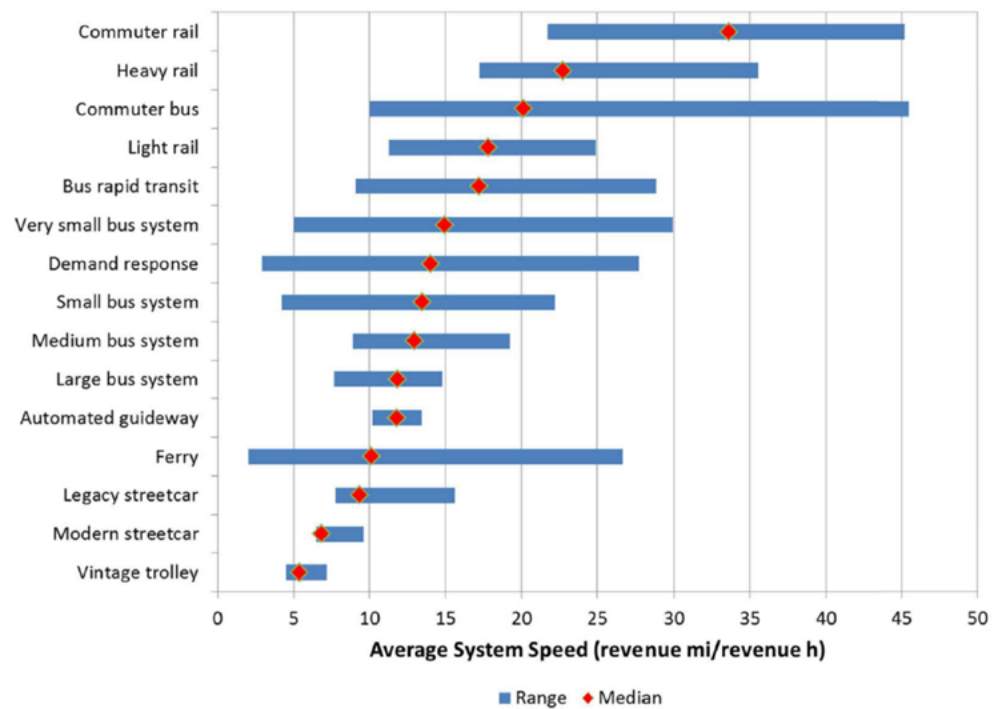
Key words: *Limited-stop bus, genetic algorithm, smart card data, multiple regression analysis, public transportation, case study*

Introduction

Because of its flexibility of route operation and excellent accessibility, bus is a major transit mode for mid- or short-distance trips in most cities. In Seoul, the capital of South Korea, with a population of 10 million, the modal share of bus transit is 27.4% (as of 2012) (City of Seoul 2014), in spite of the existing dense subway network. In Suwon, a suburban city outside of Seoul with a population of 1.2 million, the modal share of bus transit is 34.8% (as of 2011) (Metropolitan Transit Authority of Korea 2013) in an area with an insufficient number of subway lines.

In recent years, however, the modal share of bus transit in Korea has been stagnant or slightly decreasing because of several factors, such as an increase in passenger car ownership and the expansion of road and subway networks. To improve the competitiveness of public transit, two key factors, accessibility and mobility, should be assured to a certain level. These two concepts generally conflict with one another because when more bus stops are added to increase accessibility, operating speed is lowered. To satisfy these two conflicting concepts, the subway network was devoted to increasing mobility, whereas most bus transit was operated for greater accessibility. Therefore, in terms of travel time, bus transit has a limitation in terms of mobility compared to that of other modes, such as passenger car or subway. Figure 1 shows the average system speeds of a wide range of modes. As shown, the average speeds of bus systems are roughly half of that of rail systems, reinforcing the idea that bus systems are relatively less competitive as a transit mode for mid- or long-distance travels.

FIGURE 1.
Average transit system speeds by mode



Source: Ryus et al. 2013

Some rail lines in the Seoul metropolitan area and bus lines in several large cities have introduced express services while maintaining local services to satisfy both accessibility and mobility needs; however, there exists a need for a systematic approach to decide the optimal routes and stops for the express services. This study provides optimal limited-stop bus routes selection (LSBRS) methodology. As a flexible and economic mode of transit to introduce express service, limited-stop bus service could provide social benefits such as saving user travel time and operation costs as well as increase the number of passengers due to its more competitive service.

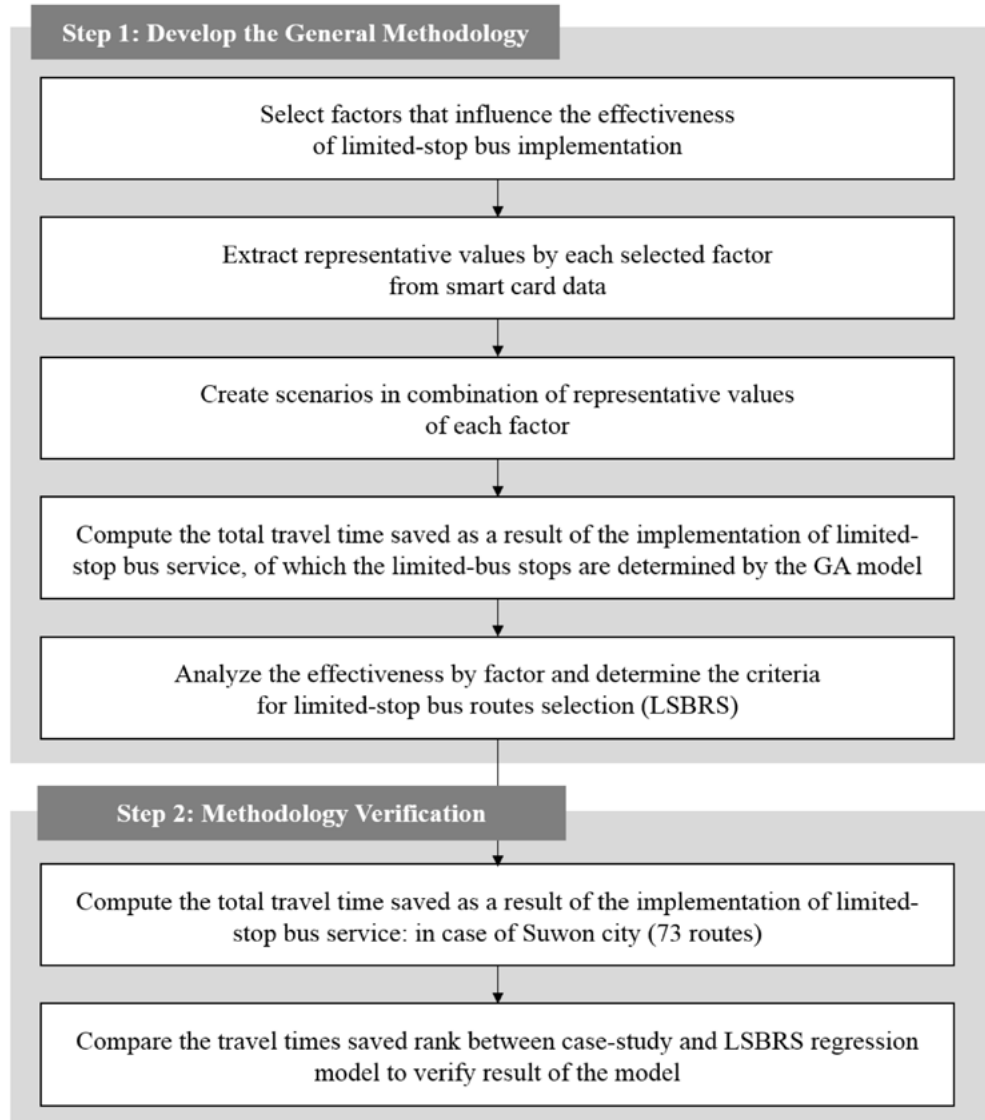
To develop the model, this study used smart card data and a genetic algorithm (GA). Smart card data, which are widely used in Korea, provide a set of complete trip data. Because the public transit fare of the Seoul metropolitan area is based on travel distances, users tag smart cards when boarding and alighting. As a result, the origin-destination (OD) location and time of each passenger can be obtained. Smart card data are widely used in the transit research area, especially in modal and route choice estimation models (e.g., Morency et al. 2007; Kurauchi et al. 2014; Jánošíková et al. 2014), OD estimation (e.g., Wang 2010; Jun and Dongyuan 2013; Nassir et al. 2011), or travel behavior analysis (e.g., Agard et al. 2006; Tao et al. 2014; Nishiuchi et al. 2013).

GA is used to solve non-linear programming problems, particularly in the transit network field. Kalantari et al. (2014) proposed a GA model considering geographic and operational similarity to solve a bus network modification problem. Nayeem et al. (2014) developed a GA model to maximize the number of satisfied passengers, minimize total travel time, and maximize the total number of passengers to solve a transit network design problem. Zargari et al. (2013) considers the location of depots in designing a bus network with a GA model to minimize deadhead travel time (travel time when a vehicle operates without regular services, such as when coming from a garage), empty seats, OD pairs that require more than two transfers, and user and operator costs. Additional studies using GA have been conducted in transit network design (e.g., Amiripour et al. 2015; Kuan et al. 2006; Fan and Machemehl 2004; Fan and Machemehl 2006) and in operational aspects such as optimizing frequency or minimizing transfer time (e.g., Cevallos and Zhao 2006; Ngamchai and Lovell 2003; Lee et al. 2014).

Although most of the existing research related to express transit services deals with restructuring the whole network or improving a single route, most cities have very well-organized transit route networks through spontaneous development or practical policies to satisfy user needs and operator efficiency. Therefore, instead of restructuring the whole transit network, this study provides the methodology to select an optimal route set from the currently-operating transit network that is maximizing system efficiency without large-scale restructuring of the whole network.

Figure 2 presents the process of this study. First, the general LSBRS methodology was developed to find the relationship between total travel time saved and various combinations of factors that influence total travel time savings. Because influencing factors from actual OD data would be biased to certain conditions, scenario ODs were created with the factors that influence the effectiveness of limited-stop bus implementation and used at this step. As a second step, the methodology was applied to the case of Suwon and compared with the LSBRS criteria for the total travel time saved.

FIGURE 2.
Process of optimal limited-stop bus routes selection



Methodology

Smart Card Data

After the implementation of distance-based integrated transit fare for the Seoul metropolitan area in 2007, smart card usage increased greatly—up to 98%—because of the implemented discount on transfer trips. In Korea, all data include temporal and spatial references for all transit modes used in one trip; these data can be gathered due to the tagging smart card when both boarding and alighting. The contents of smart card data include:

- User class (Regular, Student, Senior, Disabled ...)
- Mode codes* (bus, rail ...)

- Route ID* and vehicle ID
- Total distance (m)
- Total in-vehicle time and total time (min)
- Boarding and alighting time*
- Boarding and alighting stop ID*
- Total cost

*Recording 1st–5th mode of transit used; transfer discount offered up to 4 times

In this study, actual route and trip data from smart card data were used to extract representative values of each factor that influences the effectiveness of the limited-stop bus implementation. Trip data from the whole day of Wednesday, October 16, 2013, (663,616 passengers who boarded or alighted in Suwon city) were used to obtain average weekday trip patterns. Stop-based ODs by each route were created by each passenger's boarding/alighting time and stop information.

Selection of Influencing Factors for Limited-Stop Bus Service

To verify the factors that influence the limited-stop bus service, Schwarcz (2004) analyzed several factors such as resources, frequency share between regular service and express service, limited stops, headway distribution, distance between stops, OD demand, local and limited running time, and travel time component weights as key inputs of the model. The results showed that high concentrations of OD and long passenger trips are both critical and, additionally, that existing headway and ridership and the potential for route level running time savings influence the corridor potential for limited-stop bus service. Leiva (2010) developed limited-stop service design models that can accommodate the operating characteristics of a bus corridor, given an OD trip matrix and a set of services that are *a priori* attractive. The demand variability among different OD pairs and the average trip length strongly influence benefits. The model developed by Tétreault et al. (2010) shows that major activity points and stop spacing are key factors to operate a limited-stop service with high efficiency.

In reference to the aforementioned literature, this study selected route length, stop spacing, average trip length, and the OD pattern as the factors influencing a limited-stop bus service.

Representative values of each factor, with the exception of the OD pattern, were assumed in three cases: values of the 15th, 50th, and 85th percentiles. Table 1 shows the values extracted from route and trip data of 73 regular bus routes that operate in Suwon with smart card data. Meanwhile, representative values of the OD pattern were assumed as (1) flat: all OD pairs have similar passenger levels, (2) two peaks: two stops have highly concentrated boarding/alighting passenger levels, and (3) four peaks: four stops have highly concentrated boarding/alighting passenger levels. In total, 81 (=3⁴) scenarios were used with four factors and three representative values.

TABLE 1.
Representative Values of
Limited-stop Bus Service
Affecting Factors

	Route Length	Stop Spacing	Average Trip Length	OD Pattern*
15th percentile value	19.7 km	390 m	2.8 km	Flat
50th percentile value	32.5 km	430 m	3.4 km	Two peaks
85th percentile value	42.4 km	470 m	4.1 km	Four peaks

*OD pattern: Irrelevant to percentile values

Model Definitions

The effectiveness of the limited-stop bus is defined by the amount of passenger total travel time savings. Therefore, the objective function of this model was to minimize passenger total travel time using route k (Z_k), which is defined as the following:

$$\min Z_k = \sum_{r=1}^{N-1} \sum_{s=r+1}^N (q_{rs} \cdot TT_{rs}(i_n, h_L, h_R)) \tag{1}$$

Subject to:

$$V_L + V_R = V_T$$

$$V_L > 0, V_R > 0$$

$$i_n = [0,1], \forall i_n \in S_k$$

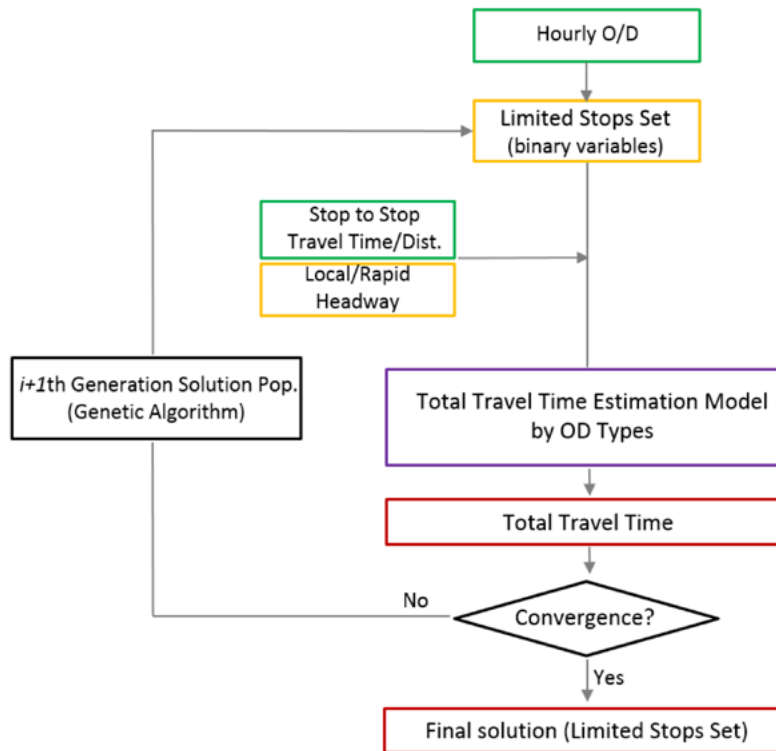
Where $h_L = \frac{60}{V_L}, h_R = \frac{60}{V_R}$

N is the total number of stops of route k , r and s are boarding and alighting stops, respectively, and q_{rs} is the number of passengers who board at stop r and alight at stop s . Total travel time for a passenger who boards at stop r and alights at stop s , TT_{rs} , is affected by stops of limited-stop bus route (i_n), headway of local bus service (h_L) and rapid bus service (h_R). S_k means total stops set of route k . Total vehicle fleet per hour (V_T) consists of local service vehicle fleet per hour (V_L) and rapid service vehicle fleet per hour (V_R), and is the same as the existing service scheme which is operated as local-only service. Stops of limited-stop bus route (i_n) are selected by the GA model which minimizes total travel time. If a limited-stop bus stops at n^{th} stop, i_n is set as 1, otherwise i_n is set as 0. Passenger travel time consists of in-vehicle travel time, waiting time and transfer time. Access time is not considered because passengers do not change their origin or destination stops against current situations, which results in an unchangeable value regardless of limited-stop bus service.

To maintain consistent levels for each scenario, the total OD amount (the sum of each OD trip) is calculated by the average number of passengers per route-km of Suwon (174 passengers/km) multiplied by route length. Running time savings by skipping a stop consists of boarding and alighting time saving, acceleration and deceleration time saving, and intersection signal delay saving. Figure 3 shows the total travel time estimation model algorithm. Stops of the limited-stop bus route (i_n) are adjusted at each

generation until total travel time is minimized. At the point at which total travel time is minimized, the travel time estimation model algorithm has finished selecting the set of limited-stop bus stops.

FIGURE 3.
Total travel time estimation
model algorithm



Model Assumptions

OD types were classified into three categories (shown in Figure 4): (1) between local-only stops (LL), (2) local-only stop to limited-stop bus stop, or limited-stop bus stop to local-only stop (LE/EL), (3) between limited-stop bus stops (E-E), "LL" in (1) and "LE/EL" in (2) should be "L-L" and "L-E/E-L" just like "E-E" in (3).

FIGURE 4.
Examples of OD types



In the case of L-L and L-E/E-L, total travel time by local bus and total travel time by local bus and limited-stop bus with transfer were compared to assign a passenger route to that of the one with shorter travel time. Running speed was assumed as 20 km/h, an average of regular bus routes in Suwon. In total, 50% of the total fleet was assigned

to the limited-stop bus service to minimize the waiting time for both bus services. Passengers who use the local-only stop do not change their initial boarding stop and final alighting stop even though a neighboring stop operates limited-stop bus service and ensures shorter travel time. This assumption was required to ease the complexity of the model that is repetitively applied to a number of routes and would be considered after the selection of limited-stop bus routes for detailed decisions about limited-stop bus route stops.

OD Creating Method (for Scenario-based Analysis)

In the case of scenario-based analysis, the assumption of OD form is one of the most critical points. First, traffic was generated for each stop by the OD pattern. In the case of flat type, the average traffic amount of each stop (referred to as $Trips_k$ for k th stop) is the total OD amount (Tot) divided by the total number of boardable stops ($StopNo-1$; deduct last stop from the number of total stops). By normal distribution with $Trips_k$ as the average, the following process generates random traffic volume with the number of stops and is applied to variation.

$$Trips_k \sim N(Tot/StopNo-1, (StopNo)^2) \quad (2)$$

where $\forall k \geq 1$ and $k \leq (StopNo-1)$

Divide by average stop spacing distance; average trip distance is substituted to average number of traveled stops ($Trip$). By normal distribution with $Trip$ as average, the following process generates the number of random travel stops ($TripTo_j^k$) for each passenger (as the amount of j) who boards at k th stop. The variation is proportional to the number of remaining stops to reflect trip distance diversity.

$$TripTo_j^k \sim N(Trip, (Trip/k)^2) \quad (3)$$

where $\forall k \geq 1$ and $k \leq (StopNo-1)$

$$\forall j \geq 1 \text{ and } j \leq Trips_k$$

In the case of two or four peaks types, a certain portion of total OD amount is reserved to be assigned for each type; 30% for two peaks and 40% for four peaks. First, the same method used to create the OD pattern of flat type is applied to the rest of the OD amount. The amount of the reserved portion is additionally applied. For two peaks type, 15% of total OD amount is boarding at the first peak stop and 15% of total OD amount is alighting at the second peak stop. For four peaks type, 10% of total OD amount is boarding at the first peak stop, 10% of total OD amount is boarding and alighting at the second and third stop each, and 10% of total OD amount is alighting at the fourth peak stop. Locations of peak stops are determined with equal partition; 33rd percentile and 67th percentile ordered stops are designated as peak stops for two peaks type, and 20th, 40th, 60th, 80th percentile ordered stops are designated as peak stops for four peaks type. The distribution of peak stops is identically applied as Equation 3.

Travel Time Estimation

In this study, modification of the limited-stop bus routes was not taken into account although there are shortcut paths between limited-stop bus stops without stopping at the local-only stop(s). In other words, line alignments of both local bus routes and limited-stop bus routes were assumed as the same. The calculation of the rapid bus travel time between the r stop and s stop (t_{rs}) was dependent on whether the limited-stop bus stops at the n^{th} stop. In-vehicle local bus travel time, t_{rs}^L , and in-vehicle rapid bus travel time, t_{rs}^R , were calculated according to the following:

$$t_{rs}^L = \sum_{n=r}^{s-1} t_{n,n+1} \quad (4)$$

$$t_{rs}^R = \sum_{n=r}^{s-1} t_{n,n+1} - \sum_{n=r}^{s-1} t_{n,n+1}^{\text{reduced}} \cdot (1 - i_n) \quad (5)$$

Where:

$t_{n,n+1}$ = bus travel time from n^{th} stop to $n+1^{\text{th}}$ stop

$t_{n,n+1}^{\text{reduced}}$ = reduced travel time when bus passes the n^{th} stop, calculated as $AccDcc + OnOffTime_n + Signal_n$

$AccDcc$ = time lost while decelerating from and accelerating to cruise speed for passengers boarding or alighting at stops (11.6 sec. [Robinson 2013])

$OnOffTime_n$ = boarding and alighting time at n^{th} stop (2.3 sec/passenger for boarding and 2.0 sec/passenger for alighting (from smart card data), applying larger value between total boarding time and total alighting time)

$Signal_n$ = expected signal delay reducing time by skipping n^{th} stop

Expected signal delay reducing time ($Signal_n$) reflects earlier arriving at the intersection when the limited-stop bus skips a local-only stop prior to the intersection, which allows for the increasing probability of passing through the intersection without stopping because of a red signal phase. In general, the signal coordination is aimed for regular private vehicles, which do not stop at bus stops. That means a bus which stops at a bus stop is more likely to miss the signal progression at the next signal because of the additional time consumption at the bus stop and increased travel time to the next intersection. If a bus does not need to stop at the bus stop and can skip the bus stop, most likely the bus can have a higher chance to enjoy the signal coordination just like the regular private vehicles. "Von Stain's law of transit stop locations," which refers to the bus stop location placement strategy with consideration for coordinated signals

to minimize the effects caused by signal delays, introduced the similar idea (Vuchic 2007). Using the average values of operating attributes of Suwon, with 161 seconds for average cycle time and 42% for g/C (green time/Cycle time), the probability that a vehicle receives a green signal when arriving at the intersection is 68 seconds (42% of 161), and that of receiving a red signal is 93 seconds (58% of 161). In this situation, expected average signal delay time is 27 seconds ($\sum_{i=1}^{93} i / 161$). If the bus arrives earlier at the intersection as much as X seconds because of boarding and alighting time and acceleration and deceleration time savings, expected average signal delay time is reduced as much as $\sum_{i=X}^{93} i / 161$.

Total travel time calculation is applied distinctly by three OD categories: L-L, L-E/E-L, and E-E. Total travel time is calculated by multiplying travel time and travel demand for every OD pair. In the case of L-L or L-E/E-L, total travel time is compared when using a local bus only and when using a local bus and limited-stop bus with transfer. After the comparison, all travel demand of OD pairs is assigned to one that takes less travel time:

$$TT_{rs}^{LL} = \min (VTT_{rs}^L, VTT_{rs}^{L+E+L}) \quad (\text{OD Type 1: L-L}) \quad (6)$$

$$TT_{rs}^{LE} = \min (VTT_{rs}^L, VTT_{rs}^{L+E}) \quad (\text{OD Type 2: L-E}) \quad (7)$$

$$TT_{rs}^{EL} = \min (VTT_{rs}^L, VTT_{rs}^{E+L}) \quad (\text{OD Type 3: E-L}) \quad (8)$$

$$TT_{rs}^{EE} = VTT_{rs}^E \quad (\text{OD Type 4: E-E}) \quad (9)$$

Where:

$$VTT_{rs}^L = W_{\text{wait}} \times T_{L\text{wait}} + t_{rs}^L + \sum_{n=r}^{s-1} \text{OnOffTime}_n$$

$$VTT_{rs}^E = W_{\text{wait}} \times T_{E\text{wait}} + t_{rs}^R + \sum_{n=r}^{s-1} \text{OnOffTime}_n \cdot (1 - i_n)$$

$$VTT_{rs}^{L+E} = W_{\text{wait}} \times T_{L\text{wait}} + W_{\text{trf}} \times T_{E\text{wait}} + t_{ra}^L + t_{as}^R + \sum_{n=r}^{a-1} \text{OnOffTime}_n$$

$$+ \sum_{n=a}^{s-1} \text{OnOffTime}_n \cdot (1 - i_n)$$

$$VTT_{rs}^{E+L} = W_{\text{wait}} \times T_{E\text{wait}} + W_{\text{trf}} \times T_{L\text{wait}} + t_{ra}^R + t_{as}^S + \sum_{n=r}^{a-1} \text{OnOffTime}_n \cdot (1 - i_n)$$

$$+ \sum_{n=a}^{s-1} \text{OnOffTime}_n$$

$$VTT_{rs}^{L+E+L} = W_{\text{wait}} \times T_{L\text{wait}} + W_{\text{trf}} \times (T_{L\text{wait}} + T_{E\text{wait}}) + t_{ra}^L + t_{ab}^R + t_{bs}^L$$

$$+ \sum_{n=r}^{a-1} \text{OnOffTime}_n + \sum_{n=a}^{b-1} \text{OnOffTime}_n \cdot (1 - i_n) + \sum_{n=b}^{s-1} \text{OnOffTime}_n$$

T_{Lwait} = Local bus average waiting time (1/2 of headway)

T_{Ewait} = Limited-stop (express) bus average waiting time (1/2 of headway)

W_{wait} = waiting time weight

W_{trf} = transfer time weight

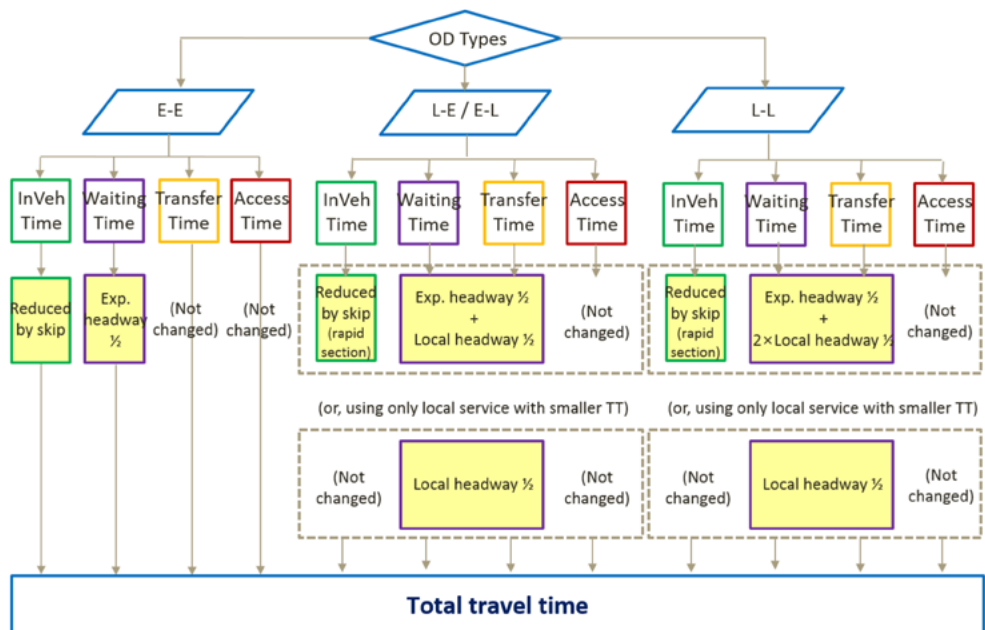
t_{rs}^L = in-vehicle local bus travel time

t_{rs}^R = in-vehicle rapid bus travel time

$OnOffTime_n$ = boarding and alighting time at n^{th} stop

Although research such as Fan and Machemehl (2009) considered passenger arrival model, average waiting time in this study is assumed as half of headway because maximum headway is set as 20 minutes without schedule information, which is a common condition for regular urban bus service in Korea. Weight for waiting and transfer time is referenced from Son et al. (2007), 1.83 times and 1.37 times of in-vehicle time, respectively. The total travel time calculation process is shown in Figure 5. If the limited-bus service stops at both origin and destination bus stops (E-E), in-vehicle time is reduced by skipping local-only stops. When the limited-bus service stops at only one of the origin or destination bus stops (L-E/E-L), there are two options: using both local and limited-stop buses with transfer in consideration of additional waiting time and reduced in-vehicle time, or using only the local bus to the destination if total travel time (TT) is shorter than using both local and limited-stop buses with transfer. If the limited-bus service does not stop at both origin and destination bus stops (L-L), travel time of using a limited-stop bus with two transfers and travel time of using only a local bus are compared.

FIGURE 5.
Total travel time calculation process



Genetic Algorithm Analysis

This study used a GA to obtain an optimal solution efficiently that contains an iterative calculation of the limited-bus stops combination and total travel time of passengers. The limited-bus stops were used as chromosomes, and the binary integer matrix were used as a gene (0: limited-bus skips the stop, 1: limited-bus stops at the stop). In every iteration, a gene was evolved until total travel time was tolerantly minimized. For example, optimal limited-bus stops of the certain bus route which has 10 stops were decided as 1st, 3rd, 7th, and 9th stops, the final gene is expressed as [1,0,1,0,0,0,1,0,1,0]. The fitness of each gene was evaluated based on the objective function – the total travel time. Detailed setting values are as follows:

- Population size: 200 (to attain optimal value from enough population)
- Population creation function: Uniform (design variable type is binary)
- Fitness scaling function: Rank (scales the raw scores based on the rank of each individual instead of its score)
- Selection function: Stochastic uniform (lays out a line in which each parent corresponds to a section of the line of length proportional to its scaled value)
- Elite count: $0.05 \times (\text{population size})$ (to prevent losing excellent solution while evolve to next generation)
- Reproduction crossover fraction: 0.8 (80% of former population is produced by crossover to prevent excessive changing)
- Mutation function: Uniform (rate: 0.01) (each gene is given a probability rate and replaced to an initial value when probability is lower than setting rate [0.01])
- Crossover function: Scattered (creates a random binary variable and selects the genes where the vector is 1 from the first parent, and the genes where the vector is 0 from the second parent, and combines the genes to form the child)
- Migration direction: Forward (migration takes place toward the last subpopulation)
- Stopping criteria: Function tolerance 10^{-7} (the algorithm stops if the average relative change in the best fitness function value which is less than or equal to 10^{-7})

Analytical Results

Scenario-based Analysis

The results shown in Table 2 are the average values of five repeated analyses by MATLAB. Among the various influencing factors, the OD pattern influenced travel time savings the most. Therefore, the route having certain stops that show highly concentrated boarding or alighting behavior would be chosen for a limited-stop bus

route. Also, routes that have longer route length, average trip length, or shorter stop spacing have an advantage as a limited-stop bus route. This is because longer route length ensures a greater number of passengers and longer average trip length results in a higher travel time savings rate when using a limited-stop bus. When the original stop spacing is short, a local bus should frequently repeat acceleration and deceleration at each bus stop to board and alight passengers. If a limited-stop bus is introduced, travel time savings effects by skipping several stops are higher than longer stop spacing for certain distances.

TABLE 2.
Travel Time Savings Rate
after Limited-stop Bus
Introduction, Compared to All
Local Services

Route Length	H (42.4km)	M (32.5km)	L (19.7km)	Max. / Min.
	5.6%	5.4%	5.0%	112%
Stop Spacing	H (470m)	M (430m)	L (390m)	Max. / Min
	4.9%	5.3%	5.9%	121%
Average Trip Length	H (4.09km)	M (3.36km)	L (2.84km)	Max. / Min
	5.7%	5.3%	5.0%	115%
OD Pattern	Flat	Two Peaks	Four Peaks	Max. / Min
	4.2%	5.8%	6.0%	142%

H = High, M = Medium, L = Low, Max./Min. = Maximum value divided by minimum value among high, medium, and low values

Multiple regression analysis between travel time savings rate and each factor was performed as presented in Table 3. The equation of the multiple regression model is as follows:

$$TTSR = 8.194 + 0.026 \times ODVar - 0.015 \times SS + 0.630 \times ATL \quad (10)$$

Where:

TTSR = Travel time savings rate

ODVar = OD variance

SS = Stop spacing

ATL = Average trip length

Adjusted R-squared value (0.864) indicates that the regression line highly fits the data. From the collinearity statistics, VIF values were around 1, which means there is low probability of multicollinearity among the explanatory variables. The OD variance factor (represents OD pattern as a quantified value) shows the highest standardized coefficient value (0.803), which means this factor should be considered first to the LSBRS, and is followed by stop spacing factor (-0.451) and average trip length factor (0.298). OD variance was calculated by the variance between the number of passengers boarding or alighting at each stop of specific routes. When OD variance is high, the stops that have concentrated passenger demand would be chosen as limited stops; therefore limited-stop bus service becomes more efficient with only a few stops. Route length factor was excluded by using a stepwise variable selection method to reduce collinearity.

TABLE 3.

Multiple Regression Model between Travel Time Savings Rate and Route Length, Stop Spacing, Average Trip Length, and OD Variance from Scenario-based Analysis

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	8.194	0.675		12.132	.000		
OD Variance	0.026	0.001	0.803	19.028	.000	0.992	1.008
Stop Spacing	-0.015	0.001	-0.451	-10.696	.000	0.992	1.008
Average Trip Length	0.630	0.089	0.298	7.081	.000	1.000	1.000
R-square	0.864		F-statistic	106.47			
Adjusted R-square	0.859		p-value	0.000			

Table 4 shows the travel time savings rate of 81 scenarios; most of the high-ranking scenarios had two or more factors among route length, stop spacing, and average trip length that satisfy each factor at the medium or high level. Therefore, this study defined LSBRS criteria as such that a limited-stop bus route should satisfy two or more of the following medium-level criteria: more than 32.5km of one-way route length, less than 430m of stop spacing, and more than 3.36km of average trip length. Also, OD patterns that have large variances would be suitable for limited-stop bus route.

TABLE 4.

Travel Time Savings Rate of 81 Scenarios (Top 20)

Rank	Route Length	Stop Spacing	Average Trip Length	OD Pattern	Travel Time Savings Rate (%)	Total Travel Time (before, min.)	Total Travel Time (after, min.)
1	H (42.4km)	L (390m)	H (4.09km)	4 peaks	8.14	5541.0	5089.8
2	L (19.7km)	L (390m)	H (4.09km)	2 peaks	7.57	2309.5	2134.6
3	H (42.4km)	L (390m)	M (3.36km)	2 peaks	7.34	4864.6	4507.7
4	M (32.5km)	L (390m)	M (3.36km)	4 peaks	7.33	3651.8	3384.1
5	H (42.4km)	M (430m)	H (4.09km)	4 peaks	7.27	5502.8	5102.8
6	H (42.4km)	L (390m)	H (4.09km)	2 peaks	7.11	5533.1	5140.0
7	M (32.5km)	L (390m)	H (4.09km)	4 peaks	6.86	4051.2	3773.5
8	H (42.4km)	H (470m)	H (4.09km)	4 peaks	6.79	5579.2	5200.7
9	H (42.4km)	L (390m)	L (2.84km)	2 peaks	6.71	4435.6	4137.9
10	L (19.7km)	M (430m)	H (4.09km)	2 peaks	6.61	2387.0	2229.2
11	H (42.4km)	M (430m)	M (3.36km)	2 peaks	6.58	4921.7	4598.0
12	M (32.5km)	L (390m)	L (2.84km)	2 peaks	6.56	3406.7	3183.3
13	H (42.4km)	L (390m)	M (3.36km)	4 peaks	6.56	4955.3	4630.2
14	M (32.5km)	M (430m)	M (3.36km)	4 peaks	6.54	3705.0	3462.7
15	L (19.7km)	L (390m)	M (3.36km)	2 peaks	6.47	2123.2	1985.9
16	M (32.5km)	L (390m)	H (4.09km)	2 peaks	6.44	4174.4	3905.5
17	H (42.4km)	M (430m)	H (4.09km)	2 peaks	6.37	5647.2	5287.5
18	M (32.5km)	L (390m)	L (2.84km)	4 peaks	6.25	3337.8	3129.1
19	L (19.7km)	M (430m)	M (3.36km)	2 peaks	6.19	2145.5	2012.8
20	M (32.5km)	H (470m)	M (3.36km)	4 peaks	6.10	3713.8	3487.4

Case Study Analysis

As a result of applying the model to 73 regular bus routes that operate in Suwon, travel time savings rate placed between 9.0% and 19.0%, which is larger than one of the scenario-based analysis. This is because the variation of actual OD is larger than that of scenario OD, which means passenger coverage is widened under the same number of limited-stops.

LSBRS criteria and the LSBRS regression model, which are proposed in the scenario-based analysis, are applied to the routes of case study. As presented in Table 5, most of the selected routes by LSBRS criteria are located in the upper rank along with higher values of travel time savings, according to the case-study analysis. Also, the travel time savings rank proposed by the LSBRS regression model shows a similar tendency with that of the case-study analysis, supported by Wilcoxon signed ranks test in Table 6, meaning that the assumption of difference between two pairs of the LSBRS regression model and the case-study analysis results are rejected (Asymp. Sig. [2-tailed] = 0.952 > 0.05).

TABLE 5. Travel Time Savings Rate of Case Study Routes Compared to LSBRS Criteria and LSBRS Regression Model

Rank	Route No.	Route Length (roundtrip, km)	Average Trip Length (km)	Average Stop Spacing (m)	OD Variance	Travel Time Savings (TTS) Rate (%)	Satisfying LSBRS Criteria	LSBRS Regression Model	
								TTS Rate (%)	Rank
1	10-2	20.0	4.28	345	152	19.0	X	9.7	21
2	400	97.0	8.20	519	313	17.5	O	13.7	3
3	10	85.0	8.54	503	222	17.2	O	11.8	7
4	61	62.6	3.61	396	132	16.7	X	7.9	43
5	660	76.4	8.35	527	236	16.2	O	11.7	9
6	990	82.4	7.15	535	319	16.2	O	13.0	5
7	34-1	50.6	5.38	444	148	16.1	X	8.8	31
8	60	93.3	6.14	438	165	16.0	X	9.8	19
9	10-5	47.0	6.07	435	181	15.9	X	10.2	14
10	700-2	57.2	6.42	427	207	15.9	O	11.2	10
11	66	65.0	6.86	428	138	15.8	X	9.7	20
12	400-4	68.5	6.57	493	290	15.8	O	12.5	6
13	35	53.1	8.61	482	185	15.7	X	11.2	11
14	4-1	37.4	4.18	411	110	15.6	X	7.5	55
15	38	41.7	9.77	522	284	15.6	X	13.9	2
16	13-4	45.8	4.80	463	457	15.6	X	16.2	1
17	34	60.5	5.13	451	149	15.3	X	8.5	36
18	900	83.4	12.77	502	177	14.9	O	13.3	4
19	7	63.4	4.29	425	232	14.8	O	10.5	12
20	20	57.7	5.68	473	161	14.8	X	8.9	29
21	7-2	66.2	4.65	409	194	14.7	O	10.0	17

TABLE 5 (cont'd). Travel Time Savings Rate of Case Study Routes Compared to LSBRS Criteria and LSBRS Regression Model

Rank	Route No.	Route Length (roundtrip, km)	Average Trip Length (km)	Average Stop Spacing (m)	OD Variance	Travel Time Savings (TTS) Rate (%)	Satisfying LSBRS Criteria	LSBRS Regression Model	
								TTS Rate (%)	Rank
22	2-2	41.6	3.07	408	134	14.7	X	7.5	57
23	66-4	76.0	5.49	404	121	14.4	X	8.7	32
24	310	36.9	4.15	415	189	14.1	O	9.5	23
25	720-3	53.6	3.70	436	145	14.1	X	7.8	45
26	730	70.2	4.44	444	184	13.9	O	9.1	27
27	46	42.5	4.22	448	171	13.8	X	8.6	35
28	27	52.1	4.64	401	117	13.8	X	8.1	39
29	7-1	38.7	4.68	387	161	13.5	X	9.5	22
30	720-2	81.4	4.44	419	176	13.5	O	9.3	24
31	13-1	48.7	3.11	380	150	13.4	X	8.3	38
32	5	45.7	4.41	423	209	13.3	O	10.1	16
33	30	35.3	5.00	484	220	13.1	X	9.8	18
34	300	73.6	9.66	522	202	13.1	O	11.7	8
35	63	50.3	4.22	405	100	13.0	X	7.4	59
36	11-1	49.6	4.26	459	199	12.9	X	9.2	26
37	99	80.5	3.57	426	126	12.9	X	7.3	61
38	777	55.8	6.29	537	241	12.8	X	10.4	13
39	202	46.3	4.18	482	131	12.7	X	7.0	70
40	13-5	50.3	4.63	479	175	12.7	X	8.5	37
41	20-1	47.1	4.80	486	138	12.6	X	7.5	56
42	25	45.5	5.41	489	134	12.5	X	7.7	46
43	720-1	91.5	4.53	428	112	12.5	X	7.5	54
44	3	38.5	3.77	374	87	12.5	X	7.2	65
45	301	76.2	5.54	476	166	12.5	X	8.8	30
46	62	34.8	3.61	430	124	12.4	X	7.2	64
47	9-1	52.5	4.21	520	214	12.4	X	8.6	34
48	62-1	62.6	4.17	396	107	12.3	X	7.7	49
49	37	46.2	3.77	399	135	12.3	X	8.1	40
50	99-2	51.1	3.66	433	119	12.2	X	7.1	68
51	5-1	44.6	4.08	479	163	12.2	X	7.8	44
52	65	51.7	4.48	438	121	12.2	X	7.6	53
53	82-2	36.0	3.31	409	133	12.1	X	7.6	52
54	9-2	39.9	4.36	464	236	12.0	X	10.1	15
55	88	42.5	3.22	401	134	11.9	X	7.7	48
56	2-1	38.9	3.10	377	159	11.7	X	8.6	33
57	88-1	40.4	3.18	429	149	11.6	X	7.6	50
58	64	70.1	4.11	438	124	11.6	X	7.4	58

TABLE 5 (cont'd). Travel Time Savings Rate of Case Study Routes Compared to LSBRS Criteria and LSBRS Regression Model

Rank	Route No.	Route Length (roundtrip, km)	Average Trip Length (km)	Average Stop Spacing (m)	OD Variance	Travel Time Savings (TTS) Rate (%)	Satisfying LSBRS Criteria	LSBRS Regression Model	
								TTS Rate (%)	Rank
59	51	34.4	3.67	453	140	11.5	X	7.4	60
60	15-1	58.8	3.78	474	209	11.2	X	8.9	28
61	85	29.0	3.27	414	116	11.1	X	7.1	69
62	80	33.5	3.18	419	97	11.0	X	6.4	73
63	36	53.0	3.33	449	144	10.9	X	7.3	62
64	83-1	22.3	2.84	371	87	10.7	X	6.7	71
65	82-1	33.8	2.78	402	146	10.5	X	7.7	47
66	11	70.4	4.22	499	182	9.9	O	8.1	41
67	9	35.4	3.57	437	156	9.9	X	7.9	42
68	98	49.7	3.42	401	107	9.7	X	7.1	66
69	13	33.9	3.97	458	207	9.7	X	9.2	25
70	92-1	49.4	3.60	437	142	9.5	X	7.6	51
71	39	33.3	2.39	411	143	9.4	X	7.2	63
72	92	36.8	2.78	405	125	9.4	X	7.1	67
73	112	31.5	3.22	426	103	9.0	X	6.5	72

Therefore, the criteria proposed in this study could be applied without a complicated analysis to cities that are considering implementing a limited-stop bus service. However, some routes such as 1st rank or 4th rank in Table 5 show big differences between the results of case-study analysis and the results of LSBRS suggestion. This is because of a gap between the scenarios and the actual routes, such as (a) the stop spacing distance of actual routes has a wide range of values while that of the scenario routes have identical values, or (b) the complexity of the OD pattern of actual routes is much higher than that of the scenario routes.

TABLE 6.

Wilcoxon Signed Ranks Test for Travel Times Saved Rank between (a) Case Study and (b) LSBRS Regression Model

		N	Mean Rank	Sum of Ranks
(b) – (a)	Negative Ranks	37	34.82	1288.50
	Positive Ranks	34	37.28	1267.50
	Ties	2		
	Total	73		
	Z	-0.060		
	Asymp. Sig. (2-tailed)	0.952		

Conclusions

The bus system is one of the most easily accessible systems among the various transit modes because of its short distances between stops. However, this attribute causes slow operation speeds and weakens its competitiveness when compared to other

transportation modes. In recent years, express bus service has come into the spotlight by overcoming its limitations to travel time while maintaining its accessibility when it operates with local bus services. To achieve an efficient bus system, a systematic approach to determine the optimal routes and stops for the express services is necessary. This study used smart card data and a genetic algorithm to develop the LSBRS criteria and the regression model. More specifically, the total travel time savings rates were calculated for various scenarios with their influencing factors to set the LSBRS criteria and regression model, and then these methods were applied to the case of Suwon, Korea.

Among the factors that influence the effectiveness of limited-stop bus implementation, concentrated OD pattern (represented by OD variance) influences travel time savings the most. Also, shorter stop spacing and longer average trip length have an advantage in maximizing the effectiveness of limited-stop bus implementation. In terms of the details of the criteria, limited-stop bus routes should have a large OD variance and satisfy two or more of the following medium-level criteria: more than 32.5km of one-way route length, less than 430m of stop spacing and more than 3.36km of average trip length. In reference to the coefficient values of the regression model, the OD variance factor should be considered first to the LSBRS criteria, followed by stop spacing factor and average trip length factor.

Comparing the rankings of the travel time savings proposed by the LSBRS regression model and the case study of Suwon, the pairs of two ranks show a similar tendency supported by the Wilcoxon signed ranks test. Therefore, the method proposed in this study could be applied to cities that are considering the implementation of a limited-stop bus service.

A limited-stop bus is one of the alternatives that satisfies both accessibility and mobility without great financial investment. Further studies focused on finding the adequate range of the number of limited-stop bus routes or enhancing the accuracy of LSBRS model are required.

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