Volume 19, No. 3, 2016

Journal of Public Transportation

USF University of South Florida

National Center for Transit Research

Joel Volinski, *Editor*
Lisa Ravenscroft, *Assistant to the Editor*
Patricia Ball, *Managing Editor*

EDITORIAL BOARD

Robert B. Cervero, Ph.D.
University of California, Berkeley

Chester E. Colby
E & J Consulting

Gordon Fielding, Ph.D.
University of California, Irvine

Jose A. Gómez-Ibáñez, Ph.D.
Harvard University

Naomi W. Ledé, Ph.D.
Texas Transportation Institute

William W. Millar
American Public Transportation Association

Steven E. Polzin, Ph.D., P.E.
University of South Florida

Lawrence Schulman
LS Associates

George Smerk, D.B.A.
Indiana University

Vukan R. Vuchic, Ph.D., P.E.
University of Pennsylvania

The contents of this document reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation, University Research Institute Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Volume 19, No. 3, 2016
ISSN 1077-291X

CONTENTS

Analysis of Bus Fires Using Interpretative Structural Modeling

Shumin Feng and Zhenning Li
Harbin Institute of Technology, China

Xianglong Sun
Northeast Forestry University, China

Abstract

There has been a worldwide growing public concern regarding transit bus fires, mainly because of their association with severe loss of human life and property. As a result, numerous studies have been carried out to investigate the causes, factors, and features of such accidents, along with research focusing on the simulation of bus fire scenarios. However, a detailed analysis on the causes of bus fires and the inter-relationships of risk factors is lacking. This study identified 17 risk factors associated with bus fires through an analysis of accident records from China using the Delphi approach. An integrated interpretative structural modeling (ISM) was adopted to explore the interactions among risk factors associated with bus fires, providing a useful hierarchy of risk factors whose individual relationships are unambiguous but whose group relationships are too complex to organize intuitively. This can help practitioners better understand risk dependencies and prioritize risk mitigation efforts. Results show that a lack of safety education and safety knowledge popularization and inadequate laws and regulations are the two most important risk factors associated with bus fires. Drivers also play an important role in preventing accidents. The analysis can be extended to risk analysis in other types of accidents, i.e., railway accidents and coach accidents.

Keywords: *Bus fires; risk factors; Delphi approach; ISM*

Introduction

Transit bus fires have drawn considerable attention worldwide owing to their frequent occurrence. Although buses generally are considered to be a relatively safe means of transportation, the loss of property and human life caused by bus fires is far from negligible. Generally, bus drivers and passengers can quickly flee the scene during a bus fire, leading to fewer casualties in comparison to bus crashes. However, in most cases, it is very likely that the bus will completely burn within 15–20 minutes after the start of a fire (Meltzer and Ayres et al. 2010), causing property damage in the tens of thousands of dollars up to the replacement cost of the bus (estimated to be $100,000). Numerous reports on bus fires, particularly those with high casualties, provide unprecedented examples of the potential human toll of a transit bus fire. According to documents of the China Fire Department of Ministry of Public Security (FDMPS), approximately 3,000 bus fires occurred in China in 2014, a number that has grown steadily since 2010, with no indication of an improvement in this trend. These fires caused an estimated annual average of 50 civilian deaths, 300 civilian injuries, and $30.2 million in direct property damage per year. Therefore, extensive research is needed to determine the causes of bus fires to reduce the frequency of bus fire accidents.

Previous Research

Previous research on bus fires focused primarily on the following two aspects:

- *Accident factors and features* – Chow conducted several studies on bus fire accidents. He analyzed different materials that affect fire safety and their release rate (Chow 1999) and then used empirical equations for analyzing types of materials that are more easily subjected to flashover (Chow 2001). He applied the test results to a sandwich panel sample commonly used in the construction industry with a calorimeter to study the manner in which incident thermal radiation heat flux affects the behavior of materials subjected to fire (Chow 2003), then investigated the flowing and diffusing mechanism of smoke in bus fires and proposed a smoke control strategy (Chow 2006). Lönnermark (2005) analyzed the characteristics of bus fires that occurred in tunnels and determined a method for calculating the CO/CO_2 ratio, flame length, and other indexes. Chun-ming (2006) analyzed several bus fire incidents in China and summarized the features and factors of bus fires through a systemic analysis.
- *Simulation of bus fire scenario* – Some studies have used full-scale vehicles to simulate bus fires; for instance, Johnsson and Yang (2015) placed several thermocouples (TCs) in wheels, tires, wheel wells, and other locations to monitor the heat release rate (HRR) of each vehicle part. Other studies used small-scale vehicles to simulate bus fires; for example, Försth et al. (2013) used the different materials of different bus components such as walls, ceilings, seats, curtains, instrument boards, etc., to test their horizontal burning rate, vertical burning rate, and critical heat flux, and determine whether they could pass the ISO (International Organization for Standardization) 3795, ISO 6941, and ISO 5658-2 tests. Other studies on bus fires mainly used numerical simulation software such as Fire Dynamics Simulator (FDS), Smokeview, and PyroSim. Based on the descriptions of evacuees and rescuers, as well as combustion evidence from the scene, Bi et al. (2010) reconstructed a bus fire scene by adopting parallel operation. The simulation results obtained were compared with the fire site reconnaissance results, demonstrating reliable prediction of the fire process and smoke movement calculation. Jia-lei et al. (2010) simulated two types of typical bus fires and confirmed that different interior materials have different impacts

on bus fires; they also determined that bus fires were influenced by whether the doors or windows were open or closed and, accordingly, developed some fire control strategies.

As indicated, previous research on bus fires mainly focused on accident factors and features as well as the burning characteristics of different materials; however, not many studies have been conducted to investigate the reasons for bus fires and the inter-relationships of risk factors. Further, past cases on bus fires also have not been used to conduct an analysis. Therefore, this study aimed to confirm the risk factors affecting bus fires by analyzing numerous bus fire accidents and to identify and summarize the relationships among these factors by using interpretative structural modeling (ISM) to classify their importance for undertaking specific measures to prevent bus fires.

Data

Only a few studies have focused on bus fires despite their frequent occurrence. This likely is because of the difficulty in acquiring related data. For example, departments, agencies, databases, etc., associated with bus fires often lack detailed statistics and analysis of data. On a positive note, however, there is growing concern over bus fires from society and the media, which makes it simpler to obtain the time, place, number of casualties, cause, and even details of accidents from the Internet. In the current research, we obtained data from reports of the Chinese media, the investigation results of the FDMPS, and accident particulars from the China fire services yearbook (2011–2014). Basic information on accidents is shown in Table 1, which lists 12,633 accidents, of which 20 typical accidents were selected for detailed analysis (Table 2).

TABLE 1.
Basic Information on Bus Fires in China

Categories/Variables	Number	Percentage
Year		
2011	2,984	23.62%
2012	3,172	25.11%
2013	3,083	24.40%
2014	3,394	26.87%
Primary Causes		
Arson	2,984	23.62%
Electrical fault	3,172	25.11%
Vehicle fault	3,083	24.40%
Playing with fire (harmlessness)	3,394	26.87%
Smoking	618	4.89%
Spontaneous combustion	5,047	39.95%
Lighting stroke	1,891	14.97%
Static	674	5.33%
Unknown	715	5.66%

TABLE 2.
Characteristics of Typical Accidents

No.	Location	Date	Causalities	Causes				
				Driver	*Passenger*	*Arson*	*Vehicle*	*Environment*
1	Beijing	5/29/2014	0		✓		✓	✓
2	Changchun	5/6/2013	0					✓
3	Chengdu	5/6/2009	101	✓	✓	✓		
4	Guangzhou	7/15/2014	34		✓	✓		
5	Guiyang	2/27/2014	37	✓	✓	✓		
6	Hangzhou	7/21/2010	0				✓	✓
7	Hangzhou	7/5/2014	32		✓	✓		
8	Harbin	6/13/2014	0	✓			✓	
9	Hefei	6/27/2014	0	✓			✓	✓
10	Huhehot	3/14/2015	0	✓			✓	
11	Jinzhou	10/14/2014	2		✓	✓		
12	Liuzhou	11/21/2014	18	✓				
13	Qufu	3/12/2015	0	✓			✓	
14	Sian	3/6/2015	0				✓	
15	Taizhou	8/22/2013	0	✓			✓	✓
16	Wuhan	4/8/2013	0		✓		✓	✓
17	Wuhan	6/21/2012	0				✓	✓
18	Xiamen	6/7/2013	81		✓	✓		
19	Xiamen	1/16/2015	12		✓	✓		
20	Yantai	8/20/2014	20	✓	✓	✓		

Research Method

The aim of this research was to identify key risk factors associated with bus fires and explore how these risk factors interact with each other. Previous methods such as those involving a questionnaire survey are not adequate, as they cannot distinguish the relationships between risk factors. Therefore, the Delphi method was chosen to identify these risk factors associated with bus fires, and interpretive structural modeling (ISM) was adopted to explore the interactions among them.

Delphi Method

There are two stages in the Delphi method. The first involves drawing a final list of risk factors, and the second involves investigating the interactions of the risk factors. All information was collected via Delphi questionnaires. Questionnaires were sent to 15 experts having different jobs in this area who agreed to participate in this research via e-mail. The profiles of the experts are presented in Table 3.

TABLE 3.
Profile of Delphi Experts

Codename	Working Organization	Role in Organization
A	Transportation authority	Director
B	Transportation authority	Director
C	Fire department	Director
D	University	Professor
E	University	Professor
F	University	Professor
G	University	Professor
H	University	Professor
I	University	Professor
J	University	Associate Professor
K	University	Associate Professor
L	Vehicle company	Chief Engineer
M	Vehicle company	Engineer
N	Bus operating company	General Manager
O	Bus operating company	Bus driver

First Stage of Delphi Method

The aim of the first stage was to search for risk factors; to this end, the following steps are taken:

1. Experts that fit the criteria were selected.
2. An information sheet and a list of questions were sent to all experts via e-mail. The information sheet contained background, current situation, and data of overall accidents and a detailed description of typical bus fire records.
3. All experts were asked to identify at least 10 key risk factors that affect bus fires and to provide descriptions of those risk factors within 150 words.
4. The risk factors identified by the experts and the findings of the literature survey were included in a new information sheet.
5. The new information sheet was provided to the experts, who then were invited to add or modify the list. In the end, a consensus was reached through three rounds of feedback sessions.

Second Stage of Delphi Method

The second stage involved investigating the relationships between risk factors determined from the first stage. During this stage, the experts were asked to evaluate if there are interactions between each pair of risk factors associated with bus fires:

- Questionnaire (a): Please identify those risk factors that influence S_i.
- Questionnaire (b): Please identify those risk factors that are influenced by S_i.

After three rounds, a consensus was reached, and the interactive relationships between risk factors associated with bus fires were analyzed via an integrated ISM model.

Interpretive Structural Modeling

ISM, first proposed by Warfield in 1973 with the aim of analyzing complex socioeconomic systems, is an effective tool for determining the interactions between specific items (Singh and Kant 2008). Generally, the major steps involved in the ISM technique are as follows:

1. *Set the reachability matrix*. A reachability matrix is used to represent the extent to which different nodes in a directed graph can reach (i.e., indirect influence) each other through certain channels. The feature of transformation means that if there is one channel that element S_i can reach S_j directly, there is also one channel that S_j can reach S_k. Therefore, there must be two channels that S_i can reach S_k. M is used to present reachability matrix. Matrix A is used to achieve M. A is the adjacent matrix obtained from the second stage of Delphi method. The element in it, a_{ij}, equals to 1 when S_i has influence on S_j, otherwise it equals to 0. The following formula presents the process of using A to achieve M. The Boolean algebra operation rules are selected for the matrix power operation in the formula.

$$\mathrm{A} = (a_{ij})_{n\times n},\ \ a_{ij} = \begin{cases} 1, & S_i R S_j \\ 0, & S_i \overline{R} S_j \end{cases}$$

$$I = (i_{kj})_{n\times n},\ \ i_{kj} = \begin{cases} 1, & k = j \\ 0 & k \neq j \end{cases}$$

$$(A+I) \neq (A+I)^2 \neq (A+I)^3 \neq \quad \neq (A+I)^{\lambda} = (A+I)^{\lambda+1} = \quad = (A+I)^n$$

Finally,

$$M = (A+I)^{\lambda} = (A+I)^{\lambda+1}$$

2. *Partition the reachability matrix*. According to the reachability matrix, the reachability sets and antecedent sets of every factor must be determined. The reachability set is composed of all the related elements that S_i can reach (has an impact). The antecedent set is the set composed of all the elements that can reach S_i.

3. *Draw the ISM relationship diagram*. In accordance with the results of partitioning the reachability matrix, the reachability matrix is rearranged, and then the structure matrix S can be obtained. With the help of S, a multilevel hierarchical structural diagram can be drawn.

Identification of Risk Factors Associated with Bus Fires

Using the Delphi method, a final list of 17 risk factors was obtained, which were mainly related to three entities: people, vehicle, and environment. From Tables 1 and 2, we can conclude that the causes can be classified under these three entities, and the risk factors associated with bus fires caused by these three entities were identified.

People

People play the most important and active part in bus fires; this entity can be further divided into drivers and passengers.

Risk factors attributed to drivers include the following:

- *Negligence of routine safety inspection*. This may lead to the risk of fire starting in the engine, electric devices, and other undetected interior structures in the bus; in addition, the loss or damage of emergency hammers and extinguishers also may lead to more casualties (Knipling and Hickman et al. 2003; Underwood and Chapman et al. 2003). Focusing on cases 9, 10, and 13 from Table 2, all the drivers neglected safety inspection, resulting in the bus experiencing spontaneous combustion on the road; fortunately, there were no casualties, and only the buses were burnt.
- *Lack of safety awareness and knowledge*. Historically, the education level of bus drivers in China is extremely low, lower than the average level of the whole society. Since driving a bus is stressful and poorly paid, fewer and fewer people want to be bus drivers, especially young people with a higher education level. Accident records also show that the drivers primarily are middle-age and have low safety knowledge, a serious condition that is common in China and a factors mentioned by all Delphi experts.
- *Risky driving behaviors*. Overloading may render passenger evacuation difficult, and driving at high speed, under the influence of alcohol, or while fatigued may cause drivers to react and respond to fire hazards slowly, resulting in more severe accidents (Tseng 2012; Nirupama and Hafezi 2014; Mallia and Lazuras et al. 2015). For instance, case 18 in Table 2 was caused by arson and resulted in 48 deaths and 33 injuries. Overloading contributed significantly to the serious casualties, since it was impossible for nearly 100 occupants to escape from the burning bus quickly (in 2 minutes or so) in panic circumstances.

Risk factors attributed to passengers include the following:

- *Possession of flammable and explosive goods*. Unlike stations for subways, trains, planes, and other modes of transport, usually there are no security inspection devices at bus stations, thus allowing passengers to carry anything aboard. According to FDMPS, this has led to hundreds of bus fires every year in China, especially in small cities. There is also some concurrence from the Delphi experts, one of whom noted that "… in my career, there are always people carrying alcohol, gasoline, or other explosive goods when taking buses; especially during the Chinese Spring Festival, almost everyone carries all kinds of firecrackers, and this kind of behavior may lead to fire easily…."

- *Possession of fire sources*. Generally, the interiors of vehicles in China are made of numerous flammable materials. Some buses designed for the cold north area contain cotton seat cushions, and some advertisements in the bus are made of paper or other flammable sources. A spark to a flammable material in a bus can easily lead to fire accidents. For example, a person smoking in a bus caused a fire in Liuzhou (case 12). Some Delphi experts mentioned that although smoking and lighters in buses are not common in big cities, they are very common in small cities, especially in poor provinces.
- *Delay in reporting suspicious circumstances to drivers*. There is usually a certain smell, smoke, and/or sound when a bus first catches fire; in addition, arsonists carrying combustible goods usually behave strangely. If passengers would report these circumstances in a timely manner, the consequences of a fire may decrease and perhaps could be prevented.
- *Arson and destruction*. Arson and destruction are frequent occurrences, and the circumstances of fires caused by arson are generally the same. Most arsonists have fire sources and liquid flammable goods with them and set fires from blind areas in the bus. The beginning of a fire set by an arsonist can be is difficult to recognize because arsonists tend to hide the fire. As a result, the fires are more swift and violent than those caused by smoking or bad weather. Cases 3, 4, 5, 7, 18, 19, and 20 were all mainly caused by arson, and the number of injuries and deaths was extremely high. It is worth noting that all the Delphi experts listed this entry on their answer sheets. Arson is a significant cause of bus fires, and from the yearbooks of FDMPS, the proportion of bus fires caused by arson has risen steadily since 2010.

Vehicle

In many cases, the bus itself is the source of a fire, and it also plays an important part in accidents. Risk factors attributed to the vehicle include the following:

- *Design defect*. With plenty of flammable materials on buses and inappropriate structure design, the likelihood of bus fires has increased (Parsons 1990). There are still no specific standards on bus fireproofing, and China's local vehicle companies are not forced to produce fireproof buses for economic reasons. There were no fireproof buses in China until 2009, and a so-called "fireproof" bus can spray water only on the command of the bus driver when a fire occurs. In addition, some buses are not suitable for lengthy driving in bad weather, such as hot temperatures and lightning. Some buses are designed for the cold north area, but some cities in the hot south area use buses that could result in bus fires (e.g., case 9).
- *Performance aging*. Service over a long period of time may cause the equipment to age, particularly the engine, electrical equipment, and exhaust system, which

can be hazardous (Ming and Tian et al. 2009). It is common in China that transit buses in small cities, especially in underdeveloped provinces, are obsolete buses that previously were used for years in bigger cities. This also was noted by all Delphi experts.

- *Lack of maintenance*. A driver usually fixes a minor problem with a bus during operation; however, this could cause a fire hazard (Hammarström et al. 2008). In addition, some maintenance agencies may not have proper qualifications for bus maintenance, and parts for buses may not be ordered or installed correctly. Also, if a bus does not undergo regular routine maintenance, the equipment inside it may age, increasing the probability of fire. In the opinion of the Delphi experts, performance aging and lack of maintenance are inter-related factors: a lack of routine maintenance leads to aging of a bus, and as a bus ages, drivers are less likely to maintain it regularly.
- *Low-quality fuel*. Some refueling stations may supply low-quality fuel, and some drivers prefer to purchase fuel in bulk instead of from refueling stations. According to results of the examination of gas stations in Shandong Province, fuel supplied at 2,083 of 6,630 gas stations were found to not meet standard quality. More specifically, some of the fuels had lower ignition temperatures or were very volatile, which can increase the possibility of fires. Some Delphi experts strongly encouraged the inclusion of this risk factor, noting that extended use of low-quality fuel can easily lead to poor performance and premature wear and may result in engine damage.
- *Lack of fire-extinguishing and emergency escape installations*. Fire extinguishers are either not installed or lose efficacy in some buses, resulting in a delay in suppressing a fire. In addition, safety hammers, relief valves, and other survival equipment often are lost or broken, making evacuation difficult.

Environment

Risk factors attributed to the environment include the following:

- *Social contradictions*. Intensified social conflicts increase the probability of arson, malicious damage, and even terrorist attack.
- *Lack of safety education and safety knowledge popularization*. Owing to an unclear understanding of safety knowledge, drivers do not know how to prevent fires, put out fires in a timely manner, and evacuate passengers. In addition, passengers are unaware of what type of goods can be carried safely and how to escape effectively.
- *Inadequate laws and regulations*. Compared with car accidents, attention to bus fires is limited, resulting in a lack of effective laws, regulations, and accountability; hence, it is difficult to warn about and prevent illegal behavior.
- *Bad roads*. Road alignment, road profile, surface type, and traffic capacity impact bus safety differently (Kaplan and Prato 2012).

- *Bad weather.* The probability of bus fires increases considerably in hot conditions and thunderstorms. For instance, approximately 10 bus fires occur every year in the U.S. because of bad weather (Ahrens 2006).

The 17 risk factors and their relationships were determined, after agreement among by Delphi experts. These relationships are presented in Table 4.

TABLE 4.
Relationships between Risk Factors Associated with Bus Fires

No.	Risk Factors (S_i)	Risk Factors Influenced by S_i
Driver Level		
1	Negligence of routine safety inspection	8, 9, 10, 11, 12
2	Lack of safety awareness and knowledge	1, 3, 4, 5, 7, 8, 9, 10, 11, 12
3	Risky driving behaviors	4, 5
Passenger Level		
4	Possession of flammable and explosive goods	7
5	Possession of fire sources	7
6	Delay in reporting suspicious circumstances to driver	7
7	Arson and destruction	-
Vehicle Level		
8	Design defect	9, 10, 12
9	Performance aging	10
10	Lack of maintenance	9
11	Low-quality fuel	-
12	Lack of fire-extinguishing and emergency escape installations	-
Environment Level		
13	Social contradictions	7
14	Lack of safety education and safety knowledge popularization	1, 2, 3, 4, 5, 6, 7, 12
15	Inadequate laws and regulations	1, 2, 3, 4, 5, 7, 11, 12
16	Bad road	-
17	Bad weather	-

ISM Analysis

In the previous sections, the identification of risk factors associated with bus fires was proposed according to the Delphi approach. In this section, ISM is employed to explore how these risk factors interact with each other. An adjacency matrix, reachability matrix, and all iterations results are presented in Tables 5, 6, and 7, respectively. Elements 1–17 represent the 17 risk factors. In addition, a digraph of risk factors associated with bus fires is shown in Figure 1 and shows the levels of all the risk factors.

TABLE 5.
Adjacency Matrix

Elements (*i/j*)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
2	1	0	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0
3	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
14	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0
15	1	1	1	1	1	0	1	0	0	0	1	1	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

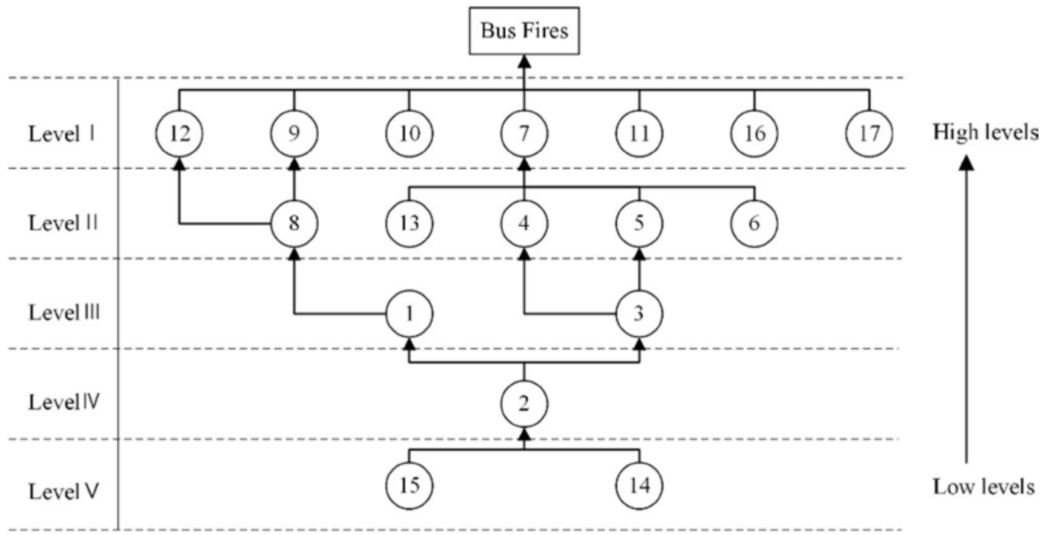
TABLE 6.
Reachability Matrix

Elements (*i/j*)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
2	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0
3	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
13	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
14	1	1	1	1	1	1	1	0	0	0	0	1	0	1	0	0	0
15	1	1	1	1	1	0	1	0	0	0	1	1	0	0	1	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

TABLE 7.
All Iterations' Results

Element (S_i)	Reachability Set: $R(S_i)$	Antecedent Set: $A(S_i)$	Intersection $R(S_i) \cap A(S_i)$	Level
1	1, 8, 9, 10, 11, 12	1, 2, 14, 15	1	
2	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12	2, 14, 15	2	
3	3, 4, 5, 7	2, 3, 14, 15	3	
4	4, 7	2, 3, 4, 14, 15	4	
5	5, 7	2, 3, 5, 14, 15	5	
6	6, 7	6, 14	6	
7	7	2, 3, 4, 5, 6, 7, 13, 14, 15	7	I
8	8, 9, 10, 12	1, 2, 8, 14, 15	8	
9	9, 10	1, 2, 8, 9, 10, 14, 15	9, 10	I
10	9, 10	1, 2, 8, 9, 10, 14, 15	9, 10	I
11	11	1, 2, 11, 14, 15	11	I
12	12	1, 2, 8, 12, 14, 15	12	I
13	7, 13	13	13	
14	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14	14	14	
15	1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 15	15	15	
16	16	16	16	I
17	17	17	17	I
1	1, 8	1, 2, 14, 15	1	
2	1, 2, 3, 4, 5, 8	2, 14, 15	2	
3	3, 4, 5	2, 3, 14, 15	3	
4	4	2, 3, 4, 14, 15	4	II
5	5	2, 3, 5, 14, 15	5	II
6	6	6, 14	6	II
8	8	1, 2, 8, 14, 15	8	II
13	13	13	13	II
14	1, 2, 3, 4, 5, 6, 8, 14	14	14	
15	1, 2, 3, 4, 5, 8, 15	15	15	
1	1	1, 2, 14, 15	1	III
2	1, 2, 3	2, 14, 15	2	
3	3	2, 3, 14, 15	3	III
14	1, 2, 3, 14	14	14	
15	1, 2, 3, 15	15	15	
2	2	2, 14, 15	2	IV
14	2, 14	14	14	
15	2, 15	15	15	
14	14	14	14	V
15	15	15	15	V

FIGURE 1.
Digraph of risks in bus fires



From Figure 1, we conclude some useful findings:

- All the risk factors associated with bus fires can be classified into five levels. The factors in the first level will directly affect bus fires. The factors in middle levels (II, III, and IV) are elements that indirectly influence bus fires and play a role in connecting the levels above and below. The last level (V) presents the macro-level factors of bus fires. In addition, factors at a higher level will be influenced by those at lower levels, and there are direct impacts between factors at adjacent levels. In other words, changes in low-level factors will emerge in middle-level factors, so low-level factors can "control" middle-level factors, which is why they are more important in the whole hierarchical structure.
- Seven superficial factors have a direct impact on bus fires: arson and destruction (7), performance aging (9), lack of maintenance (10), low-quality fuel (11), lack of fire-extinguishing and emergency escape installations (12), bad roads (16), and bad weather (17). These factors cannot influence the others—that is, they are independent factors.
- The factors in levels II, III, and IV are influenced by the lower levels and do not directly influence bus fires. Level II includes possession of flammable and explosive goods (4), possession of fire sources (5), delay in reporting suspicious circumstances to the driver (6), design defects (8), and social contradictions (13). Level III includes negligence of routine safety inspection (1) and risky driving behaviors (3). Level IV includes lack of safety awareness and knowledge (2). The main impact of these factors on bus fires can be likened to connection links; in other words, they are connective factors.
- Level V factors influence others but are not influenced by others: lack of safety education and safety knowledge popularization (14) and inadequate laws and regulations (15). These factors are at the bottom of ISM structure, symbolizing that they have a fundamental impact on bus fires—namely, depth factors.

- Most vehicle-level elements are present in the high levels (I and II), indicating that vehicles play a direct role in bus fires; of course, the vehicle is also the locality of a bus fire. Table 1 also shows that vehicle fault and electrical fault are the direct causes of more than 50% accidents, so measures on vehicle levels will directly influence bus fires.
- Arson and destruction (7) are driven by possession of flammable and explosive goods (4), possession of fire sources (5), delay in reporting suspicious circumstances to the driver (6), and social contradictions (13). Arsonists are anti-society, and it is difficult to recognize them. Obviously, arsonists need flammable, explosive goods and fire sources to set fires. When they bring them onto buses, if other passengers recognize them and report them to the driver, the fire may be prevented. In addition, when an arsonist sets a fire, instead of screaming or escaping in a disorderly manner, passengers could take measures such as using a fire extinguisher; in this way, the consequences of the fires may be mitigated while allowing for an increase in evacuation time.
- Most passenger-related elements are connective factors, and all are driven by driver-related factors; in other words, drivers have influence on passengers. This indicates that passengers should not only be asked to control their own behaviors but also need drivers to keep an eye on them. As noted in some accident records, the reason for a fire was that a driver failed to forbid passengers from carrying forbidden goods, smoking, and so on.
- All driver-related elements are present in the middle levels (III and IV), and they are influenced by depth factors. More specifically, negligence of routine safety inspection (1) and risky driving behaviors (3) are driven by a lack of safety awareness and knowledge (2), which is driven by a lack of safety education and safety knowledge popularization (14) and inadequate laws and regulations (15). As described above, in developing countries such as China, bus drivers are usually middle-age persons who mostly are not very well educated. In addition, owing to economic situations, only a few training programs on bus safety are provided by operator companies and society. In addition, specific laws and regulations are lacking, as little attention is paid to bus fires. This could possibly be because cases of arson have become frequent only recently; previously, bus fires were mainly caused by self-ignition with only a few casualties. In summary, drivers, particularly those who are not very well educated, lack safety knowledge and safety awareness, which is the direct reason for drivers neglecting routine safety inspection and engaging in risky driving.
- In summary, we can determine the delivery mechanism of the influence of risk factors: depth factors influence driver-related factors, then are passed on to passenger-related factors, and finally to the outcome, bus fires. Vehicle-related factors and other environment factors are independent factors and are not influenced by depth factors.

Summary and Conclusions

This study identified and prioritized 17 critical risk factors associated with bus fires using previous accident records and the Delphi approach. These risk factors involve subjective assessment, so they are difficult to model. Hence, it was necessary to identify the dominant risk factors by studying their influence-dependence. ISM was used as a tool for preparing the hierarchical structure of these risk factors.

Based on the results of ISM analysis, findings and recommendations include the following:

- **Inadequate laws and regulations is one of the most important risk factors associated with bus fires, and establishing appropriate laws and regulations would be advantageous for enhancing bus fire safety.** Specific measures include the following: 1) The government should undertake efforts to establish specialized laws related to bus fires. Taking other risk factors into consideration, laws should be established to punish arsonists and delinquent drivers, trace accountability to bus operator companies, and penalize passengers who do not prevent or report suspicious circumstances to drivers or who possess explosive goods or fire sources. 2) Bus administrative departments and operator companies should enact more stringent regulations based on laws and local conditions, and actions should be taken to ensure that the regulations are being effectively implemented.
- **Lack of safety education and safety knowledge popularization causes significant risk**, and measures for addressing it include 1) the government investing in safety education, 2) social organizations and commonweal organizations conducting lectures and training for bus drivers and passengers, and 3) conducting proper fire drills.
- **Drivers play an important role in bus fires because all driver-related elements fall into the relative low levels in the ISM**. Measures that can be taken to counter driver-associated risk factors include the following: 1) Establish rules of pre-intervention in hiring bus drivers, aimed at selecting safer drivers who have less risky driving behaviors and who have a clearer understanding of bus safety. 2) Increase driver pay and decrease work intensity. In China, hiring bus drivers have become increasingly difficult; few young people are willing to be bus drivers mainly because the salary is poor, resulting in an increase in the average age of drivers who are not very well educated. Moreover, drivers have more work stress, which can lead to more accidents. Therefore, economic factors may have favorable impact on bus fire safety. 3) Establish and improve training systems and ascertain scientific training and evaluation methods. In this way, regulations can be carried out effectively, and driving behaviors could improve.

With regard to risk factors related to the vehicle (bus), some measures could be taken: 1) Routine maintenance and daily checking should be conducted, and aging buses should be put out of service. 2) More human-friendly and safer designs should be employed, such as emergency buttons both inside and outside the bus for shutting down all systems, a bus fire early warning system, an armored window glass bursting remote control system, an automatic alarm, a door opening and spraying device for a bus (Yu 2014), automatic fire suppression systems permanently installed in the engine compartments (Brandt and Modin et al. 2013), impulse fine dry powder fire extinguishing technology (Yang and M et al. 2006), highly-integrated data bus automatic fire extinguishing system (Frasure and Norris et al. 2013), and other new technologies and devices.

The results of current research indicate that more studies should to be conducted to improve bus safety, and the following research directions are proposed: the development of 1) technology for pre-identifying dangerous passengers; 2) a simple security device for buses or stations; and 3) more effective fire recognition technology and extinguishing devices.

Acknowledgments

This work was financially supported by the Grant from the National High Technology Research and Development Program of China (863 Program, No. 2014AA110304).

References

Ahrens, M. 2006. "Vehicle Fires Involving Buses and School Buses." NFPA Fire Analysis and Research Division.

Bi, K., Qiu, R., Jiang, Y, and Zheng, J.C. 2010. "Reconstruction of a Bus Fire Based on Numerical Simulation." *Journal of University of Science and Technology of China*, 40(4): 387-394.

Brandt, J., Modin, H., Rosen, F., Försth, M., and Ochoterena, R. 2013. "Test Method for Fire Suppression Systems in Bus and Coach Engine Compartments." SAE Technical Paper.

Chow, W. K. 1999. "Preliminary Notes on Fire Protection in Buses." *Journal of Applied Fire Science*, 9(1): 79-89.

Chow, W. K. 2001. "Flashover for Bus Fires from Empirical Equations." *Journal of Fire Sciences*, 19(1): 81-93.

Chow, W. K. 2003. "Observation on Two Recent Bus Fires and Preliminary Recommendations to Provide Fire Safety." *International Journal on Engineering Performance-Based Fire Codes*, 5(1): 1-5.

Chow, W. K. 2006. "Smoke Control Design for Double-Deck Bus Fires with a Zone Model." Begel House, Inc.

Chun-ming, X. I. 2006. "Research of Prevention against Fire for Urban Transit." *Technology & Economy in Areas of Communications*, 3: 055.

Försth, M., Modin, H., and Sundström, B. 2013. "A Comparative Study of Test Methods for Assessment of Fire Safety Performance of Bus Interior Materials." *Fire and Materials*, 37(5): 350-357.

Frasure, D., Norris, R. J., Wetzork, J., Embry, B., Wyatt, J. D., and Cooke, J. 2013. Highly Integrated Data Bus Automatic Fire Extinguishing System. Google Patents.

Hammarström, R., Axelsson, J., Försth, M., Johansson, P., and Sundström, B. 2008. "Bus Fire Safety." SP Report 41.

Johnsson, E., and J. C. Yang. 2015. "Experimental Study on Hardening a Motorcoach against Tire Fire Penetration." *Fire and Materials*, 40(3), 416-426.

Kaplan, S., and C. G. Prato. 2012. "Risk Factors Associated with Bus Accident Severity in the United States: A Generalized Ordered Logit Model." *Journal of Safety Research*, 43(3): 171-180.

Knipling, R. R., Hickman, J. S., and Bergoffen, G. 2003. "Effective Commercial Truck and Bus Safety Management Techniques." Transportation Research Board.

Lönnermark, A. 2005. "On the Characteristics of Fires in Tunnels." Lund University.

Mallia, L., Lazuras, L., Violani, C., and Lucidi, F. 2015. "Crash Risk and Aberrant Driving Behaviors among Bus Drivers: The Role of Personality and Attitudes towards Traffic Safety." *Accident Analysis & Prevention*, 79: 145-151.

Meltzer, N. R., G. Ayres et al. 2010. "Motorcoach Fire Safety Analysis: The Causes, Frequency, and Severity of Motorcoach Fires in States." In FIVE (Fires in Vehicles), 2012.

Ming, Z., Tian, Y., and Zhang, F. 2009. "Design of Arc Fault Detection System-based on Can Bus." IEEE.

Nirupama, N., and H. Hafezi. 2014. "A Short Communication on School Bus Accidents: A Review and Analysis." *Natural Hazards*, 74(3): 2305-2310.

Parsons, G. G. 1990. "Motor Vehicle Fires in Traffic Crashes and the Effects of the Fuel System Integrity Standard." US Department of Transportation, National Highway Traffic Safety Administration.

Singh, M. D., and R. Kant. 2008. "Knowledge Management Barriers: An Interpretive Structural Modeling Approach." *International Journal of Management Science and Engineering Management*, 3(2): 141-150.

Tan, J. L., Jin, L. Z., Wang, T., and Hu, B. 2010. "Study on Typical Bus Fire Simulation and Control Technology." IEEE.

Tseng, C. 2012. "Social Demographics, Driving Experience and Yearly Driving Distance in Relation to a Tour Bus Driver's At-Fault Accident Risk." *Tourism Management*, 33(4): 910-915.

Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., and Crundall, D. 2003. "Visual Attention while Driving: Sequences of Eye Fixations Made by Experienced and Novice Drivers." *Ergonomics*, 46(6): 629-646.

Yang, Q., Mi, Q. L., and Deng, Q. 2006. "The Application of Impulse Fine Dry Powder Fire Extinguishing Technology to the Building Fire Protection Design." *Fire Science and Technology*, 4: 020.

Yu, G. 2014. Automatic Alarming, Door Opening and Spraying Device of Bus. Google Patents.

About the Authors

Shumin Feng (*fengshuminhit@sina.com*) is a Professor at the Harbin Institute of Technology, Faculty of School of Transportation Science and Engineering, Department of Transportation Engineering, where he studies and teaches about public transport.

Zhenning Li (*fredtoby@yeah.net*) is a master's candidate at the Harbin Institute of Technology, School of Transportation Science and Engineering, Department of Transportation Engineering.

Xianglong Sun (*1848382861@qq.com*) is an Associate Professor at Northeast Forestry University, Faculty of Civil Engineering. His areas of interest include transportation technology and public transport.

Public Transport Accessibility Levels for Ahmedabad, India

Jay Shah
Transport Planning Consultant, India

Bhargav Adhvaryu
CEPT University, India

Abstract

Public transport plays an important role in a city's economy and its social equity. It is also instrumental in reducing automobile dependence and traffic congestion. Several factors must come together to achieve well-functioning public transport systems. One major factor is the level of accessibility offered by the public transport system. To better understand and consequentially enhance accessibility, we must be able to measure it and map it, which is the key aim of this paper.

The methodology in this study, which was originally developed by the London Borough of Hammersmith and Fulham and later adopted by Transport for London (TfL) has been adapted to the case study city of Ahmedabad, India. A GIS mapping tool was used to generate a visual representation of public transport accessibility levels (PTAL) taking into account average walk speed and time, distances to public transport stops, and peak-hour route frequencies of different public transport modes. The paper concludes with initiation of a discussion on the potential uses of PTAL mapping to enhance planning practice, such as formulating development/master plans with land use–transport integration, prioritizing public transport and supporting investments, formulating parking policies, and developing transit-oriented zoning regulations.

Keywords: *Public transport; accessibility; Ahmedabad; PTAL*

Introduction

In 2011, urbanization across the world was 52%; for developing countries, it was 47%. Urbanization is growing at a rapid pace (United Nations 2012) and is expected to reach 56% by 2030. In India in 2011, it was 32% (Census of India 2011) and has occurred at an alarming rate (just 17% in 1951); it is expected to be around 35% by 2021 (Singh 2012).

The Indian economy grew at 6% per annum during the 1990s and at about 8% during the 2000s (Bhagat 2011). Cities and towns play a vital role in promoting economic growth and prosperity and generate more than two-thirds of the country's income and account for 90% of government revenues (Singh 2012). As per India's Eleventh Five-Year Plan, the urban sector contributes about 62% of GDP (Bhagat 2011). There is also a growing realization that an ambitious goal of double-digit GDP growth rate fundamentally depends upon the vibrancy of urban areas in India (Bhagat 2011).

Over the last two decades, bigger cities in India are experiencing higher growth. This has put tremendous pressure on infrastructure systems and has raised questions on the ability of Indian cities to absorb the rapid growth. Urban transition is considered a major challenge, requiring a massive expansion in urban infrastructure and services (Bhagat 2011). Public transport systems already are experiencing the pressure, which is likely to increase. Efficient, comfortable, safe, fast, and affordable urban transport systems are necessary to enhance the advantage offered by cities in economic growth. In addition, the benefits of effective public transport systems also permeate to improve the quality of life and make cities more livable and sustainable (Planning Commission of India 2011).

Currently, public transport systems in India are ineffective at many levels. The rapid growth of India's urban population has put enormous strains on all transport systems (Pucher et al. 2004); they are congested and unreliable, lack spatial network coverage, and have not been able to cope with the rising demand. The availability of transport infrastructure is not only inadequate but also used sub-optimally in Indian cities. The area occupied by roads and streets in Class I cities (population more than 100,000) in India is only 16% of the total developed area, whereas the corresponding figure for the U.S. is 28% (Singh 2012). Most bus and train services are overcrowded, undependable, slow, inconvenient, uncoordinated, and dangerous. Moreover, public ownership and operation of most public transport services has greatly reduced productivity and inflated costs. India's cities desperately need improved and expanded public transport service (Pucher et al. 2004).

Accessibility to the public transport system is the key to improving the level of service in line with rising demand. To improve accessibility, it is important to be able to measure it as accurately as possible. Better understanding of accessibility levels of the public transport systems will not only be necessary to improve the level of service but also to plan and budget for resources (capital costs, operations & maintenance costs, etc.).

Literature Review

Various disciplines define accessibility in different ways. One meaning of accessibility is the ease by which physically-challenged people can access the various elements of the built environment (including transport infrastructure); this study is not concerned with this type of accessibility. The other definition comes from geography and transport disciplines. Geographers define accessibility as the relative ease of reaching a particular location or area in the city. Hansen (1959) defines accessibility as the potential of opportunities for interaction with emphasis on the intensity of the possibility of interaction rather than just ease of interaction (Hansen 1959). Murray et al. (1998) distinguish between the terms "access" and "accessibility" and suggest that "access" is the opportunity for use based on proximity to the service and its cost, whereas "accessibility" is the suitability of the network to get individuals from their system entry point to their system exit location in a reasonable amount of time (Murray et al. 1998).

This study focuses on accessibility to public transport, which, in turn, provides accessibility to various destinations in the city. When considering definitions particular to public transport accessibility, the idea is emphasized in Hillman and Pool (1997), as cited in Joyce and Dunn (2010), who make a distinction between "local" and "network" public transport accessibility. Local accessibility is the accessibility of a particular location to a public transport system; network accessibility is the accessibility of locations in a city by the public transport system. The public transport accessibility levels (PTAL) concept essentially addresses local accessibility, but indirectly also incorporates network accessibility by using route and frequency data. A study by Litman (2008), as cited in Joyce and Dunn (2010), attempts to incorporate both aspects by defining public transport accessibly as the quality and ease of transit service at a particular location.

The key objectives of this study were to measure PTAL (excluding paratransit modes), map it, and initiate a discussion of its importance in application to enhancing planning practice. Several studies have made considerable progress on developing service indices to measure transit accessibility.

Different measures have been designed to reflect differing points of view. Some measures of public transport accessibility focus on local accessibility and consider both spatial and temporal coverage. The Time-of-Day tool developed by Polzin et al. (2002), as cited in Mamun and Lownes (2010), is a measure that considers both spatial and temporal coverage at trip ends. In addition to the inclusion of supply-side temporal coverage, this tool overtly recognizes and considers the demand side of temporal coverage by incorporating the travel demand time-of-day distribution on an hourly basis. This integration makes the tool distinctive to public transport planners. The *Transit Capacity and Quality of Service Manual* (TRB 2003), as cited in Mamun and Lownes (2010), provides a systematic approach to assessing transit quality of service from both the spatial and temporal dimensions. The transit level-of-service (TLOS) indicator developed by Ryus et al. (2000), as cited in Mamun and Lownes (2010), provides an accessibility measure that uniquely considers the existence and eminence of pedestrian routes connected to stops. It also combines population and job density with different spatial and temporal features to measure transit accessibility. This tool emphasizes various aspects (walking distance and access to stops, wait time at stops, availability of service at user's required time) in the consideration of accessible public transport service by a person.

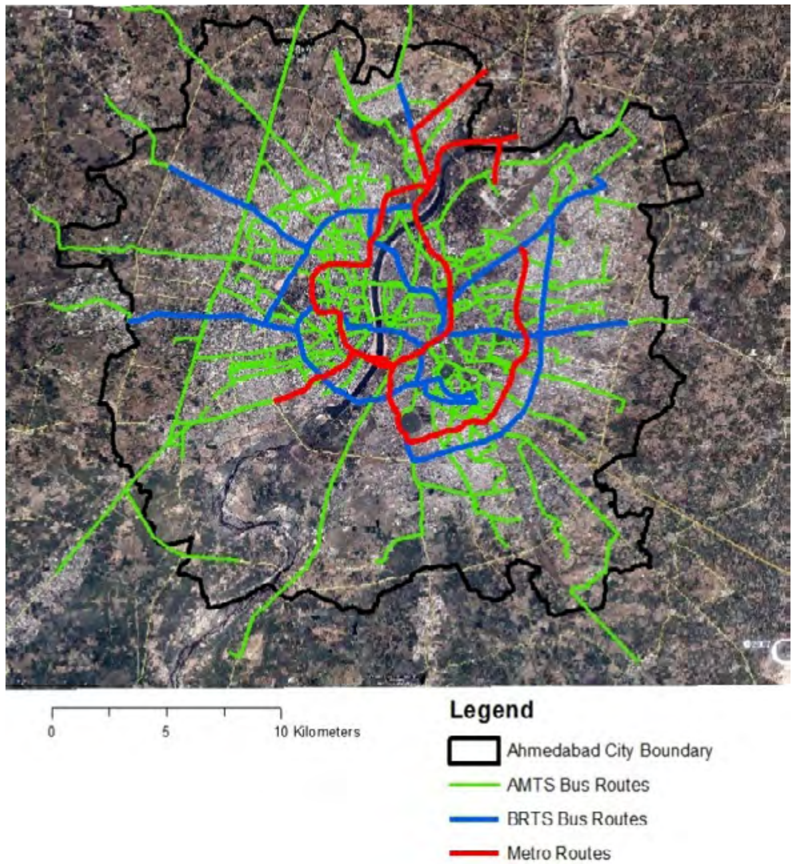
The Land Use and Public Transport Accessibility Index (LUPTAI) seeks to measure how easy it is to access common destinations (e.g., health, education, retail, banking, employment) by walking and/or public transport. This is in contrast to the traditional method of measuring accessibility by road distance and is the first of its kind to consider public transport as a means of access rather than a facility to be accessed (Pitot et al. 2005). A new travel time-based method to visualize and analyze transit service coverage—a computer application called the Time-Based Transit Service Area Tool (TTSAT)—was developed as a new approach to mapping transit accessibility by incorporating total trip travel time into the transit service area maps it generates. To make these travel-time estimates realistic, TTSAT integrates all segments of a complete, door-to-door transit trip into the trip time calculations. TTSAT's mapping and analysis capabilities offer numerous potential applications for planners, developers, and members of the public working to create transit-accessible communities. TTSAT users can customize the time-based transit service area (TTSA) maps they generate by specifying details of passengers' expected travel behavior, such as walking speed or the maximum time they are willing to spend going to and from public transport stops (Cheng and Agrawal 2010).

This study uses the PTAL calculation method developed by the London Borough of Hammersmith and Fulham in 1992, which was later adopted by Transport for London (TfL), as the standard method for calculation of public transport accessibility in London (Transport for London 2010). In addition to the UK, public transport accessibility ratings are used in a number of countries such as the U.S., the Netherlands, Australia, and New Zealand (Joyce and Dunn 2010). The methodology in this paper was appropriately adapted from London (Transport for London 2010) to fit Ahmedabad data.

Ahmedabad and Its Public Transport

The city of Ahmedabad, India, was founded in AD 1411 and is the largest city in Gujarat and the seventh largest in India, with a population of 6.35 million in 2011 (Census of India 2011). Ahmedabad has two major public transport systems: the Ahmedabad Municipal Transport Service (AMTS), a bus service running in mixed traffic, and the BRTS, operated by Ahmedabad Janmarg Ltd (AJL), which runs on dedicated corridors (except junctions and a few other links). Both AMTS and BRTS are wholly-owned subsidiaries of the Ahmedabad Municipal Corporation (AMC). A metro rail system called the Metrolink Express Gandhinagar Ahmedabad (MEGA) has been proposed and is in the advanced stages of planning. Figure 1 shows the public transport network in Ahmedabad.

FIGURE 1.
AMTS, BRTS and Metro routes



Note: Routes shown are those used in the calculation of PTAL per the existing routes of AMTS and BRTS in 2013 and the proposed routes of MEGA in the same year. However, some alignment changes and new routes have been proposed thereafter.

Ahmedabad has a high percentage of population living in slums. According to the Ahmedabad Urban Development Plan 2011 (AUDA 2002), in 1998, 32% of the city's population lived in slums, with 60% of these households falling below the poverty line. According to the Global Report on Understanding Slums (2003), the percentage of Ahmedabad housing categorized as slums increased from 17% in 1961 to 23% in 1971 to 26% in 2011. One study suggested that 40% of Ahmedabad's population lives in slums (informal settlements) and chawls (tenements) (Somani 2011). The modal share in Ahmedabad is 17% public transport (all buses) and 54% non-motorized transport (NMT) (walking and cycling) (LGBC 2001). This suggests that a very high percentage of the urban poor population cannot afford public transport for commuting. Mapping public transport accessibility levels can be a useful tool in achieving the goal of improving the level and quality of service of public transport system (including the upcoming metro rail system).

Overview of London PTAL Methodology

PTAL is a detailed and accurate measure of the accessibility of a specific point to the public transport network, taking into account walk access time and service availability. It measures the accessibility level for a specific point (origin) considering the accessibility index (AI) for all available modes of transport from that point. The inclusion of total access time to measure the level of accessibility is an important feature of this method (Mamun and Lownes 2010). The methodology is briefly described below, broken down into key steps for calculation. For a more detailed explanation, please refer Transport for London (2010).

Step 1: Define points of interest (POI) and service access points (SAP) – POI is defined as a point for which the accessibility level is to be measured with reference to an SAP, which is a public transport stop (such as bus stop, metro station, etc.).

Step 2: Calculate walk access time from POI to SAP – The actual road network distance from POI to SAP is measured and, assuming a walk speed of 4.8 km/h, walk time (WT) is calculated. The maximum walk times for bus and metro rail are 8 and 12 minutes, respectively. Any SAPs beyond these distances are not taken into account to calculate PTAL for that particular POI.

Step 3: Identify valid routes at each SAP and calculate average waiting time (AWT) – The valid routes are bus and metro routes for the peak hour (8:15–9:15 AM),[1] and the frequency of services on all these routes during this hour is used in the calculation of AWT.

AWT is the defined as the period from when a passenger arrives at an SAP to the arrival of the desired service. In the calculation, the hourly frequency (f) is halved because the scheduled waiting time (SWT) is estimated as half the headway. For example, a 10-minute service frequency (6 buses per hour) would give an SWT of 5 minutes. In addition, to make the calculations more realistic, a "reliability factor" (K) is added to the SWT depending on the transport mode, which is assumed to be 2 minutes for buses and 0.75 minutes for rail services (see Equation 1):

$$AWT = 0.5\frac{60}{f} + K \tag{1}$$

Step 4: Calculate minimum total access time (TAT) for each valid route at each SAP – This is done as shown in Equation 2 by adding times obtained in steps 2 and 3.

$$TAT = WT + AWT \tag{2}$$

[1] This assumption leads to a PTAL map for the peak period only, which is also followed for this study.

Step 5: Convert TAT into equivalent doorstep frequency (EDF) – This is obtained as 30 divided by TAT (see Equation 3)[2]. The principle is to treat access time as a notional average waiting time as though the route was available at the doorstep of the selected POI.

$$EDF = 30/TAT \tag{3}$$

Step 6: Obtain the accessibility index (AI) for each POI – In this step, the most dominant route, i.e., the route with the highest frequency, is assigned the weighting factor of 1.0; for all other routes, a weighting factor of 0.5 is assigned. Thus, for a transport mode (m), the AI_m is calculated as shown in Equation 4:

$$AI_m = EDF_{\max} + 0.5 \sum_{\text{all other routes}} EDF \tag{4}$$

Then, the accessibility index for a POI (AI_{POI}) is calculated, as shown in Equation 5:

$$AI_{POI} = \sum_m AI_m \tag{5}$$

Step 7: Map PTAL – The AIs obtained for each POI are allocated to eight bands of PTAL, as shown in Figure 2 (where Range of Index means AI of the POI). A POI with a value of 0 indicates no access to the public transport network within the parameters given and is not colored on the map.

FIGURE 2.
London PTALs

PTAL	Range of Index	Map Colour	Description
1a (Low)	0.01 – 2.50		Very poor
1b	2.51 – 5.00		Very poor
2	5.01 – 10.00		Poor
3	10.01 – 15.00		Moderate
4	15.01 – 20.00		Good
5	20.01 – 25.00		Very Good
6a	25.01 – 40.00		Excellent
6b (High)	40.01 +		Excellent

Source: Transport for London (2010), Table 3, p. 6

The calculation steps in the methodology are the same as the London PTAL methodology. However, for mapping of PTALs in Ahmedabad, the parameters and assumptions considered in the London PTAL methodology were altered to suit the conditions of Ahmedabad.

[2] The reason for dividing 30 (minutes) by TAT is that it re-applies the half-the-headway rule. This is applied twice because the values have different meanings. In the Step 3, frequency is converted into AWT, and in the Step 5, TAT is converted back into a frequency (EDF). The first step calculates TAT, i.e., the time it takes to leave home/point of origin and get on a service. This is made up of three elements: walk time + AWT (assumed to be half the headway) + reliability factor. TAT is now converted into a number that is comparable to service frequency but that takes into account the additional walk time taken to reach the stop along with reliability. Thus, the half the headway rule is applied again to TAT in Step 5 to give the doorstep frequency.

Data Collection

To adapt the London PTAL methodology to Ahmedabad, data listed in Table 1 were needed. However, in some cases, the data were not available and, therefore, were collected by field observation and map measurements in GIS software.

TABLE 1.
Data Types and Sources

Sr. No.	Data Type	Source
1	Ahmedabad city base map (satellite image)	Google Earth
2	AMC boundary limit (GIS shape file)	Prepared by authors from information available on AMC website
3	AMTS bus stop locations (GIS shape file)	CEPT University study
4	AMTS bus routes (GIS shape file)	Prepared by authors from route information on AMTS website
5	AMTS peak hour bus frequency	Available from this report (AUDA, Government of Gujarat 2011)
6	BRTS bus stops locations (GIS shape file)	Prepared by authors from Google Earth
7	BRTS bus routes (GIS shape file)	Prepared by authors from the route information on BRTS website
8	BRTS peak hour bus frequency	Available from this report (AUDA, Government of Gujarat 2011)
9	MEGA metro station locations (GIS shape file)	MEGA office (available in .kml file format)
10	MEGA metro routes (GIS shape file)	Prepared by authors from route information on MEGA website
11	MEGA peak hour metro frequency	MEGA office

AMTS – Ahmedabad Municipal Transport Service, BRTS – Bus Rapid Transit System, MEGA – Metro-link Express for Gandhinagar and Ahmedabad.

Data collection in developing countries is always a challenge. This study was met with several obstacles, such as refusal to part with data, requiring tremendous persuasion and personal references. Creating the GIS base map and relevant layers (as shape files) also consumed significant initial research time. The authors wish to appeal urban local bodies involved in planning to create public data bases (which could also be a nominal paid service) that are accessible to academicians and practitioners. As a sign of good faith, the authors agreed to share the database and maps created in this study on a website.

Methodology for Calculation of Accessibility Index in Ahmedabad

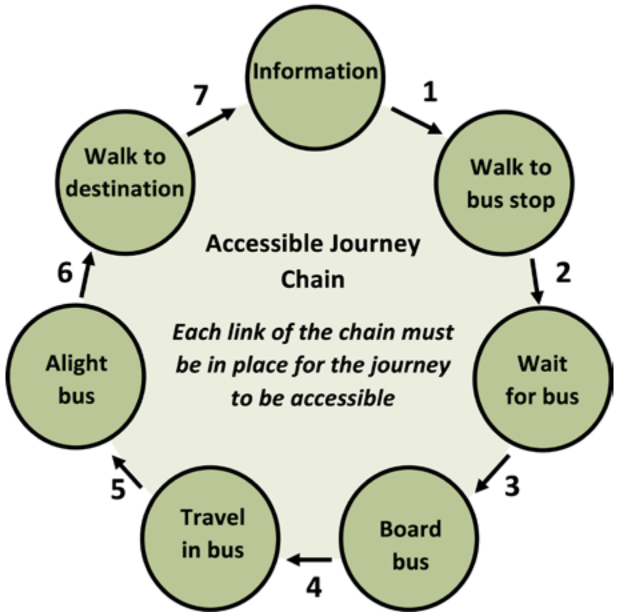
Given that the Ahmedabad urban agglomeration area is about 1866 km^2, it was necessary to limit the geographical extent of the study area. Since the public transport services in the urban agglomeration region outside the AMC boundary (465 km^2) are minimal, the AMC area was selected as the boundary for the study area.

Within the study area are about 1,300 AMTS bus stops and 175 AMTS bus routes. The BRTS has 104 bus stops within the AMC boundary (as of February 2013). In addition, of the 62 proposed metro rail stations, 36 (as of February 2013) fall in the AMC boundary, which have been considered for the PTAL calculations.

In the London methodology, POIs were considered by built development (e.g., plotwise). However, given the time constraints and data resource limitations—i.e., lack of availability of a building footprint for the study area—this study deviates from the London methodology by dividing the study area into 1 km^2 grid cells, resulting in 675 grid cells. The centroid of each cell represented the POI for the measurement of the PTAL score of that particular cell. In addition to the data resource constraints, the grid-cell approach made the analysis much faster. The authors believe that the difference in accuracy of input data does not translate into a huge variation in PTAL mapping; since the application of PTAL was sought at a macro-scale (i.e., development/master plan level), the current output based on the grid cell method is adequate. If needed, the application can be easily developed at the local area planning level should building footprint data be available. Also, the fare structure can be considered in the PTAL calculation to further enhance PTAL mapping. However for Ahmedabad, AMTS and BRTS fares are nearly the same and the metro rail is not yet built. If in the future there are different fare structures among these public transport modes for competing services, then the fare structure could be considered in the PTAL calculations.

The next step was reconsidering London PTAL assumptions regarding walk speed, reliability, and peak-hour factors. The majority of the roads in Ahmedabad do not have footpaths and, if any, are usually encroached by street vendors and parking. People are forced to walk on the road (the black-top surface), which creates unsafe and potentially hazardous situations, such that walking is avoided as much as possible, even for short trips. Therefore, walk speed was decreased to account for this discomfort. To arrive at a quantitative estimate, a small convenience-based sample was obtained in various neighborhoods of Ahmedabad. The walk speeds ranged from 3.4–3.8 km/h, with a mean of 3.6 km/h. However, the model can be easily updated following a more detailed sample survey. It is clear that the first and last mile connectivity to public transport is predominantly by walk/cycling (i.e., non-motorized transport [NMT]). Tyler (2002) indicates that if the accessibility chain (see Figure 3) is breached (in this case, links 1 and 7 of Figure 3), then a journey cannot be performed. Therefore, improved pedestrian facilities to better facilitate first/last mile connectivity are imperative in public transport accessibility. Should more reliable surveys—by different neighborhoods of Ahmedabad, by age groups, etc.—be conducted in the future, the model can be easily updated.

FIGURE 3.
Accessibility Chain



Source: Redrawn from Tyler (2002)

Bus reliability factors are also increased to account for traffic delays caused due to unpredictable traffic conditions and disobedience of traffic rules. Considering the usual office hours of 10:00 AM–6:00 PM, the peak hour was changed to begin half an hour earlier. The parameter values for Ahmedabad are shown in Table 2.

TABLE 2.
Parameter Comparison for Accessibility Index Calculation

<table>
<tr><th>Parameters</th><th>Units</th><th>London Values</th><th colspan="2">Ahmedabad Values</th></tr>
<tr><td>Peak hour</td><td>-</td><td>08:15–09:15 AM</td><td colspan="2">09:30–10:30 AM</td></tr>
<tr><td>Walk speed</td><td>km/h</td><td>4.8</td><td colspan="2">3.6</td></tr>
<tr><td>Walk speed</td><td>m/min</td><td>80</td><td colspan="2">60</td></tr>
<tr><td>Bus</td><td>-</td><td>London Bus</td><td>AMTS Bus</td><td>BRTS Bus</td></tr>
<tr><td>Reliability (K)</td><td>min</td><td>2</td><td>2.5</td><td>1</td></tr>
<tr><td>Max. walk time</td><td>min</td><td>8</td><td colspan="2" rowspan="2">Not applicable (calculated for each POI using actual road network)</td></tr>
<tr><td>Max. walk distance</td><td>m</td><td>640</td></tr>
<tr><td>Rail</td><td>-</td><td>Underground, Tram, DLR, Overhead rail</td><td colspan="2">MEGA metro rail</td></tr>
<tr><td>Reliability (K)</td><td>min</td><td>0.75</td><td colspan="2">0.75</td></tr>
<tr><td>Max. walk time</td><td>min</td><td>12</td><td colspan="2" rowspan="2">Not applicable (calculated for each POI using actual road network)</td></tr>
<tr><td>Max. walk distance</td><td>m</td><td>960</td></tr>
</table>

POI to SAP distances were measured from Google Earth using the distance measurement tool. Then, using the above parameters, calculations of AI for each of the 675 grid cells were carried out, per the steps outlined previously. Table 3 shows a sample format for calculating AI for a POI. The next step was to assign PTAL bands to AIs.

TABLE 3. Sample Format for Accessibility Index Calculation

POI ID	Mode	SAP Name	Route No.	Distance (m)	Frequency (per hr)	Weight	Walk Time (min)	SWT (min)	TAT (min)	EDF	AI
307	AMTS	Vijay Cross Roads	40/3	338	1	0.5	5.63	32.5	38.13	0.78	0.39
			n^{th} route	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		Memnagar Tube well stop	200	427	5	1	7.11	8.5	15.61	1.92	1.92
			n^{th} route	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		n^{th} SAP	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	BRTS	Valinath Chowk	1	824	24	1	13.73	2.25	15.98	1.87	1.87
	MEGA	Vijay Cross Roads	1	300	20	1	5	2.25	7.25	4.13	4.13
	Total (AI for a POI 307)										**56.41**

PTAL Mapping

After calculating the AIs for all the POIs, the next important step is to graphically represent the values in a format that is easily interpreted by policymakers. The AIs for each POI ranged from 0.78 to 205. An important consideration to further this objective was to make classes/bands of AIs that can be represented by a color code. GIS software with thematic mapping capability was used, which provided four alternatives for classifying the values: 1) equal breaks, 2) natural breaks (Jenks), 3) standard deviation, and 4) quantile breaks. For all methods, the higher the PTAL value, the higher the accessibility. Keeping the number of classes same, the frequency distribution of AIs by the four methods is shown in Figure 4.

As can be seen from Figure 4, the equal breaks method and the natural breaks method produced a skewed or lopsided distribution, with the majority of the lower values concentrated over a few classes. Comparatively, the standard deviation method produced a better distribution of values. However, the quantile breaks method distributed values such that all classes had a nearly equal number of values. The PTAL map of equal breaks, as shown in Figure 5, displayed heavily the color code of level 1 (blue), and very few spaces in the map show the higher level accessibility color code (red). This map seems misleading in terms of accessibility to public transport in Ahmedabad.

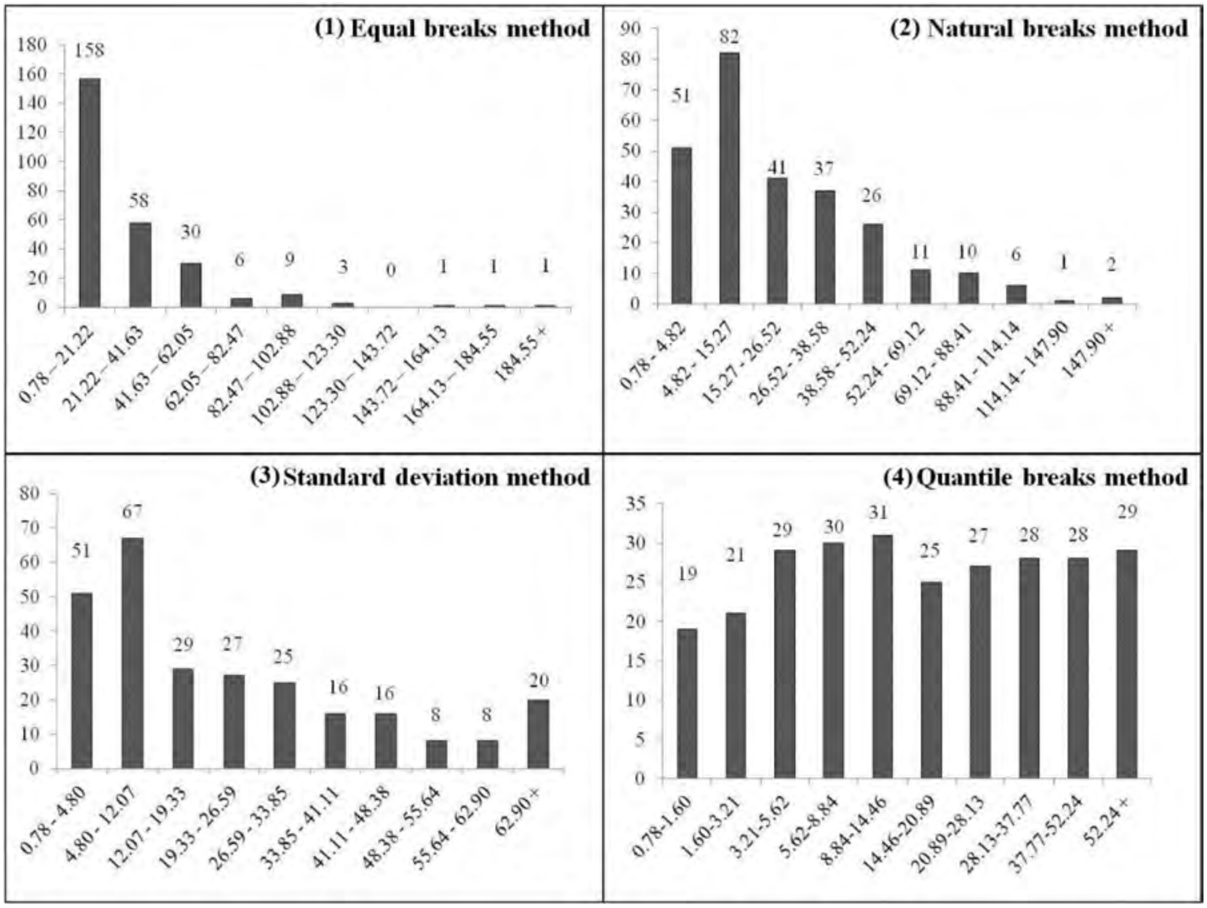
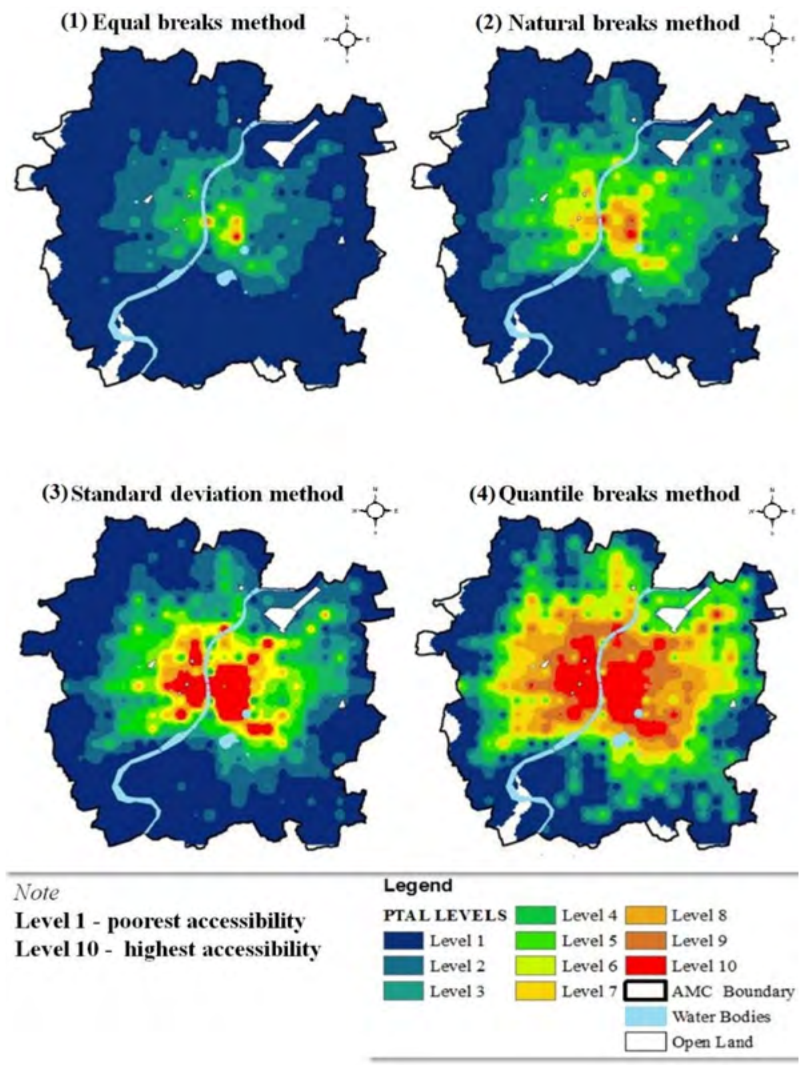


FIGURE 4. Comparison of frequency distribution

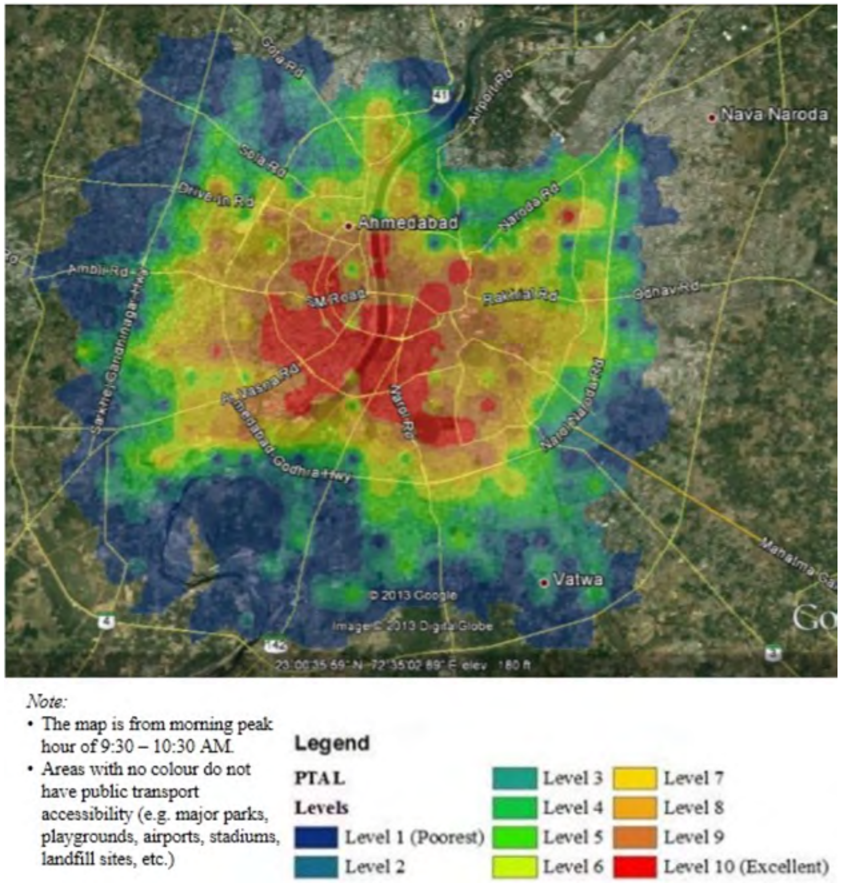
Considering the other two options of the maps shown in Figure 5 (standard deviation method and natural breaks method), these displayed comparatively better visual output, in which the gradation of accessibility was more visible compared to the map of the equal breaks method, with the map using the quantile breaks method producing the best visualization of gradation of accessibility. The quantile breaks method map had approximately equal distribution of PTAL values among all the defined levels (from level 1 to level 10). This allows areas with high, medium, and low accessibility to be easily identified on a map. Therefore, this method produces the best visual representation of PTAL. In other words, the first three methods under-represented the areas that are known to have a higher public transport accessibility index.

FIGURE 5.
Comparison of Ahmedabad PTAL maps



The final PTAL map adopted in this study was generated by the quantile breaks methods. This map was the best match with our intuitive understanding (repeated in Figure 6 at a bigger scale). For example, the city center area (east of the river) has the densest public transport routes, which in the first two maps are depicted as the areas with PTALs ranging predominantly from level 6 to level 8, with slightly more levels 8, 9, and 10 in the third map. Although, technically, this is correct given the method of calculation, it seems to override our intuitive understanding. Given a choice of the four methods in GIS software, we propose quantile breaks as the best candidate that visually depicts PTAL that aligns our intuitive understanding.

FIGURE 6.
Final Ahmedabad PTAL map



Observations from Ahmedabad PTAL Map

From the final Ahmedabad PTAL (Figure 6), it was found that the accessibility to public transport services is excellent in the core city area, as expected, and gradually becomes poorer moving away from the city center. Also, there are few scattered, leap-frogged areas with excellent PTAL surrounded by medium PTAL; these areas represent newer commercial development with a high level of road connectivity (which is also used by public transport). This pattern connects well with the radial pattern growth of the city. Urban sprawl in the city is occurring in radial form. The accessibility levels in the outskirts of Ahmedabad are poor along Sardar Patel Ring Road, which is on the periphery of the city limits of Ahmedabad. These areas of low accessibility to public transport are the areas dominated by higher-income households. In such areas, the dominant mode of transport is private vehicles; there is less dependency on public transport modes and, hence, the accessibility levels to public transport are poor. However, the BRTS system, which is currently in an expansion phase, is extending the connectivity to these areas which will, in turn, improve the accessibility index in such areas. Moreover, the completion of construction of metro rail routes (MEGA) also will improve the accessibility index of these areas once the trains are operational.

Conclusions and Recommendations

Providing public transport service and the supporting infrastructure will not fulfill public transport's full potential. The system must offer high accessibility geographically and to all sections of society. Commuters and other tripmakers will consider public transit as an option for tripmaking when the system is properly accessible to and from their trip origins/ destinations (spatial coverage) and when service is available at preferred travel times (temporal coverage).

Accessibility refers to people's ability to reach goods, services, and activities, which is the ultimate goal of most transport activity. Many factors affect accessibility, including mobility (physical movement), the quality and affordability of transport options, transport system connectivity, mobility substitutes, and land use patterns. Conventional planning tends to overlook and undervalue some of these factors and perspectives. More comprehensive analysis of accessibility in planning expands the scope of potential solutions to transport problems. Therefore, PTAL maps are an easy and smart representative tool for accessibility.

PTAL maps such as those generated in this study can be of a value for urban and transport planning authorities:

1. PTAL maps can be used by development/master planning authorities to integrate land use zoning with public transport accessibility—a very important aspect usually ignored by Indian planners (Balachandran et al. 2005). A more detailed critique of the urban planning process in Ahmedabad can be found in Adhvaryu (2011). By allowing future transport improvements to be incorporated into PTAL calculations, a future PTAL map becomes an important tool in supporting land use and zoning decisions for local authorities. It can also be useful in testing "what if" scenarios using land use and transport integration model (e.g., see Adhvaryu 2010).
2. PTAL maps can be used to improve the existing public transport system by recognizing areas with poor accessibility, thereby enabling decisionmakers to prioritize investments in public transport systems and support NMT facilities.
3. Parking policies can be formulated using PTAL maps. For example, park-and-ride facilities can be provided to supplement areas with low and medium PTAL, and parking may be restricted or charged at a higher rate in areas with high PTAL.
4. PTAL mapping can help cities that are planning to introduce transit-oriented development (TOD), as PTALs already incorporate walkability criteria from POIs, an important D (distance to transit) in the 6Ds of TOD (Cervero and Ewing 2010).
5. Several sections of society can use PTAL maps. Households can use them to inform their residential location choices, especially low-income households that are captive public transport users. Real estate developers (who supply housing and commercial spaces) can use PTAL maps (both existing and future) for locating potential sites, especially low-income housing. Government agencies can use PTAL maps to locate housing for economically weaker sections.

Given the ease of building and updating the PTAL model, as and when new public transport and NMT facilities are built, the methodology overall has significant potential to become a useful tool as a decision support tool for urban and transport planning. The authors are in the process of initiating a dialogue with local planning agencies to discuss application of this study as a planning support decision tool.

References

Adhvaryu, B. 2010. "Enhancing Urban Planning Using Simplified Models: SIMPLAN for Ahmedabad, India." *Progress in Planning*, 73(3): 113-207.

Adhvaryu, B. 2011. "The Ahmedabad Urban Development Plan-Making Process: A Critical Review." *Planning Practice and Research*, 26(2): 229-250.

Ahmedabad Municipal Corporation. 2011. City Development Plan for Ahmedabad. Ahmedabad Municipal Corporation.

Ahmedabad Municipal Transport Services. (n.d.) AMTS Route Details. http://www.amts.co.in/, accessed March 2013.

AUDA and Government of Gujarat. (2011). Greater Ahmedabad Integrated Mobility Plan. Ahmedabad.

Balachandran, B., B. Adhvaryu, and A. Lokre. 2005. "Urban Transport in India—Problems, Responses and Strategies." Environmental Planning Collaborative.

Bhagat, R. B. 2011. "Emerging Pattern of Urbanisation in India." *Economic and Political Weekly*: 10-12.

Government of India. 2011. Census of India. 2011. http://www.censusindia.gov.in/, accessed February 2014.

Cervero, R., and R. Ewing. 2010. "Travel and the Built Environment, A Meta-Analysis." *Journal of American Planning Association*, 3.

Cheng, C.-L., and A. W. Agrawal. 2010. "TTSAT: A New Approach to Mapping Transit Accessibility." *Journal of Public Transportation*, 13(1): 55-69.

ESRI. 1996. "Symbolizing Your Data." In E. S. Institute, *Using ArcView GIS Guide for Software Version*:103-109.

Hansen, W. G. 1959. "How Accessibility Shapes Land Use." *Journal of the American Planning Association*: 73-74.

Joyce, M., and R. Dunn. 2010. "A Methodology for Measuring Public Transport Accessibility to Employment – A Case Study." Auckland, NZ. *Transportation Research Record*: 5-6.

LGBC. 2001. "Feasibility Study on Integrated Public Transport System (IPTS)." Gandhinagar: Gujarat Industrial Development Board (GIDB).

Litman, T. 2008. "Evaluating Accessibility for Transportation Planning." Victoria Transport Policy Institute.

Mamun, M. A., and N. E. Lownes. 2010. "An Aggregated Public Transit Accessibility Measure." 51st Annual Transportation Research Forum, Arlington, VA, Transportation Research Forum.

Murray, A., R. Davis, R. Stimson, and L. Ferreira. 1998. "Public Transportation Access." *Transportation Research Part D: Transport and Environment*, 3(5): 319-328.

Planning Commission of India. 2011. Recommendations of Working Group on Urban Transport for 12th Five Year Plan.

Pucher, J., N. Korattyswaroopam, and N. Ittyerah. 2004. "The Crisis of Public Transport in India." *Journal of Public Transportation*, 7(4): 1-2.

National Institute for Urban Affairs. (n.d.). "Urban Transport Initiatives in India: Best Practices in PPP."

Pitot, M., T. Yigitcanlar, N. Sipe, and R. Evans. 2005. "Land Use and Public Transport Accessibility Index (LUPTAI) Tool – Development and Pilot Application of LUPTAI for the Gold Coast." 29th Australasian Transport Research Forum.

Schlossberg, M., and N. Brown. 2007. "Comparing Transit-Oriented Development Sites by Walkability Indicators." *Transportation Research Record*: 1.

Singh, S. K. 2012. "Urban Transport in India: Issues, Challenges, and the Way Forward." *European Transport/Trasporti Europei*, 52(5): 1-3.

Somani, A. 2011. "Slums and Incidence of Diseases in Ahmedabad." Institute of Rural Management Anand, Gujarat, India.

Transport for London. 2010. "Measuring Public Transport Accessibility Level PTALS Summary." http://data.london.gov.uk/documents/PTAL-methodology.pdf, accessed February 19, 2014.

Tyler, N. 2002. *Accessibility and The Bus System: Concepts to Practice*. London.

United Nations. 2012. *World Urbanization Prospects, The 2011 Revision*. United Nations, Department of Economic and Social Affairs, New York.

About the Authors

Jay Shah (*jayshah19490@gmail.com*) is a transport planning consultant and has been a working professional since 2013 in activities such as public transport planning, traffic engineering, transport modeling, traffic simulation, signal design, etc. He earned an M.Tech in Infrastructure Engineering and Management from CEPT University in 2013 and a Civil Engineering degree from Gujarat University in 2011.

Bhargav Adhvaryu (*bhargav@cantab.net*) is a professor on the Faculty of Technology, CEPT University. He teaches topics related to urban and transport planning and quantitative research methods, and his research and practice includes enhancing development/master planning, urban transport infrastructure planning and design, and land use-transport interaction. He was a Fulbright Visiting Professor at UCLA in 2012 and a British Chevening Scholar in 2002–03. He has a Ph.D. from Cambridge University, an M.Sc. Transport from Imperial College and UCL, an M. Tech Planning from CEPT University, and a B.E. Civil from REC, Surat.

Exploring Passenger Assessments of Bus Service Quality Using Bayesian Networks

Jingxian Wu and Min Yang, Ph.D.
Southeast University

Soora Rasouli, Ph.D.
Eindhoven University of Technology

Chengcheng Xu, Ph.D.
Southeast University

Abstract

Studies on public transit have emphasized the role of passenger satisfaction with service quality in travel choice decisions and indicated that satisfaction depends on various service attributes. Few studies have, however, systematically examined the underlying relationships among service attributes to assess their influence on passenger overall satisfaction. Therefore, to contribute to this rapidly-emerging literature, this paper applies Bayesian networks to quantify the influence of each service aspect on passenger overall satisfaction with regular bus service quality. This analysis involved 609 passengers who participated in a 2013 regular bus service survey in Nanjing, China. The derived Bayesian network shows the relationships among service attributes and passenger overall satisfaction graphically. In particular, service aspects such as running on schedule, acceptable waiting time, available seats, clean onboard environment, pleasant environment at stations, convenient design for transfers, and air-conditioning were the key determinants of overall satisfaction with bus service.

Keywords: *Passenger satisfaction; public transit; bus service quality; Bayesian networks*

Introduction

Nowadays, an increasing reliance on private cars for daily trips poses serious problems for cities, such as congestion, air pollution, road accidents, and excessive fuel consumption (Richardson 2004). To control this continuing trend, authorities across the world have implemented restrictive policies on private car usage. On balance, these policies have not been very successful, as private cars still have some advantages over public transit due to their door-to-door service (Cheng and Liu 2012). Even after implementing strategies that promote public transit, the service quality of public transit remains questionable in many cases, which causes many travelers to forgo transit options. The limited success of these strategies can be attributed largely to the fact that current strategy formulations are focused on the interests of the operators, while passengers—the sole judges of transit service—are ignored. Accordingly, the definition of transit service attributes should be refined from the passenger perspective. In turn, this means that operators should have a good understanding of the relationship between manageable attributes of transit services and customer satisfaction (Das and Pandit 2013; Yilmaz and Celik 2008; Fu and Xin 2007). Therefore, an investigation of key influential service factors is of great significance to optimize transit service from a customer perspective, resulting in policies that could be formulated to influence traveler behavior and attract more transit users.

Several studies have been conducted to investigate the relevant service attributes that characterize transit services and analyze their impacts on passenger satisfaction. Reliability and punctuality were found to be important aspects of service quality in the studies of Beirao and Cabral (2007) and Eboli and Mazzula (2010). Dowling et al. (2002) and Litman (2008) found that the time spent walking to a bus stop and waiting time at a bus stop also were major factors influencing trip satisfaction, and Eboli et al. (2008) and Tyrinopoulos et al. (2008) found that service frequency has a major impact on overall transit service quality measures. Other studies highlighted the importance of available information, personnel attitudes, and safety (Eboli and Mazzula 2012a; Fellesson and Friman 2008). Comfort, fare, safety, and information during the journey also are elements that transit passengers care about during their trips (Nathanail 2008; Iseki and Taylor 2008).

Methodologically, a variety of measurement approaches and methods of analysis have been used to quantify the impacts of these service aspects on passenger overall satisfaction. Following a strong tradition in marketing research, some researchers have applied the ServQual method (Hu and Jen 2006), and some have used discrete choice models to investigate the influences of service attributes from the passenger perspective (Nurul-Habib et al. 2009; Hensher 2014). Others have estimated structural equation models to provide a causal representation of the relationships between service aspects and overall satisfaction (De Oña et al. 2013; Eboli and Mazzulla 2007; Eboli and Mazzulla 2012b).

Although these approaches have demonstrated their power, they share the limitation that they require their own assumptions about the distribution of the data and, usually, they assume predefined underlying relationships between the dependent and independent variables. However, these assumptions may not always hold true, and once basic assumptions are violated, erroneous estimations and incorrect inferences could be produced. However, if the aim of a study is to explore the relationship between service quality attributes and passenger satisfaction, the application of a more flexible approach would be preferable. Transit service aspects involve intangible and tangible elements, most of which are not independent but are highly interrelated, and considerable relationships among service aspects and overall satisfaction are inherently uncertain. Once an improvement occurs in one service aspect, it not only will pose an effect on overall satisfaction but also will propagate the influence to its associated aspects. Therefore, models assessing transit service should be capable of incorporating complicated uncertainties and reflect the unknown relationships between service aspects.

De Oña et al. (2012) and Garrido (2014) proposed using data mining techniques such as decision trees and neutral networks to identify the significant factors by capturing the underlying relationships among service attributes. In this study, we applied a Bayesian network (BN), which is applied in transportation fields for its multiple advantages, including the skilled handling of uncertainty and complexity and the capability of modifying the available knowledge into the model and easily updating causal relationships (Janssens et al. 2006). Based on the dependency relationships between travel behaviors and city structure, Takamiya et al. (2010) successfully applied BN to represent the relationships and forecasted travel behaviors in Nagoya, Japan. Scuderi and Clifton (2005) used BN to explore the relationship between land use and travel behavior in the Baltimore, Maryland, metropolitan region. Ma (2015) applied BNs in the analysis of multimodal mode choice behavior and showed a competitive performance compared with classical discrete choice models. Kemperman and Timmermans (2014) measured the relationship between the built environment and active travel behavior of children by BN. Karimnezhad and Moradi (2016) and De Oña et al. (2011) used BN for the diagnosis of road traffic accidents. All these have confirmed that BNs have favorable features in the data analysis, especially in the prediction of relationships among variables.

BNs are such a promising tool that some authors proposed BN applications in transit service analysis. Perucca and Salini (2014) pioneered the use of BN in the analysis of customer surveys of railway systems and found support that in the modeling of the relationships between individual characteristics and satisfaction, BN has a higher predictive capability than the "mainstream" ordered logistic regression. Wu et al. (2014) applied the approach in the assessment of public transit service and presented causal relationships among service aspects. Both proved the advantages of BN in the analysis of transit service, but neither conducted comprehensive modeling validation or evidence sensitivity analysis for influential quantifications.

The primary objective of this study was to use the BN approach to identify which service aspects are the most influential factors on passenger satisfaction, accounting for the correlations among these attributes. The study is based on a survey conducted in Nanjing, China.

Data

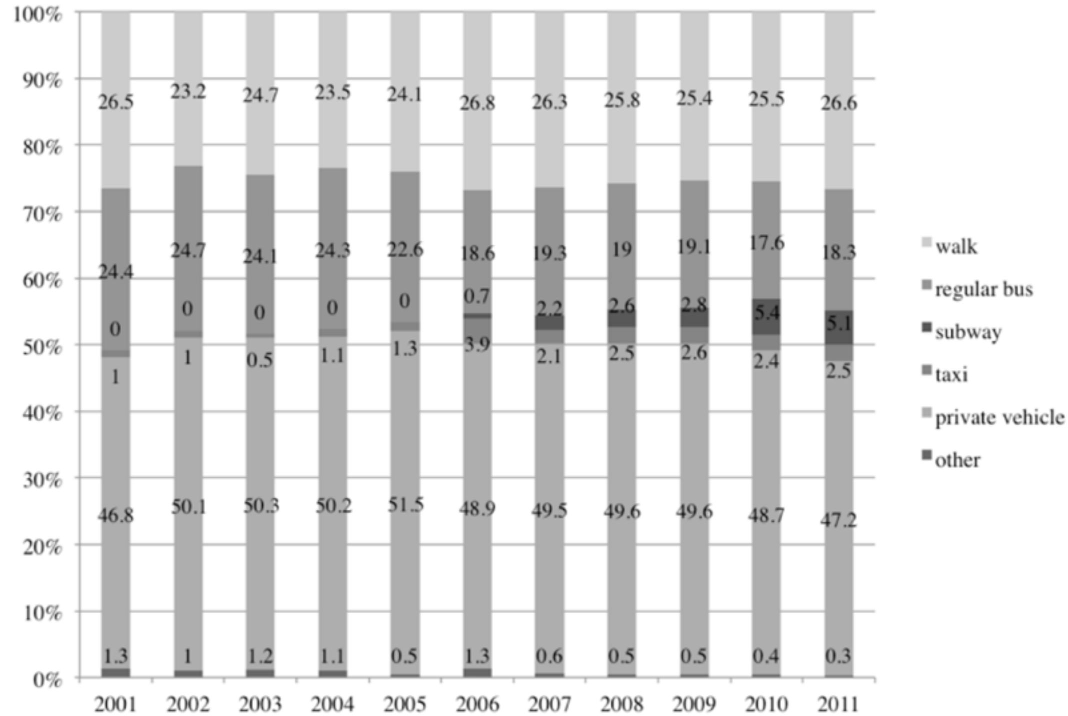
Description of Nanjing Bus System

Nanjing, the capital of Jiangsu province, is a large city located in southeast China. As shown in Figure 1, its urban area includes eight regions: Xuanwu, Gulou, Jianye, Qinhuai, Yuhuatai, Qixia, Jiangning, and Pukou. The Pukou region is separated from the other by the Yangtze River, and the Nanjing Yangtze River Bridge connects it with other parts. The population of Nanjing has been growing at a very fast rate in the last few years, from 3.72 million in 2001 to more than 5.52 million in 2011.

FIGURE 1.
Urban area of Nanjing

The city's rapid economic growth has brought a great increase in private vehicle ownership, with the number of private cars increasing by 22.8%, from 695,000 in 2010 to 853,000 in 2011, as shown in Figure 2. The bus system in the urban area involves 6,573 buses in operation that serve 510 routes with a served length of 7,959 km. In 2011, the average number of bus trips per day was 2.76 million. The ratio of regular bus in the overall modal splits in the city is 18.3%, a share that has been decreasing over the last decade (Yang and Qian 2012).

FIGURE 2.
Travel modal split in Nanjing (2001–2011)



Survey Method

A questionnaire survey of regular bus passengers in Nanjing was conducted to collect data for this study. Based on related studies, the questionnaire was designed and adjusted according to feedback from a pilot survey and was divided into three main sections. The first section included questions about personal and household characteristics of passengers (gender, age, personal income, residential location) and general information on the trip (weekly bus riding frequency, trip purpose). The second section contained 19 questions concerning passenger assessments of various aspects of bus service. Respondents were asked to rate five main transit service attributes (safety, comfort, convenience, reliability, and fare) on a four-point Likert scale ranging from 1—strongly disagree to 4—strongly agree. The items were formulated such that they could be directly interpreted in terms of service quality. The third section measured passenger overall satisfaction with the bus trip in dichotomous categories of 0—unsatisfied or 1—satisfied. Compared to prior research, both satisfaction with service attributes and overall satisfaction were measured in rather crude categories to focus on strong, dominant patterns and, therefore, subtle differences in satisfaction were ignored. An advantage of a more robust approach is capturing measurement of mood and personality that may otherwise affect satisfaction ratings (Gao et al. 2015).

The survey was conducted at various stops and stations in Nanjing on weekends from March to May 2013. A stratified sampling was employed in all regions except Pukou (because of the frequently-jammed traffic on the Nanjing Yangtze River Bridge that was the only connection facility between Pukou and other regions in 2013). To guarantee the response rate, surveyors started with the question about passenger willingness to take part in the survey and then guided respondents when completing the questionnaires. A total of 745 questionnaires were randomly distributed, and after deleting those with incomplete responses, 609 usable questionnaires were obtained for this study.

Data Description

Of the sample, 51.2% of respondents were male and 48.8% were female. Nearly half of the respondents (45.1%) were ages 20–29, and 36.7% were ages 30–39. Most respondents (66.4%) were highly-educated and held a university degree, and more than 80% of travelers had a regular job. A total of 39% had a monthly income of 2000–4000 yuan, followed by 28.9% with an income of 4000–6000 yuan. Low to medium income earners were the dominant users of public transit, which is in line with the current situation in China (since public transit fares are relatively low, those who cannot afford car payments are the majority users). This group makes up a relatively high proportion of transit users, so many policies are developed for their benefit.

Bus users from households in the central area accounted for 51.4% of the sample. The accessibility of bus service in the central area is quite different from that of the surrounding areas; people living in the central area usually enjoy a more comprehensive and mature bus service.

All persons in the sample were asked to report how many days they rode the bus in a week and their primary trip purpose. Table 1 shows that 40.5% of the respondents took the bus 1–2 days per week, 31.2% took the bus 3–5 days per week, and 17.6% took the bus 6–7 days per week. Nearly half took the bus for commuting (travel to work or school), and the remainder took the bus for leisure or shopping.

TABLE 1.
Survey Descriptive Statistics (n=609)

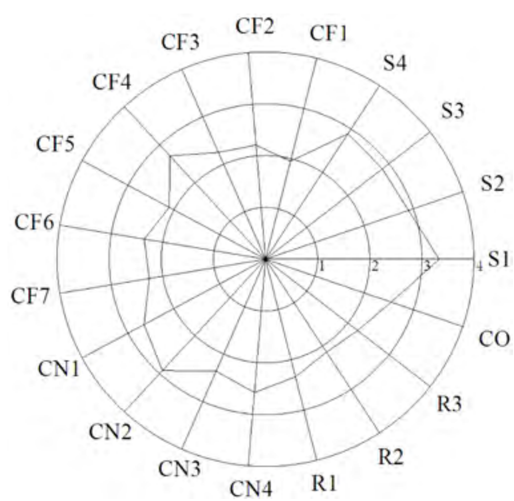
Characteristics	Statistics
Gender	Male (51.2%), female (48.8%)
Age	Ages 15–19 (1.2%), 20–29 (45.1%), 30–49 (46.3%), 50 and older (7.3%)
Education	Senior high school (21.1%), university (66.4%), master's degree or higher (12.5%)
Income	Less than 2000 yuan (10.5%), 2000–4000yuan (39%), 4000–6000yuan (28.9%), more than 6000 yuan (21.4%), unknown (0.2%)
Job	With a job (83.5%), no job (16.5%)
Household location	Central area (51.4%), surrounding area (48.4%), unknown (0.2%)
Frequency	Less than 1 day per week (10.6%), 1–2 days per week (40.5%), 3–5 days per week (31.2%), 6–7 days per week (17.6%), unknown (0.1%)
Purpose	Commuting (49.7%), non-commuting trip (50.3%)

To get a rough evaluation of bus service quality, a calculation of the average satisfaction score and a score ranking for each service aspect from low to high were made, as shown in Table 2. The average scores ranged from 1.95–3.33, suggesting that satisfaction with the service attributes was modest. Respondents overall were satisfied with the aspects of safety as well as route and schedule information, which were the highest-ranked attributes. In contrast, most aspects of comfort and reliability were rated poorly. As Table 2 shows, four of the most unsatisfactory service attributes were "not overcrowded," "riding smoothly without severe braking and acceleration," "acceptable waiting time for bus at stops," and "seats are available when riding." The overall service satisfaction was 0.425, implying that only 42.5% of respondents were satisfied with the bus services. Figure 3 shows the global view of specific service grading.

TABLE 2.
Average Score and Rank of Service Attributes

Items	Category	Code	Average	Rank
Equipped with safety facilities	Safety	S1	3.33	19
Safe for boarding on and off bus		S2	2.90	17
Handling emergency situation properly		S3	2.84	15
Good overall safety		S4	2.89	16
Not overcrowded	Comfort	CF1	1.95	1
Seats are available when riding		CF2	2.21	4
Equipped with air-conditioning		CF3	2.25	6
Good broadcasting system on board		CF4	2.71	14
Ride smoothly, no severe acceleration and braking		CF5	2.10	2
Clean environment onboard		CF6	2.36	10
Pleasant environment at stations or stops		CF7	2.26	7
Walking distance to stops is reasonable	Convenience	CN1	2.65	13
Provided with schedule and route information		CN2	2.92	18
Reasonable bus service frequency		CN3	2.36	9
Convenient design for connections and transfers		CN4	2.58	12
Run on schedule	Reliability	R1	2.34	8
Acceptable waiting time for bus at stops		R2	2.14	3
Arrival information provided is reliable		R3	2.24	5
Reasonable fare	Fare	CO	2.55	11
Overall satisfaction with bus service	Overall	AS	0.425	

FIGURE 3.
Global view of service attributes score



(1 strongly disagree, 2 disagree, 3 agree, 4 strongly agree)

Methodology

Developing the Bayesian Networks

In this study, a BN approach was used to explore the relations between bus service aspects and overall satisfaction, which was dichotomized in this study. A BN is a technique for inductive knowledge discovery and has been widely used in the combined field of artificial intelligence and machine learning (Pearl 1991). Normally, a BN is made up of two components: a directed acyclic graph (DAG) and a conditional probability table (CPT). A DAG is the structure component that includes a set of nodes depicting random variables and some directed links representing probabilistic relationships between the nodes. The parameter component (CPT) provides the statistical interpretation of the probabilistic dependencies depicted by the structure. For example, a link from node X to node Y indicates that X is a parent of Y and Y is a child of X. The link indicates that X and Y are statistically correlated. For each child node, a CPT is attached to quantify its dependency relations with its parent nodes.

Table 2 shows an overview of the variables included in the model estimation. It is challenging to incorporate so many variables in a model and capture the complex interactions. Because these service aspects are highly-correlated and the structure of service relationships is not that clear, defining an appropriate structure for them can be difficult. A BN approach can overcome such difficulties, in that it can simultaneously derive the direct and indirect relationships between the set of service aspects. In this study, all these service variables were included in the estimation with the utilization of specific network-learning algorithms. The network learning involved two main tasks: learning the network structure and then estimating the CPTs for the structure (Pearl 1991). For the first task, a network-learning algorithm named TPDA (Three-Phase Dependency Analysis) was used to identify correlations between bus service aspects, based on the three-phase dependency method developed by Cheng, Bell, and Liu (Cheng et al. 2002). The algorithm includes three phases: (1) drafting the network, (2) thickening the network, and (3) thinning the network. (For an extensive explanation of the algorithm, readers may refer to Arentze and Timmermans [2009]). In the first phase, a draft graph is created on the basis of the mutual information of each pair of variables and the mutual information is defined as follows:

$$I\left(X,Y\right)=\sum_{x}\sum_{y}p(x,y)*\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{1}$$

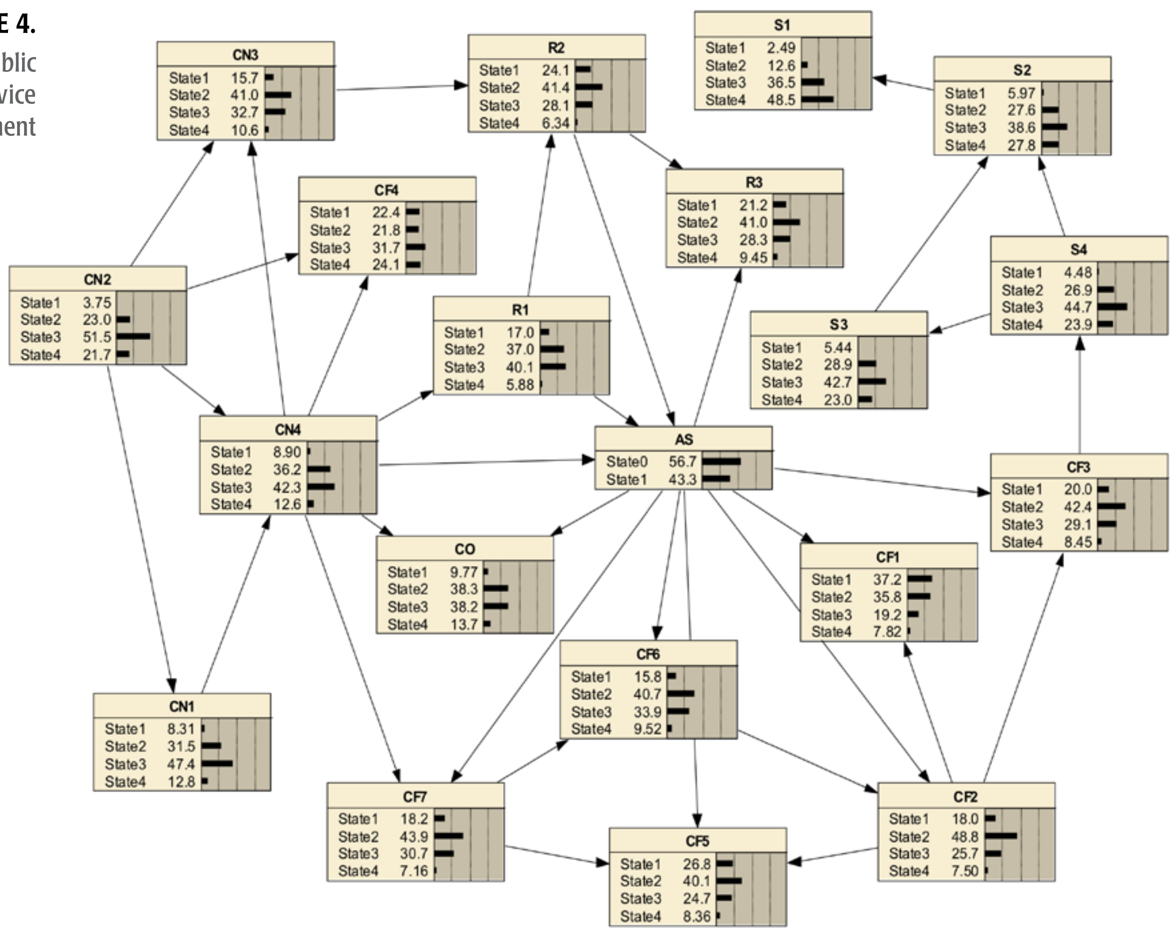
where $p(x, y)$ is the joint probability of X and Y, and $p(x)$ and $p(y)$ are unconditional probabilities of $X=x$ and $Y=y$. The mutual information between X and Y, a measure of closeness, indicates the expected information gained about Y when the value of X is given. The second phase is about thickening the network by adding connections based on the conditional independence test between pairs of variables. In this phase, all pairs of variables that have mutual information greater than the entropy but not directly connected are examined. A connection is not added only when the two variables are independent, and in this phase some wrong connections are possible to be added. In the third phase, each connection of the network is reexamined and removed if the corresponding variables are conditionally independent after the structure adjustment.

For the second task, the parameters (CPTs behind the nodes) are estimated based on the dataset by the most commonly used EM (Expectation Maximization) algorithm (Lauritzen 1995). The algorithm finds the CPTs for each node through a sequence of stepwise iterations and iterates between the expectation (E) step and the maximization (M) based on both estimated data and observed data. The process is repeated until the difference between the log-likelihoods of two successive iterations falls below a tolerance threshold. Both tasks could be done using the free software PowerConstructor (Cheng et al. 2002), where the two algorithms are embedded and well tested. The composed network was visualized and tested in Netica (Norsys Software 2006).

Modeling Results

Figure 4 shows the constructed BN. The probability distribution of each variable is shown, and the predicted distribution of AS (43.3% for overall satisfied rate) is quite close to the observed percentage in the survey data (42.5% satisfied). The link represents the relationships between the two variables, and the structure shows the existence of direct and indirect relationships between the service attributes and overall satisfaction.

FIGURE 4.
Network of public transit service assessment



As in the structure, AS plays a central role among other variables, which is less surprising, since AS is the important variable in this study. It is directly related to other 11 service aspects nodes (CF1, CF2, CF3, CF5, CF6, CF7, CO, CN4, R1, R2, and R3). The remaining variables have indirect influences on AS. Among them, R1–Run on Schedule has a direct influence on AS–Overall Satisfaction, and unreliable service would result in additional waiting time for passengers, leading to a decline in passenger satisfaction over R2–Acceptable Waiting Time for Bus, confirming the analysis by Strathman et al. (2003). CN3–Service Frequency also impacts passenger satisfaction on R2–Acceptable Waiting Time for Bus, indicating that the more frequent the service, the shorter the waiting time, which is consistent with the Transportation Research Board report (2003). Most variables of the same attribute are directly linked, such as S1, S2, S3, and S4, but some variables of different attributes also seem to affect each other, such as R2–Acceptable Waiting Time for Bus, CN3–Service Frequency, CO–Reasonable Fare, and CN4–Convenient Design for Transfers. This is not especially surprising since waiting time should depend on bus service frequency arrangement. Actually, the crossing relationships are plausible. Service reliability is always closely related to service convenience. An efficient transfer could improve the whole punctuality of transit performance.

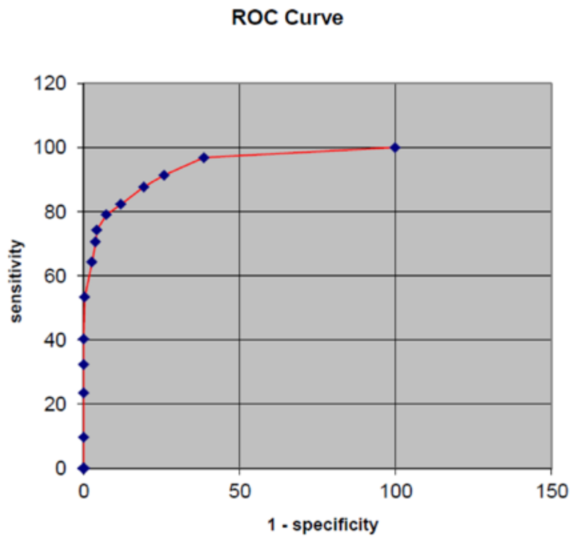
Before the analysis, appropriate validation methods on the modeling performance should be made to prove the confidence in the outputs of the model. A recommended method is to derive a confusion matrix that compares the observed values with the predicted ones (Fawcett 2006). Table 3 shows the overall BN estimation result performed in Netica (2006). As can been seen in the confusion matrix, the overall estimation error rate of this BN is 13.96%. Compared to the model accuracies between 59.72% and 62.16% in the study by De Oña et al. (2012), the estimation result obtained is quite acceptable.

TABLE 3.
Test Results of Model

Confusion	Predicted		Actual
	State0	State1	
For AS	300	50	State0
	35	224	State1
Error rate	13.96%		

Figure 5 presents alternative performance measurement quantifying model estimation accuracy for the datasets. The receiver operating characteristic (ROC) curve was employed, as the target variable AS is binary. By contrasting false positive with true positive rates, the ROC curve depicts estimation performance, and the area under the curve (AUC), which specifies overall accuracy, takes values between 0 and 1, with better performance being indicated by values closer to 1 (Marcot et al. 2006). As shown in Figure 5, the resulting ROC curve is quite close to the upper limit, and the achieved AUC value is 0.93, which indicates a high predictive quality of the BN, revealing that the BN approach performs well and its structure is capable of providing evidence sensitivity analysis based on the CPTs for each node. With the entering new evidence, the probabilities of the other nodes will be updated in the network by Bayes' Rule. The probabilistic changes of the target variable reflect the impact of the changing variable on it.

FIGURE 5.
ROC curve of BN Model



Analysis Result

An evidence sensitivity analysis and a mutual information analysis as described above were conducted to further examine the main service aspects that affect passenger overall satisfaction towards bus service in the network.

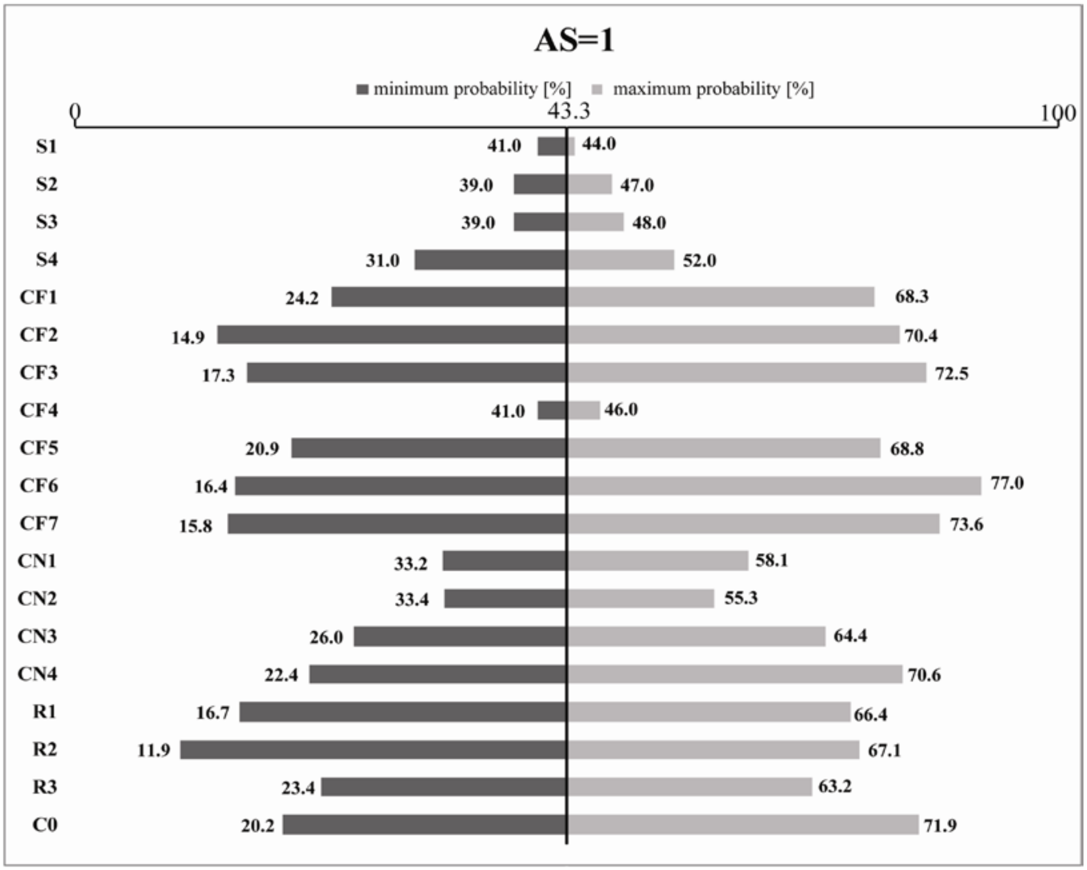
Evidence Sensitivity Analysis

The evidence sensitivity analysis, based on the compiled BN, permitted us to change the posterior distribution of each variable and observe its corresponding effect on the target variable. Once the evidence was entered into one state of one parent node, such as state 1 of CF (CF=1) in the network, the probability distribution of CF=1 changed to 100%. Meanwhile, with the application of Bayes' theorem and the CPTs of the compiled BN, its corresponding changes were calculated and reflected in the probability distributions for the states at its child variables. BN allows information to flow in opposite directions, which means a change in a given node can update the distribution probabilities of its neighboring nodes through the network (Jensen 1996).

The evidence was changed in every state, one by one, and then the corresponding newly-updated probability distribution of target variable AS was taken down. Figure 6 shows the minimum and maximum probability $p(AS=1)$ due to variations in the probability distributions of all service aspects. The bars indicate changes relative to the initial probability $p(AS=1)$. Observing the length of bars in this figure, it was found that comfort, convenience, reliability, and costs exert a strong influence on satisfaction in both positive and negative ways. Their relatively large influence can be partly attributed to their immediate adjacency to AS.

All aspects of safety influenced satisfaction within the range of 39–48%, with the exception of overall safety, whose influence range was 31–52%. These three negligible effects reflect that in most passenger perceptions, the regular bus is a safe system, providing a satisfactory level of service in which vehicles are well-equipped with security facilities and drivers are skillful in handling accidents. With respect to the latter, an unsatisfied overall safety (S4=1) poses a significant negative influence, at 12.3%. In addition, in the BN structure, these four nodes are indirectly linked to AS. Therefore, compared to the other variables, safety aspects have somewhat lower effects on overall satisfaction.

FIGURE 6.
Evidence sensitivity analysis results for each attribute



With regard to comfort, six highly-important variables were observed: CF6–Clean Environment Onboard, CF7–Pleasant Environment at Stations, CF3– Air-Conditioning Onboard, and CF2–Seats Available, which were set to state 4 and are especially evident for the maximum probability $p(AS=1)$, which increase dramatically, from 43.3% to more than 72%, compared to a decrease from 43.3% to appropriately 15% for the minimum probability $p(AS=1)$. These service aspects are more tangible and relate to infrastructure facilities. Compared to private vehicles, public transit has apparent deficiencies in these fields. For example, CF2–Seats Available is one of defining components of public transit compared to private cars; available seats on transit is necessary among passengers who commute from work to their home. CF3 and CF7 are mainly associated with the local climate in Nanjing; due to the hot summers, air-conditioning onboard and shelters at bus stops are highly valued and needed and, thus, are of primary service aspects to be improved in competition with private vehicles. CF5–Ride Smoothly and CF1–

Overcrowded Inner Space, about which passengers often complain, are two service items that vary under dynamic traffic conditions and changing passenger flow volumes during the day. For instance, in rush hour, overcrowded inner space is a common feature of high-capacity transportation, especially in developing countries. Both have a medium influence range of roughly 22–69%. CF4–Broadcasting System Onboard is the least influential variable, indicating that basic service delivery is more important than modern technology.

The variables Walking Distance to Stops and Schedule/Route Information Provided at Bus Stops have little influence on overall satisfaction. This can be due to the fact that frequent riders are satisfied with the current distance to stops and know the schedule and routes. CN3–Reasonable Bus Service Frequency, which has a close relationship with R2–Acceptable Waiting Time at Bus Stops, exerts a more significant influence on overall satisfaction, with an influence range of 26–64.4%. At the same time, CN4–Convenient Design for Connections and Transfers at Stops exhibits the greatest influence, 22.4–70.6%. This result indicates that reasonable service frequency and convenient transfer service would largely improve the efficiency of bus rides.

R2–Acceptable Waiting Time is a highly important aspect for overall service, and its negative influence is particularly high for the minimum probability of AS=1, which decreases largely from 43.3% to 11.9%; the perceived waiting time tends to cause a negative impact on overall transit service satisfaction, and the intangibility and subjectivity of waiting time makes it difficult to measure. When the waiting time is beyond passenger tolerance, they would be annoyed and tag "long time waiting" as the primary service attribute. R1–Run on Schedule is another noteworthy service aspect, with a negative impact range of 16.72–43.31%. The ratio of AS is increased by 23.14% due to increased punctuality. R3 symbolizes the reliability of the electronic information about the distance of the incoming bus on the stations or stops and has a relatively small influence range, 23.4–63.2%.

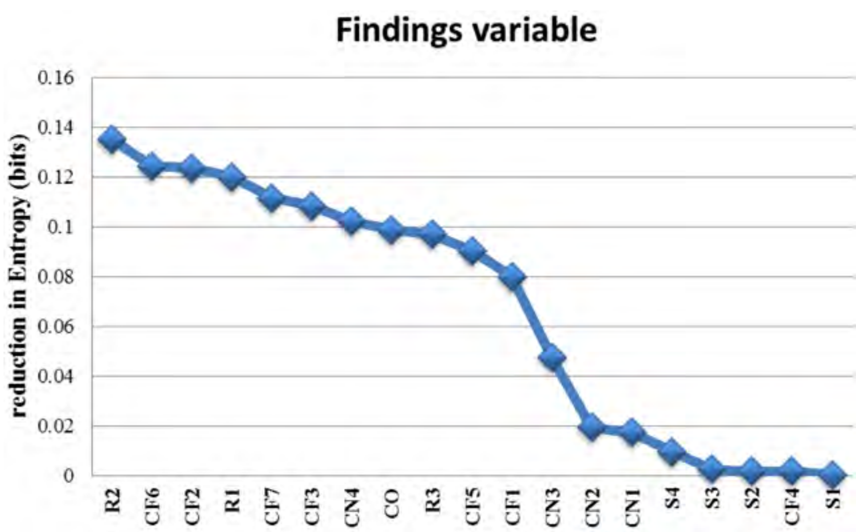
The directly-related variable CO–Reasonable Fare has a 23% negative effect and a 29% positive effect on passenger satisfaction with overall transit service quality. Compared with the impacts of other aspects, fare is not the most influential factor in overall satisfaction. This finding may be attributed to the case that riding the bus is much cheaper than driving a car; the cost is not generally perceived as important, which concurs with the study by Beirao and Cabral (2007). However, the impact range still reflects that the low travel cost of public transit is still an attractive element over private car, and policy interventions could apply price regulations to traveling by private car and adopt favorable ticket price policies for public transit to attract more potential riders.

The results indicate that R2–Acceptable Waiting Time, CF2–Seats Available, CF6–Clean Environment Onboard, CN4–Convenient Design for Transfers, CF3–Air-Conditioning Onboard, R1–Run on Schedule, and CF7–Pleasant Environment at Stations are sensitive attributes that affect overall satisfaction. Moreover, effects propagate change in linked variables. For instance, by entering evidence for state 4 of node R2, overall satisfaction is increased by 23.8%; along with the change of node R2, the other three nodes linked also experience an increase of varying degree in the fourth state of each. In particular, a significant increase that adds up to 40% occurs in the fourth state of R3.

Mutual Information Analysis

Figure 7 shows the calculated reduction of entropy in the probability distribution of AS for each variable, and the top seven variables are the same as the variables posing the negative effects in the evidence analysis. Thus, the variables that contribute most to the reduction of entropy were, in order of importance, R2–Acceptable Waiting Time (0.135), CF6–Clean Environment Onboard (0.124), CF2–Seats Available (0.124), R1–Run on Schedule (0.120), CF7–Pleasant Environment at Stations (0.112), CF3–Air-Conditioning Onboard (0.108), and CN4–Convenient Design for Transfers (0.102). Mutual information less than 0.01 indicates that a least influence on the overall satisfaction is produced, and there are five least contributing variables (the four safety attributes and the broadcasting system onboard), and the result is consistent with the result of the evidence sensitivity analysis.

FIGURE 7.
Mutual information values among all network nodes and AS



Conclusion and Recommendations

This study applied a Bayesian network to estimate passenger assessments of bus service quality and identify the key influential factors of bus service quality. The data for the analysis were obtained from a 2013 regular bus service survey in Nanjing, China. An evidence sensitivity analysis and a mutual information analysis were used to derive the degrees of influence of each service aspect on overall satisfaction.

The results of this study showed that the BN approach was useful in identifying the key influential factors of bus service. According to the detailed sensitivity analysis, several findings can be drawn to help understand how service attributes influence passengers satisfaction with public transit. First, current safety attributes are already satisfactory and exert little influence on perceived overall satisfaction with public transit services. Second, comfort, convenience, and reliability are significant influences on passenger satisfaction. Third, seven service aspects stand out as the attributes passengers care most about: running on schedule, acceptable waiting time, available seats, clean environment onboard, pleasant environment at stations, convenient design for transfers, and air-conditioning onboard. Therefore, quality improvement and management of these aspects are prerequisites to obtaining passenger satisfaction.

Achieving and sustaining a high level of customer satisfaction is a key part of a transit agency's efforts to increase public transit ridership, especially regular bus. Therefore, the policies and strategies that promote transit usage should be formulated accordingly to meet the needs of current and potential bus riders. Since passengers strongly prefer travel comfort, maintaining the vehicles in good condition, cleaning them regularly, and providing air-conditioning and an agreeable temperature inside the bus could be effective ways to keep the bus environments enjoyable. Passengers prefer convenient and efficient delivery services, which indicates that transit operators should place more emphasis in their policy planning on the connectivity of bus facilities and the design of exclusive lanes for public transit as well as the provision of reasonable time schedules such that buses are less impacted by traffic congestion and there is an improved level of reliability of existing bus service. These strategies could encourage current passengers to use the bus more often and attract new users.

Although city cultures and backgrounds of bus service differ, the BN approach presented in this study has relatively high transferability in the application and can be applied by local agencies or communities for identifying the most influential factors that needs improving, and corresponding policies can be proposed accordingly to improve passenger satisfaction. Since the current study focused on aggregate relationships, future research could examine heterogeneity in passenger satisfaction with service quality and test the needs for different kinds of passengers, allowing service providers to target different segments of the market.

Acknowledgments

This research is supported by National Natural Science Foundations of China (51378120 and 51338003) and the Postgraduate Research and Innovation Plan Project in Jiangsu Province (KYLX_0170). Fundamental Research Funds for the Central Universities and Foundation for Young Key Teachers of Southeast University and Eindhoven University of Technology are also appreciated.

References

Arentze, T. A., and H. J. P. Timmermans. 2009. "Regimes in Social-Cultural Events-Driven Activity Sequences: Modeling Approach and Empirical Application." *Transportation Research Part A*, 43(4): 311-322.

Beirao, G., and J. A. S. Cabral. 2007. "Understanding Attitudes towards Public Transport and Private Car: A Qualitative Study." *Transport Policy*, 14(6): 478-489.

Cheng, J., D. A. Bell, and W. Liu. 2002. "Learning Bayesian Networks from Data: An Information-Theory Based Approach." *Artificial Intelligence*, 137(1-2): 43-90

Cheng, Y. H., and K. C. Liu. 2012. "Evaluating Bicycle-Transit Users? Perceptions of Intermodal Inconvenience." *Transportation Research Part A*, 46:1690-1706.

Das, S., and D. Pandit. 2013. "Importance of User Perceptions in Evaluating Level of Service for Bus Transit for a Developing Country Like India: A Review." *Transport Reviews*, 33(4):402-420.

De Oña, J., R. de Oña, and F. J. Calvo. 2012. "A Classification Tree Approach to Identify Key Factors of Transit Service Quality." *Expert Systems with Application*, 39(12): 11164-11171.

De Oña, J., R. de Oña, L. Eboli, and G. Zulla. 2013. "Perceived Service Quality in Bus Transit Service. A Structure Equation Approach." *Transport Policy*, 29: 219-226

De Oña, J., R. O. Mujalli,, and F. J. Calvo. 2011. "Analysis of Traffic Accident Injury Severity on Spanish Rural Highways Using Bayesian Networks." *Accident Analysis and Prevention*, 43(1): 402-411

Dowling, R. G., D. Mcleod, M. Guttenplan, and J. D. Zegeer. 2002. "Multimodal Corridor Level of Service Analysis." *Transportation Research Record*, 1802: 1-6.

Eboli, L., and G. Mazzulla. 2007. "Service Quality Attributes Affecting Customer Satisfaction for Bus Transit." *Journal of Public Transportation*, 10(3): 21–34.

Eboli, L., and G. Mazzulla. 2008. "Willingness-to-Pay of Public Transport Users for Improvement in Service Quality." *European Transport*, 38:107-118.

Eboli, L., and G. Mazzulla. 2010. "How to Capture the Passengers' Point of View on a Transit Service through Rating and Choice Options." *Transport Review*, 30(4): 435-450.

Eboli, L., and G. Mazzulla. 2012a. "Structural Equation Modelling for Analyzing Passengers' Perception about Railway Services." *Procedia–Social and Behavioural Science*, 54: 96-106.

Eboli, L., and G. Mazzulla. 2012b. "Performance Indicators for an Objective Measure of Public Transport Service Quality." *European Transport*, 51(17):.1-21.

Fawcett, T. 2006. "An introduction to ROC Analysis." *Pattern Recognition Letters*, 27(8): 861-874.

Fellesson, M., and M. Friman. 2008. "Perceived Satisfaction with Public Transport Services in Nine European Cities." *Journal of Transportation Research Forum: Transit Issue Special*, 47(3): 93-103.

Fu, L., and Y. Xin. 2007. "A New Performance Index for Evaluating Transit Quality of Service." *Journal of Public Transportation*, 10(3): 47-69.

Gao, Y., S. Rasouli, H. J. P. Timmermans, and Y. Wang. 2015. "A Study of the Relationship between Subjective Well-Being and Travel Satisfaction." *Transportation Research*, 144-153.

Garrido, C., R. de Oña, and J. de Oña. 2014. "Neural Networks for Analyzing Service Quality in Public Transportation." *Expert Systems with Applications*, 41(15): 6830-6838.

Hensher, D. 2014. "The Relationship between Bus Contract Costs, User Perceived Service Quality and Performance Assessment." *International Journal of Sustainable Transportation*, 8(1): 5-27

Hu, K. C., and W. Jen. 2006. "Passengers' Perceived Service Quality of City Buses in Taipei: Scale Development and Measurement." *Transport Reviews*, 26(5): 645–662.

Iseki, H., and B. D. Taylor. 2008. "Style versus Service? An Analysis of User Perceptions of Transit Stops and Stations in Los Angeles." *Proceedings of the 87th Annual Meeting of the TRB*: 13-17.

Janssens, D., G. Wets, K. Brijs, K. Vanhoof, T. Arentze, and H. J. P. Timmermans. 2006. "Integrating Bayesian Networks and Decision Trees in a Sequential Rule-Based Transportation Model." *European Journal of Operational Research*, 175(1): 16-34.

Jensen, F. V. 1996. *An Introduction to Bayesian Networks*. New York: Springer-Verlag.

Karimnezhad, A., and F. Moradi. 2016. "Road Accident Data Analysis using Bayesian Networks." *Transportation Letters*: 1-8.

Kemperman, A., and H. J. P. Timmermans. 2014. "Environmental Correlates of Active Travel Behavior of Children." *Environment and Behavior*, 46(3): 583-608.

Lauritzen, S L. 1995. "The EM Algorithm for Graphical Association Models with Missing Data." *Computational Statistics & Data Analysis*, 19(2): 191-201.

Litman, T. 2008. "Valuing Transit Service Quality Improvements." *Journal of Public Transportation*, 11(2): 3.

Ma, T. Y. 2015. "Bayesian Networks for Multimodal Mode Choice Behavior Modelling: A Case Study for the Cross Border Workers of Luxembourg." *Transportation Research Procedia*, 10, 870-880.

Marcot, B. G., J. D. Steventon, G. D. Sutherland, and R. K. Mccann. 2006. "Guidelines for Developing and Updating Bayesian Belief Networks Applied to Ecological Modeling and Conservation." *Canadian Journal of Forestry Research*, 36(12): 3063–3074.

Nathanail, E. 2008. "Measuring the Quality of Service for Passengers on the Hellenic Railways." *Transportation Research Part A*, 42(1): 48-66.

Norsys Software. 2006. "Netica 3.17 for MS Windows." Vancouver, Canada.

Nurul-Habib, K. M., L. Kattan, and T. Islaam. 2009. "Why Do the People Use Transit? A Model for Explanation of Personal Attitude towards Transit Service Quality." *Proceedings of the 88th Annual Meeting of the TRB*: 11-15.

Pearl, J. 1991. "Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference." San Mateo: Morgan Kaufmann.

Perucca, G., and S. Salini. 2014. "Travellers' Satisfaction with Railway Transport: A Bayesian Network Approach." *Quality Technology and Quantitative Management*, 11(1): 71-84.

Richardson, B. 2004. "Sustainable Transport: Analysis Frameworks." *Journal of Transport Geography*, 13 (3):29-39.

Scuderi, M. G., and K. J. Clifton. 2005. "Bayesian Approaches to Learning from Data: Using NHTS Data for the Analysis of Land Use and Travel Behavior." *Journal of Transportation and Statistics*, 8(3):17-21.

Strathman, J. G, T. J. Kimpel, and S. Callas. 2003. "Headway Deviation Effects on Bus Passenger Loads: Analysis of Tri-Met's Archived AVL-APC Data." Center for Urban Studies, Portland.

Takamiya, M., K. Yamamoto, and T. Watanable. 2010. "Modeling and Estimation of Travel Behaviors Using Bayesian Network." *Intelligent Decision Technologies*, 4(4): 297-305.

Transportation Research Board. 2003. *A Guidebook for Developing a Transit Performance Measurement System*. Transit Cooperative Research Program. Washington DC: National Academy Press.

Tyrinopoulos, Y., and C. Antoniou. 2008. "Public Transit User Satisfaction: Variability and Policy Implications." *Transport Policy*, 15(4): 260-272.

Wu, J., Yang, M., Li, Z., Cheng, L., and X. Hou. 2014. "Evaluating the Service Quality of Public Transit from Passengers' Perceptions Using Bayesian Networks." *Proceedings of the 93rd Annual Meeting of the TRB*, 14-1900.

Yang, T., and L. Qian. 2012. Nanjing Transport Annual Report. Nanjing: Nanjing Urban Planning Bureau. (in Chinese)

Yilmaz, V., and H. E. Celik. 2008. "A Model for Explanation of Personal Attitudes towards Traffic of Candidate Drivers Attending Drivers' Course: Risky Candidate Drivers' Attitude Model." *Transportation Research Part F*, 11(4): 233-241.

About the Authors

Jingxian Wu (*wujingxiannn@163.com*) is a doctoral student in Transportation Engineering Department at the School of Transportation, Southeast University. She holds bachelor's and master's degrees from Southeast University.

Min Yang (*yangmin@seu.edu.cn*) is a Professor of Transportation Engineering Department at the School of Transportation, Southeast University. His areas of interest include public transport, evaluation of the quality of public transport, and travel behavior.

Soora Rasouli (*s.rasouli@tue.nl*) is an Assistant Professor in Urban Planning Group at the Eindhoven University of Technology. She has research interests in activity-based

models of travel demand, modeling of choice processes under uncertainty, and spatial analysis.

Chengcheng Xu (*xuchengcheng@seu.edu.cn*) is Assistant Professor in the Transportation Engineering Department at the School of Transportation, Southeast University. Among his areas of research specialization are urban transportation planning and traffic safety.

Modeling Bus Dwell Time and Time Lost Serving Stop in China

Chao Wang, Zhirui Ye, Yuan Wang, Yueru Xu, and Wei Wang
Southeast University, China

Abstract

The primary objective of this study was to develop a quantitative approach to estimate bus dwell time and time lost serving stop, which included acceleration and deceleration time, dead time, and time for serving boarding and alighting passengers. A polynomial model incorporating kinematics of a particle was derived for estimating bus acceleration and deceleration time. In addition, descriptive statistics methods were used to analyze dead time. A case study was conducted to show the applicability of the proposed model with data collected from the seven most common types of bus stops in China. R-square and Mean Absolute Percentage Error (MAPE) were calculated to be 0.8840 and 13.20% for non-peak and 0.8387 and 13.46% for peak, indicating the method was well-validated and could be practically used in China. Further research can be conducted to investigate the effects of different weather conditions and locations on the performance of the proposed method.

Keywords: *Bus dwell time, dead time, time lost serving stop, transit*

Introduction

Studies have shown that bus service procedure at bus stops is of great importance to estimate capacity of a bus stop (Bian et al. 2015), and it is also a major component of bus travel time (Hawas 2013; Furth and Muller 2007; Hadas and Ceder 2010; Balasubramanian and Rao 2015). Bus service procedure plays a vital role in transit network design (Szeto et al. 2011; Wu et al. 2015; Yan et al. 2013) and transit assignment analysis (Hamdouch et al. 2011; Leurent et al. 2014). Thus, bus service time estimation is essential for bus operators and public transport planners (Ceder 2007; Li et al. 2006).

There is considerable research in the literature on the service procedure of buses at bus stops. Previous research defined the time spent serving a bus stop as the time the bus is stationary or has its doors open at the bus stop, i.e., bus dwell time. However, most research studies fail to adequately consider the time lost by the bus decelerating to a bus stop and then accelerating back to running speed to serve the stop (Robinson 2013). The acceleration and deceleration time is often much longer than the time lost when the doors are open at the bus stop. In addition, it has also been noted that the characteristics of a bus stop visit are not well considered. The passage of a bus through a stopping zone can be called a bus stop visit (Robinson 2013). In light of this, bus dwell time and time lost serving stop is introduced to describe the bus service procedure in this study, which is defined as the time required for serving passengers, acceleration time, and deceleration time, with the addition of dead time. According to relevant references (Robinson 2013; Cundill and Watts 1973), dead time is the time the bus is stationary at a stop but no passengers are boarding and alighting. The contributing factors for dead time are categorized as major factors (including the average delay for re-entering the car stream (Yang et al. 2009), and other additional delay (Tirachini 2013) such as boarding lost time, bus stop failure time, and traffic signal delay, and adjustment factors (including traffic volume/capacity).

In addition, there is a variety of bus stop designs that may influence bus dwell time and time lost serving stop. Based on the right-of-way, bus lanes can be divided into exclusive bus lanes (grade-separated busways and at-grade busways) and mixed traffic lanes (KFH Group 2013; Jacques and Levinson 1997). According to TCRP Report 19 (Fitzpatrick et al. 1996), bus dwell time and time lost serving stop will be affected by the layout of the bus stop. In general, the more exclusive the stop (the less interaction that a transit vehicle has with other traffic), the fewer impacts on bus dwell time and time lost serving the stop can be achieved. In terms of form, bus stops can be classified into two categories: on-line and off-line (KFH Group 2013). Compared to an on-line bus stop, there is additional time required for buses at an off-line stop to find an acceptable time gap between consecutive vehicles. It can be concluded that the form of a bus stop has an impact on bus dwell time and time lost serving stop. Moreover, based on the location of the cross-section, bus stops can be divided into two categories: median and curbside. According to the above classifications, seven types of bus stop designs are commonly observed in China (Ye et al. 2016), as illustrated in Figure 1:

Type 1: At-grade busways separated from motor vehicle lanes by traffic markings; bus stops are on-line and set on the curbside.

Type 2: No exclusive bus lane; bus stops are on-line and set on the curbside.

Type 3: At-grade busways separated from motor vehicle lanes by traffic markings; bus stops are off-line (bay-style) and set on the curbside.

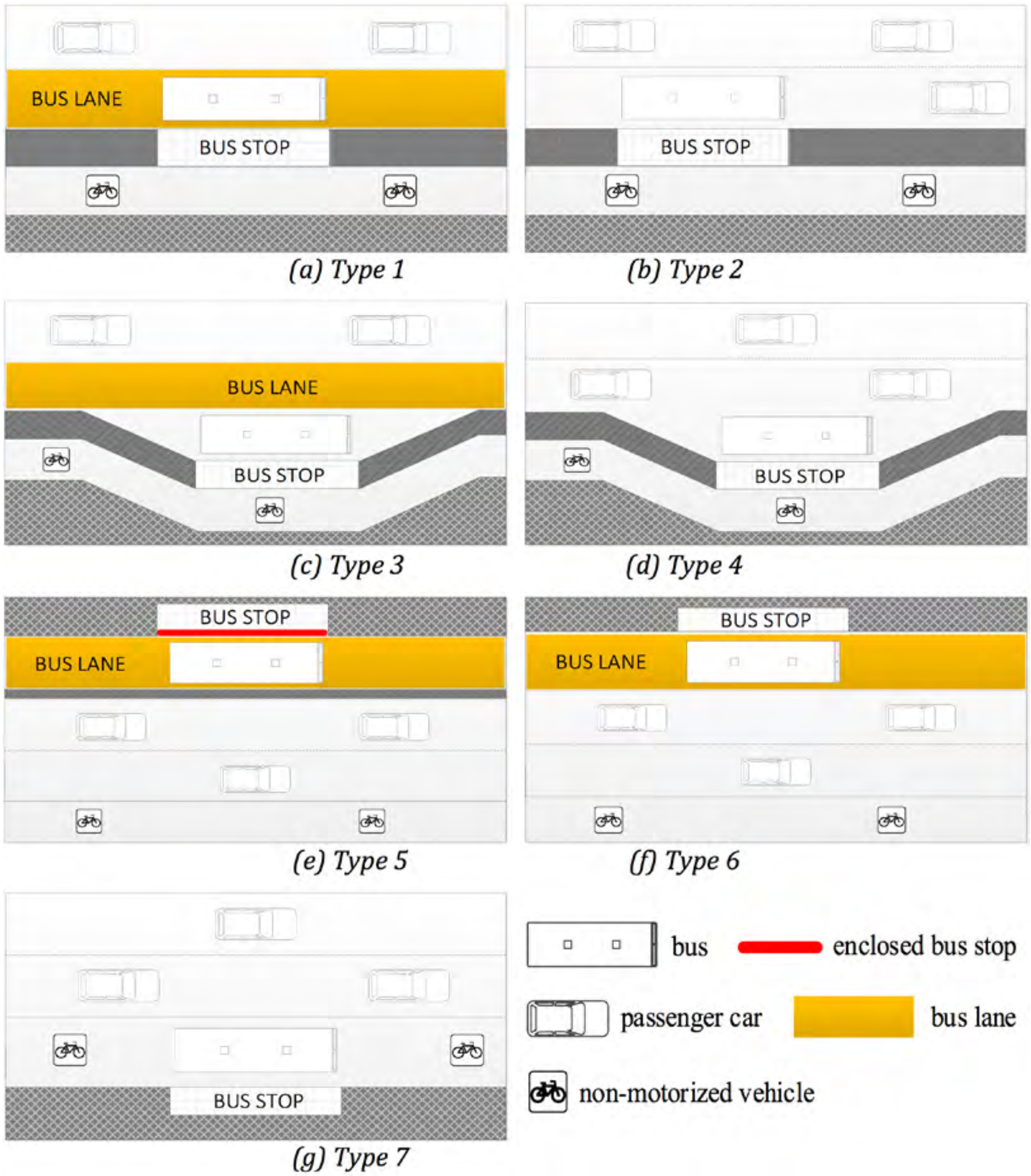
Type 4: No exclusive bus lane; bus stops are off-line (bay-style) and set on the curbside.

Type 5: Grade-separated busways separated from motor vehicle lanes by separation strips; bus stops are on-line and set in the median of the cross-section.

Type 6: At-grade busways separated from motor vehicle lanes by traffic markings; bus stops are on-line and set in the median of the cross-section.

Type 7: No exclusive bus lane; bus stops are on-line and set on the curbside, and buses pull over to the curbside and occupy bicycle lanes to dwell.

FIGURE 1.
Schematic diagram of seven most common bus stops



In light of these considerations, the primary objective of this study was to develop a quantitative approach to estimate bus dwell time and time lost serving stop for different types of bus stops. The method proposed in this paper can be used by transit agencies to measure the actual travel time of buses, removing the component of time lost serving the stop. The method can also be used to identify bus stops that may need redesign to reduce the time lost in arriving and departing. In addition, this study was inspired by several current bus speed improvement projects in China. Requirements gathered from the departments show that bus service time is ambiguous. Some business users wanted data about time spent with doors open, and others wanted the time lost serving stop. This study can meet both requirements.

Literature Review

There are two processes going on during bus service at stops (Fernandez 2010). One is the time spent for serving boarding and alighting passengers, known as bus dwell time. The earliest research on dwell time at a bus stop was given by Levinson (1983), who formulated the bus dwell time as a function of two primary contributing factors, number of alighting and boarding passengers, by using the linear regression approach. Since then, more research approaches were introduced to take into account several secondary factors that might affect the effectiveness of bus dwell time estimation. For example, Guenthner and Hamat (1988) associated bus dwell time with fare collection system. In Lin and Wilson's study (1992), a functional form that combined with the crowding effect was developed. In addition, several studies found that the dwell time also relied on vehicle occupancy and bus floor types (Levine and Torng 1994; Fernandez et al. 1995).

The other part of the service procedure is the time taken for buses to enter and leave the service area, known as time lost serving stop. The literature shows that little research has been done on that component of time lost decelerating and accelerating to a bus stop and other bus delay at a stop. Research by Jaiswal et al. (2010) suggested that the bus stop design could affect time spent at a stop. According to Robinson (2013), the time lost arriving at (i.e., decelerating) and departing from (i.e., accelerating) a bus stop was typically 11.6s in London.

Previous studies on dwell time and time lost serving stop had used limited manually-collected data sets to relate dwell time and time lost serving stop to several factors, with separate equations estimated for different operating characteristics likely to have an impact on dwell time and time lost serving stop (Dueker et al. 2004). However, the cost of collecting data manually limited the number of observations in these data sets to a handful of operators, stops, and so on (Milkovits 2008).

In recent years, advanced technologies such as automatic transit information systems provide real-time information that can assist transit agencies and researchers in collecting data of better quality and monitoring the operation of a transit system (Li et al. 2006). For instance, with the widespread application of automatic data collecting systems including automatic passenger counting (APC) and automatic vehicle location (AVL) systems, transit agencies and researchers are able to analyze a plethora of data by using an archived database (Tirachini 2013; Dueker et al. 2004). In addition, several computer simulation models have been applied in bus operation analysis at stops. The TRAF-NETSIM program, i.e., CORSIM, deals with time spent at a stop by simply depending on mean values specified by users and embedded statistical distributions rather than loading and unloading demand (FHWA 2003). VISSIM is another prevalent simulation model to analyze bus dwell time and time lost serving stop, which is estimated by two methods including dwell time distributions and advanced passenger models (PTV Group 2005).

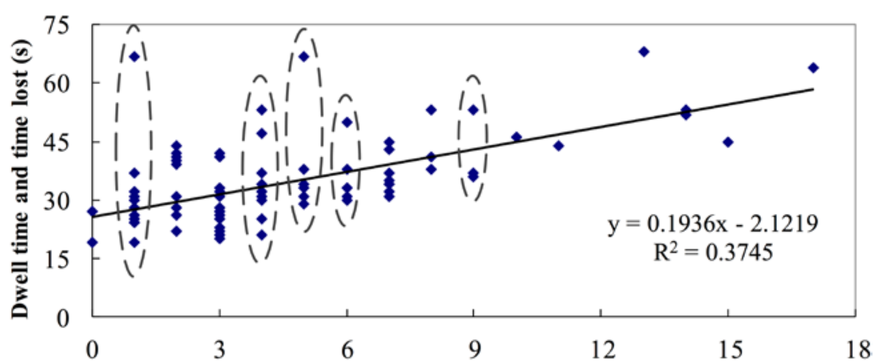
However, an automatic data collection system cannot provide all of the required data for calculating bus dwell time and time lost serving stop. Thus, this study involved the following factors based on automatically- and manually-collected data. The features of a bus stop visit can be measured by automatic data collecting systems, such as the number of passengers boarding and alighting, stop entry/exit, and zero speed start/end. As for the additional delay for buses and layout of bus stops (Gu et al. 2011; Meng and Qu 2013), however, they cannot be clearly measured by APC and AVL systems. For instance, a passenger who is far away from the alighting and boarding area may take longer to board a bus than a passenger near the area. This process can be observed by manually collecting data instead of automatically collecting data, because the latter merely records the bus delay and does not help us learn what happened in the process.

Methodology

Contributing Factors to Bus Dwell Time and Time Lost Serving Stop

Many factors can affect bus dwell time and time lost serving stop; among them the number of boarding or/and alighting passengers is the most significant contributing factor (Tirachini 2013; Milkovits 2008). A field investigation was conducted to collect bus dwell time and time lost serving stop and the number of boarding and alighting passengers associated with buses at the seven most common bus stop designs in China (Figure 2). Data were collected from 885 stopped buses. It should be noted that the bus stops in this study were selected randomly, and all pilot studies have been conducted with the findings, on the assumption that these seven bus stops can well represent the results for their relevant bus stop categories.

FIGURE 2.
Dwell time and time lost serving stop vs. number of boarding and alighting passengers



According to the types of bus stop design, these 885 samples enabled us to establish a respective linear relationship between the bus dwell time and time lost serving stop and the number of alighting and boarding passengers by the linear regression approach that had been widely used in existing studies (Meng and Qu 2013). Unfortunately, the linear relationship did not hold due to the relevant low R-square value (R^2=0.3912, on average). Figure 2 presents the linear regression results at one of the bus stops selected for this study—Public Transport Corporation bus stop. Interestingly, as can be seen in Figure 2, these data scattered on a 2-dimensional plane, in which the abscissa axis denoted the number of boarding and alighting passengers and the ordinate axis denoted the bus dwell time and time lost serving stop, apparently indicating bus dwell time and time lost serving stop differed greatly among the same number of passengers (i.e., the dotted line circles in Figure 2). For instance, bus dwell time and time lost serving stop ranged from 21s to 53s when the number of passengers was equal to 4. As analyzed above, it is problematic to estimate bus dwell time and time lost serving stop merely by relying on the number of boarding and alighting passengers, and it is necessary to take into account other factors such as dead time and acceleration and deceleration time.

Bus Acceleration and Deceleration Time

As shown in Figure 3, a bus stop includes three areas: bus entry area, alighting and boarding areas for passengers, and bus exit area. These entry and exit areas allow a bus to safely enter the bus stop from the shoulder lane and leave the bus stop to merge into traffic on the shoulder lane. According to the *Transit Capacity and Quality of Service Manual* (TCQSM) (KFH Group 2013), it takes time for a bus to slow from its running speed to serve a bus stop, and additional time to accelerate back to its running speed after serving the stop at a comfortable deceleration rate of 1.2m/s^2 and acceleration rate of 1.0m/s^2, compared to proceeding past the bus stop without stopping.

FIGURE 3.
Structure of bus stop

Acceleration and deceleration distances and time, together with the initial and final speeds during acceleration and deceleration processes, are the key information for modeling acceleration and deceleration of vehicles. A polynomial model incorporating kinematics of a particle is derived for estimating the bus acceleration process in the exit area and deceleration process in the entry area.

Acceleration Process in Exit Area

When a bus begins to accelerate away from a stop immediately after it last closes its doors, the acceleration distance to accelerate back to its running speed at a constant acceleration is:

$$S_1 = (a_{ac}/2) \times (v/a_{ac})^2 = v^2/(2 \times a_{ac}) \tag{1}$$

where S_1 is the acceleration distance, a_{ac} represents the acceleration rate (1.0m/s^2), and v is the bus running speed. If the length of the exit area is too long, so that the bus is still in this area when it accelerates back to the running speed, the remaining distance in the exit area ΔS_{ac} can be expressed as:

$$\Delta S_{ac} = S_{ac} - S_1 = S_{ac} - v^2/(2 \times a_{ac}) \tag{2}$$

where S_{ac} is length of the exit area. Thus, the acceleration time of a bus t_{ac} is as follows:

$$t_{ac}=\begin{cases} v/a_{ac}, & \Delta S_{ac}\le 0 \\ v/a_{ac}+\Delta S_{ac}/v=S_{ac}/v+v/(2\times a_{ac}), & \Delta S_{ac}>0 \end{cases} \tag{3}$$

Deceleration Process in Entry Area

Similar to the acceleration process in the exit area, the deceleration distance of a bus, which slows from its running speed to serve a bus stop at a constant deceleration, is:

$$S_2=(a_{de}/2)\times(v/a_{de})^2=v^2/(2\times a_{de}) \tag{4}$$

where S_2 is the deceleration distance and a_{de} represents the deceleration rate (1.2m/s^2). If the length of the entry area is too long, the remaining distance in the entry area ΔS_{de} can be expressed as:

$$\Delta S_{de}=S_{de}-S_2=S_{de}-v^2/(2\times a_{de}) \tag{5}$$

where S_{de} is length of the entry area. Thus, the deceleration time of a bus t_{de} is as follows:

$$t_{de}=\begin{cases} v/a_{de}, & \Delta S_{de}\le 0 \\ v/a_{de}+\Delta S_{de}/v=S_{de}/v+v/(2\times a_{de}), & \Delta S_{de}>0 \end{cases} \tag{6}$$

The acceleration and deceleration time of a bus $t_{ac\text{-}de}$ in the exit and entry areas can be summarized as follows:

$$t_{ac-de}=t_{ac}+t_{de}=\begin{cases} v/a_{ac}+v/a_{de}, & \Delta S_{ac}\le 0,\ \Delta S_{de}\le 0 \\ v/a_{ac}+S_{de}/v+v/(2\times a_{de}), & \Delta S_{ac}\le 0,\ \Delta S_{de}>0 \\ S_{ac}/v+v/(2\times a_{ac})+v/a_{de}, & \Delta S_{ac}>0,\ \Delta S_{de}\le 0 \\ S_{ac}/v+S_{de}/v+v/(2\times a_{ac})+v/(2\times a_{de}), & \Delta S_{ac}>0,\ \Delta S_{de}>0 \end{cases} \tag{7}$$

Serving Boarding and Alighting Passengers

Bus dwell time and time lost serving stop may be affected by boarding demand (e.g., in the PM peak period when relatively empty buses arrive at a heavily-used stop), by alighting demand (e.g., in the AM peak period at the same location), or by total interchanging passenger demand (e.g., at a major transfer point). In all cases, the time for serving boarding and alighting passengers is proportional to the boarding and/or alighting volumes and the amount of time required to serve each passenger (KFH Group 2013).

Several main factors influence the time for serving passengers. The number of people passing through the highest-volume door is a key factor in how long it will take for all passengers to be served. The proportion of alighting to boarding passengers through the busiest door also affects how long it takes all passenger movements to occur. The average time to pay a fare is a major influence on the time required to serve each boarding passenger. Some types of fare payment procedures allow passengers to board through more than one door at busy stops, thus allowing all to be served more quickly. Having to ascend or descend steps while getting on and off the bus increases the amount of time required to serve each passenger. In addition, when standees are present on a bus, it takes more time for boarding passengers to clear the farebox area, as other passengers must move to the back of the bus (KFH Group 2013).

In this study, the time for serving boarding and alighting passengers t_s is the time required to serve passengers at the busiest door plus the time required to open and close the doors. A value of 2–5s for door opening and closing is reasonable for normal operations (Levinson 1983; Meng and Qu 2013).

$$t_s = \begin{cases} P_{up} \times t_{up} + P_{down} \times t_{down} + t_{oc}, & N_{up} + N_{down} = 1 \\ \max\left\{\left(P_{up} \times t_{up}\right)/N_{up},\ \left(P_{down} \times t_{down}\right)/N_{down}\right\} + t_{oc}, & N_{up} + N_{down} \geq 2 \end{cases} \tag{8}$$

where P_{up} is number of boarding passengers, P_{down} denotes number of alighting passengers, N_{up} is number of doors for boarding, N_{down} denotes number of doors for alighting, and t_{oc} is door opening and closing time. According to TCQSM (KFH Group 2013), the service time for each passenger t_{up} and t_{down} is defined in Table 1. Table 1 can be used to estimate the time for typical situations where only one direction of passengers uses a door at a time and all passengers board through a single door. When passengers may board through multiple doors, Table 2 can be used instead to estimate the time. According to the field investigations described above, these data from TCQSM can be reflective of Chinese conditions.

TABLE 1.
Passenger Service Time with Single-channel Passenger Movement

Situation		Service Time (sec per passenger)
Boarding	Pre-payment	2.5
	Single ticket or token	3.5
	Exact change	4.0
	Swipe or dip card	4.2
	Smart card	3.5
Alighting	Front door	3.3
	Rear door	2.1

Source: Transit Capacity and Quality of Service Manual (KFH Group 2013)

TABLE 2.
Passenger Service Time with Multiple-channel Passenger Movement

Number of Doors	Service Time (sec per passenger)		
	Boarding Time	*Front Door Alighting Time*	*Rear Door Alighting Time*
1	2.5	3.3	2.1
2	1.5	1.8	1.2
3	1.1	1.5	0.9
4	0.9	1.1	0.7
6	0.6	0.7	0.5

Source: Transit Capacity and Quality of Service Manual (KFH Group 2013)

It is noted that when there are passengers standing in the bus, the boarding time will increase by 20%. For low-floor buses, the boarding time is reduced by 20%, the front door alighting time decreases by 15%, and the rear door alighting time is shortened by 25% (KFH Group 2013).

Bus Dead Time at Bus Stop

Bus dead time at a bus stop consists of average delay for re-entering the traffic stream and other additional delay such as boarding lost time, bus stop failure time, and traffic signal delay. Average delay for re-entering the traffic stream is a function of the capacity and the degree of saturation in the vicinity of a bus stop (Yang et al. 2009; HCM 2000). It is important to note that, for grade-separated busways (Type 5) and at-grade busways (Types 1, 3 and 6), average delay for re-entering the traffic stream is equal to 0. That is because the buses in grade-separated and at-grade busways cannot be disturbed by other non-bus vehicles. The analytical model used to estimate average delay assumes that the demand is less than capacity for the period of analysis. According to the *Highway Capacity Manual* (2000), if the degree of saturation is greater than about 0.9, average delay for re-entering the traffic stream is significantly affected by the length of the analysis period. In most cases, the recommended analysis period is 15 minutes.

$$t_{ad} = 3600/C + 900 \times T \times \left(V/C - 1 + \sqrt{(V/C-1)^2 + (3600/C) \times (V/C)/(450 \times T)} \right) \quad (9)$$

where t_{ad} is average delay for re-entering the car stream, and T represents the analysis time period, T=0.25 for a 15-minute period.

In addition to average delay for re-entering the traffic stream, there are several sources of delay that influence bus dead time at bus stops:

- *Boarding lost time t_b* – This is the time spent waiting for passengers to walk to the bus door(s) from their waiting position at the stop. When passengers wait at bus stops with multiple loading areas, such as high-volume stations served by multiple routes, they do not know in advance at which loading area the bus will stop when it arrives. According to a relevant reference (Jaiswal 2010) and our observations, passengers tend to concentrate within half a loading area length of the front of the second loading area-the point where the door of the second bus would be located. Once this optimal area becomes too crowded, passengers first spill toward the front loading area and later toward the rear loading area. When a bus arrives, there is typically a delay from when the bus doors open and when the first passenger arrives to board the bus. It depends on where the passengers were waiting relative to where the bus stopped, how quickly they could determine where the bus would stop, and how crowded the platform area was.
- *Bus stop failure time t_f* – A bus arrives at a stop to find all loading areas occupied, forcing it to wait until other buses leave the stop. In addition, when a bus is ready to depart from a stop, it also has to wait if it is blocked by other buses at the stop. These are examples of bus stop failure. In this case, the bus will have a delay (i.e.,

bus stop failure time) waiting for all of the buses at the stop to finish serving their passengers.

- *Traffic signal delay* t_{sd} – This is the time spent waiting for a green light after passenger flow has been completed. A traffic signal located in the vicinity of a bus stop and its loading areas will serve to meter the number of buses that can enter or exit the stop. For instance, at a far-side stop of a signalized intersection, buses can enter the stop only during the portion of the hour when the signal is green for the street on which the stop is located. The shorter the green time provided to the street, the lower the capacity and the longer a bus is likely to wait if it has to wait for the traffic signal to turn green again.

Bus Stop Dwell Time and Time Lost Serving Stop

The bus stop dwell time and time lost serving stop T_{dl} is based on the bus acceleration and deceleration time, time for serving boarding and alighting passengers, and bus dead time at bus stop. The final model is given in the following equation:

$$T_{dl} = t_{ac} + t_{de} + t_s + t_{ad} + t_b + t_f + t_{sd} \tag{10}$$

To intuitively describe the model, the equation for bus dwell time and time lost serving stop is represented by an expression tree in Figure 4. As shown in Figure 4, the nodes consist of variables, constants, and arithmetic symbols, such as +, -, ×, and ÷.

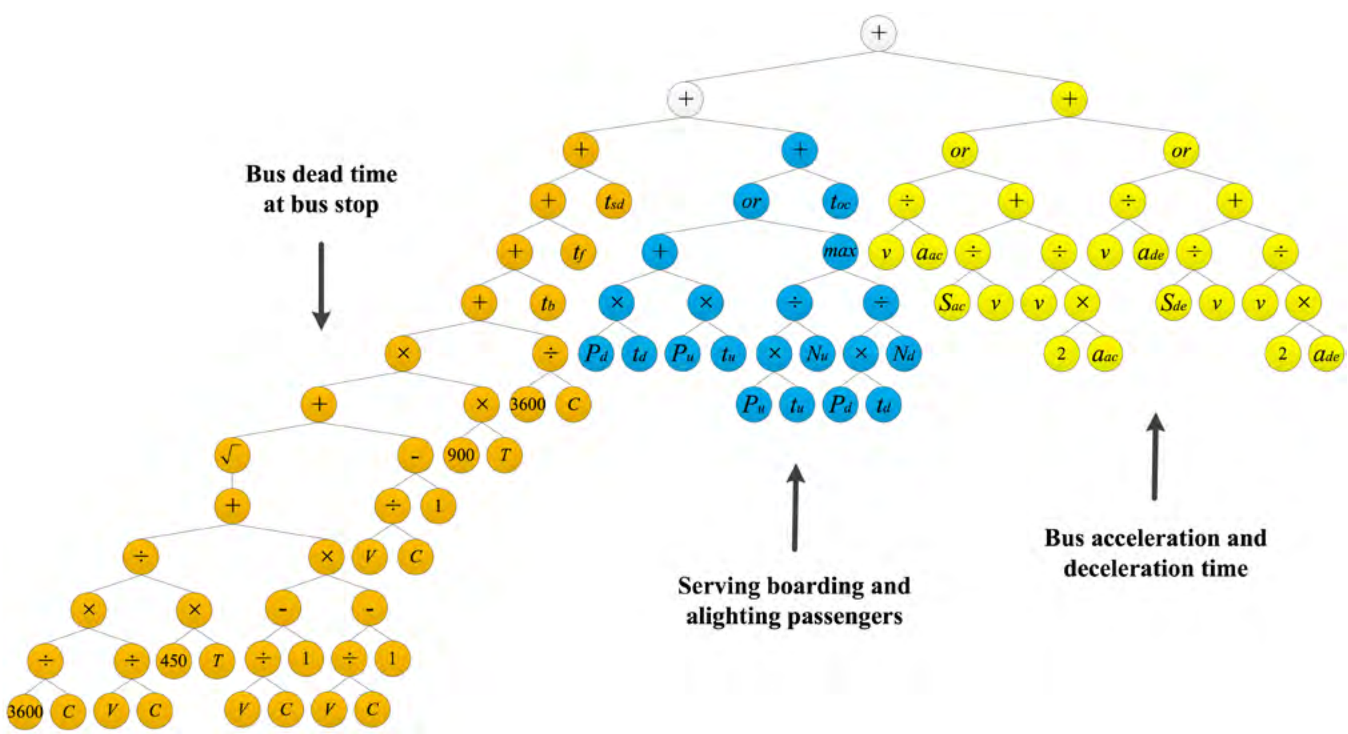


FIGURE 4. Expression tree for bus dwell time and time lost serving stop

Data Collection and Analysis

In this study, data were collected at seven different types of bus stops in the cities of Nanjing, Changzhou, and Guangzhou, China. The data were collected under good weather conditions between May 19 and June 15, 2014, to exclude potential influence of adverse weather. In addition, there was no curb parking around the stops.

Three video cameras were used at each stop to record traffic data, with one set up on a high location and one each set up in front of and behind the bus stop. The recorded videos were reviewed by several trained graduate students to obtain traffic volume and bus average speed near the bus stop. The site and traffic flow characteristics of the bus stops are shown in Table 3.

TABLE 3.
Site and Traffic Flow Characteristics of Bus Stops

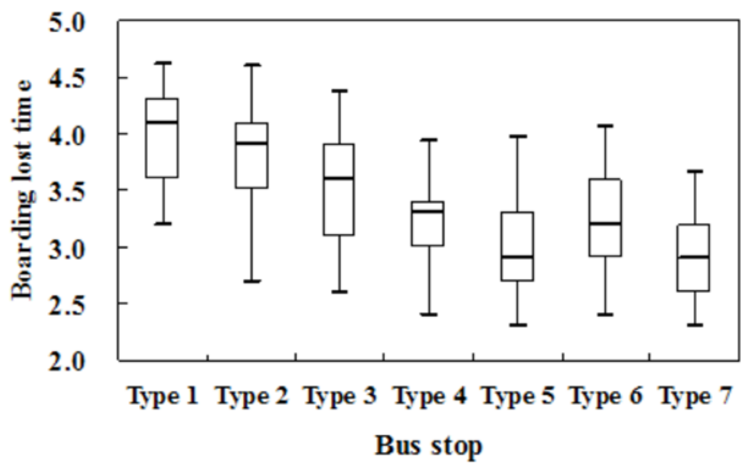
No.	Bus Stop	Type	BSL[a]	TC[b]	SS[c]	V[d]	C[e]	BS[f]
1	Gulou North	Type 1	47.5	Peak	67	2677	4500	21.4
2				Non-peak	47	1723	4500	24.4
3	Beiji Huitang	Type 2	20.0	Peak	113	3017	3900	18.9
4				Non-peak	108	2155	3900	22.5
5	Public Transport Corporation	Type 3	72.3	Peak	96	3378	4500	23.7
6				Non-peak	101	2286	4500	26.0
7	Xuanwuhu Park	Type 4	78.6	Peak	40	3850	4500	22.6
8				Non-peak	56	3054	4500	25.7
9	Renmin Park	Type 5	38.1	Peak	34	2398	4000	19.6
10				Non-peak	40	1755	4000	22.9
11	Gangding	Type 6	33.5	Peak	51	2848	4500	21.9
12				Non-peak	52	2205	4500	26.8
13	Danfeng Street	Type 7	17.4	Peak	39	2078	3000	15.9
14				Non-peak	41	1386	3000	20.2

a: Length of bus stop area (m)
b: Traffic condition (peak period or non-peak period)
c: Sample size of buses (veh)
d: Traffic flow rate (veh/h)
e: Capacity (veh/h)
f: Bus average speed near the bus stop (km/h)

In Table 3, BSL represents the length of the bus stop area, which consists of the bus entry area, alighting and boarding areas of passengers, and the bus exit area. The length of the bus stop area can be measured by tapeline in the field investigations. SS represents the sample size of buses. The duration of data collection for each bus stop was two hours for peak and two hours for non-peak. BS represents the bus average speed near the stop, which is the running speed before and after the bus stop. In general, a stopped bus will slow from its running speed about 50m before the bus stop and will accelerate back to its running speed about 30m after the stop. In this study, bus average speed near the stop was calculated by measuring the elapsed time to travel a specific distance (typically about 4.5 m) in the video. The VideoStudio application was used to process the video files in a frame-by-frame way so the observer could view videos at 25 frames per second.

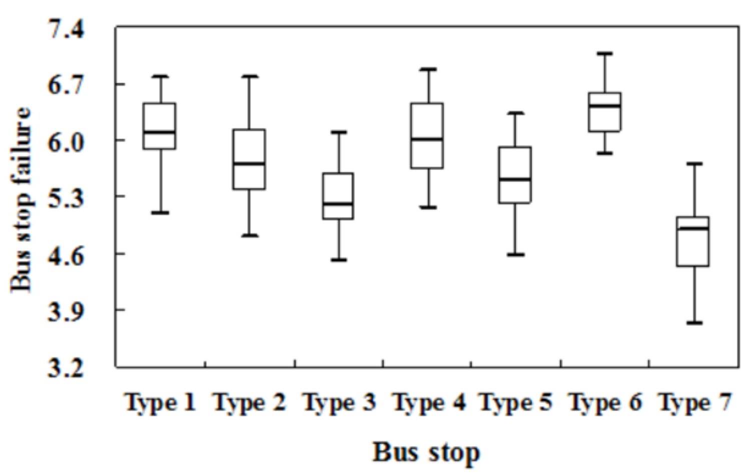
- *Boarding lost time* t_b – According to the field investigations described above, the amount of boarding lost time was found to vary by different types of bus stop designs, with median values ranging from 2.9–4.1s and interquartile range values ranging from 0.4–0.9s. The distributions of boarding lost time at the seven common bus stops are shown in Figure 5. From Figure 5, a fairly concentrated distribution can be observed for each type of bus stop, with a range of 0.7s on average between upper quartile and lower quartile. Thus, we use median values as boarding lost time for each bus stop.

FIGURE 5.
Distributions of boarding lost time at seven common bus stops



- *Bus stop failure time* t_f – According to the field investigations, the amount of bus stop failure time was also found to vary by different types of bus stops, with median values ranging from 4.9–6.4s and interquartile range values ranging from 0.5–0.9s. The distributions of bus stop failure time at the seven common bus stops are shown in Figure 6. Similar to Figure 5, it also has a fairly concentrated distribution for each type of bus stop, with a range of 0.7s on average between upper quartile and lower quartile. Thus, the median values can be used as bus stop failure time.

FIGURE 6.
Distributions of bus stop failure time at seven common bus stops



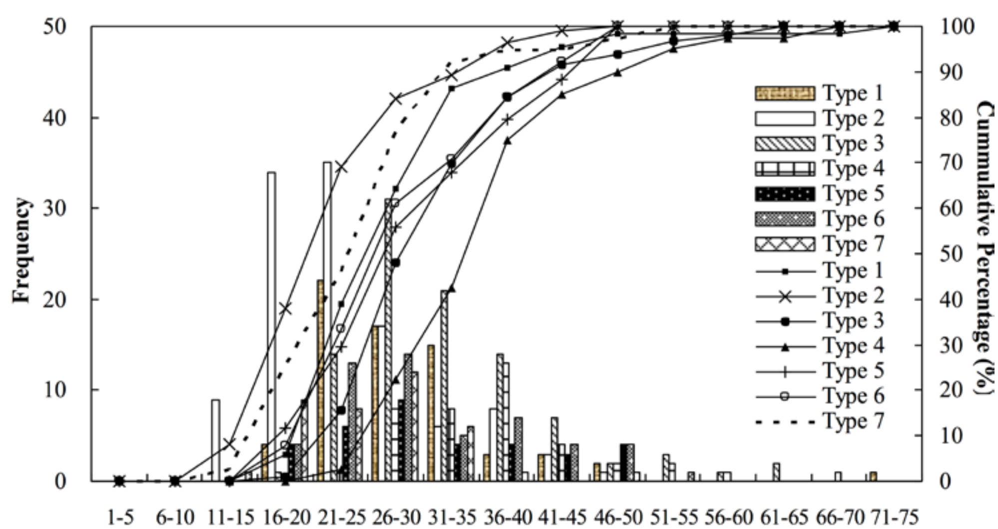
- *Traffic signal delay* t_{sd} – According to the field investigations, the amount of traffic signal delay was found only at bus stops where a traffic signal is nearby, with median values ranging from 14.5–21.1s and interquartile range values ranging from 12.1–12.8s. When traffic signal delays at bus stops are frequent enough, they should be added into the bus dwell time and time lost serving stop. However, in this study, traffic signal delay was rare. According to TCQSM (KFH Group 2013), in this case, the impact of traffic signal delay was accounted for by dwell time variability instead of added into the bus dwell time and time lost serving stop.

Model Validation

Comparison of Results

Frequency histograms and cumulative distribution curves for bus dwell time and time lost serving stop during peak and non-peak periods at the seven types of bus stops are presented in Figure 7. From Figures 7(a) and 7(b), cumulative curves for calculated bus dwell time and time lost serving stop at Type 2 and Type 7 bus stops were invariably to the left of the curves for other types of bus stops during peak and non-peak periods. This indicated that dwell time and time lost serving stop at Type 2 and Type 7 were shorter than at other types, owing to the short distance of bus stop areas. By contrast, the cumulative curve for Type 4 was invariably to the right of the curves for other types of bus stops during peak and non-peak periods. For other types of bus stops, it could be observed that peak and non-peak periods had obvious influences on calculated bus dwell time and time lost serving stop. On the other hand, from Figures 7(a) and 7(c) and Figures 7(b) and 7(d), it could be shown that frequency histograms and cumulative distribution curves for calculated values closely followed those observed values during both peak and non-peak periods.

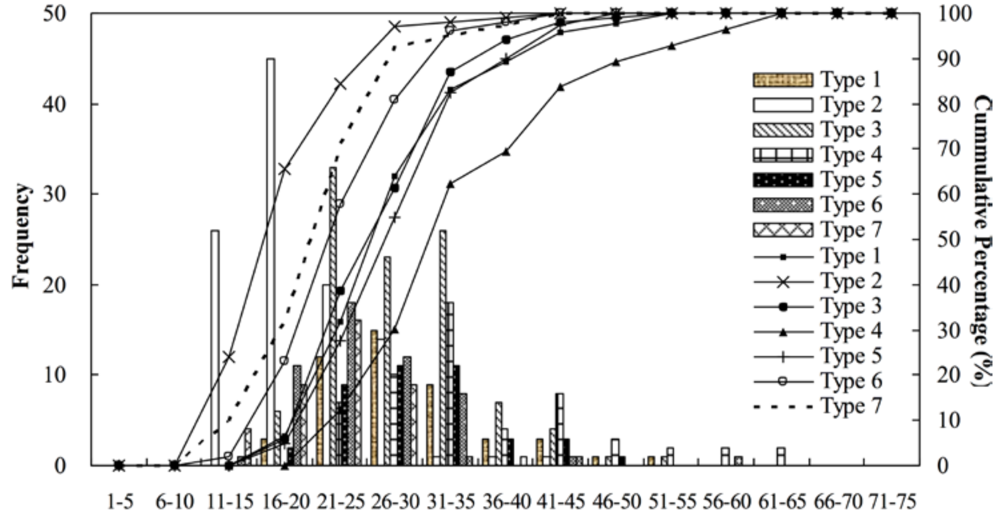
FIGURE 7.
Comparison of calculated and observed bus dwell time and time lost serving stop between peak and non-peak periods



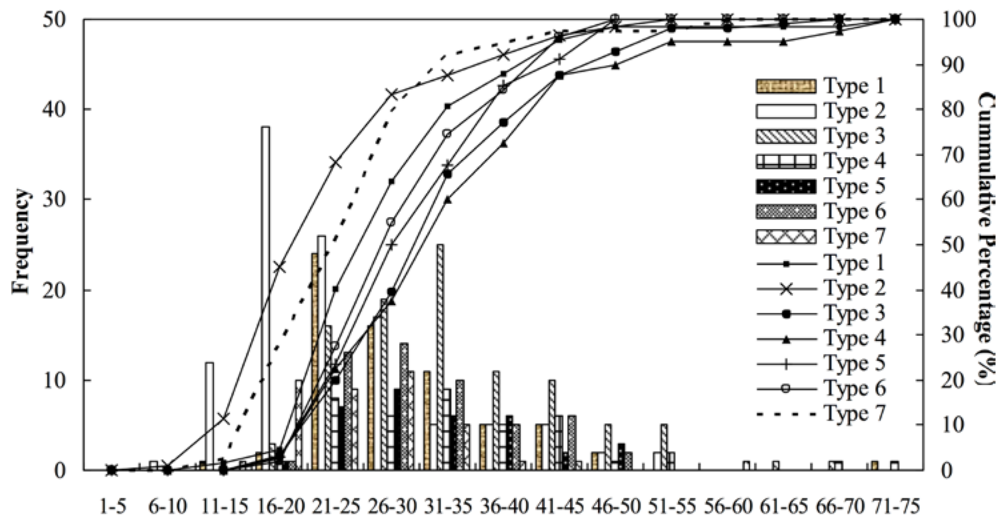
(a) Calculated bus dwell time and time lost serving stop (peak period)

FIGURE 7. (cont'd)

Comparison of calculated and observed bus dwell time and time lost serving stop between peak and non-peak periods

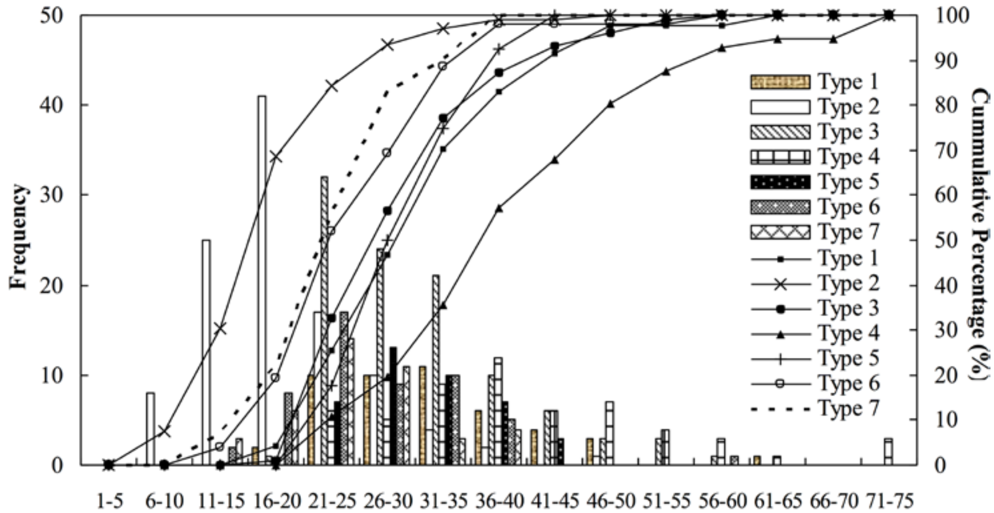


(b) Calculated bus dwell time and time lost serving stop (non-peak period)



(c) Observed bus dwell time and time lost serving stop (peak period)

FIGURE 7. (cont'd)
Comparison of calculated and observed bus dwell time and time lost serving stop between peak and non-peak periods



(d) Observed bus dwell time and time lost serving stop (non-peak period)

In addition, we distinguished between passengers by age: adults (including children) and older adults (age 65+), which allowed us to estimate the different boarding and alighting times of each passenger group. Among all passengers, the percentages of adults and older adults are 82% and 18%, respectively. The boarding time for adults and older adults had, on average, a difference of 1.01 seconds per passenger, indicating that older people are slower to board buses. The difference due to age also is observed in alighting: whereas each adult takes, on average, 1.52 seconds to alight, each older adults takes 2.68 seconds. Thus, older adult passengers are slower to board and alight than younger travelers.

The Mean Absolute Percentage Error (MAPE) was used to measure the differences between the observed and calculated bus dwell time and time lost serving stop. MAPE has no requirement for sample size and shows an obvious advantage in evaluating discrete data. The value of MAPE in this study can be calculated using the following equation:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{T^{i}_{dwell} - t^{i}_{dwell}}{t^{i}_{dwell}}\right| \tag{11}$$

where N denotes the sample size, and T^{i}_{dwell} and t^{i}_{dwell} are calculated and observed bus dwell time and time lost serving stop, respectively.

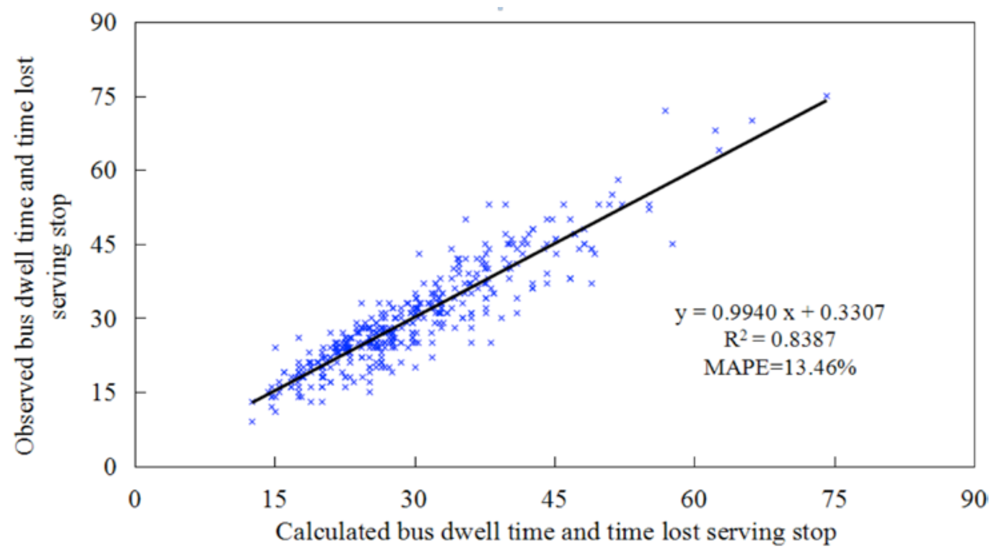
Table 4 presents several measures of effectiveness, including MAPE and R-square values for estimating bus dwell time and time lost serving stop at different bus stops. According to the results of R-square and MAPE, the bus stops having exclusive bus lanes (Types 1, 3, 5, and 6) had better performance than those having mixed traffic lanes (Types 2, 4, and 7). The buses in mixed traffic lanes may be disturbed by other motor vehicles and non-motor vehicles, causing variability for estimating bus dwell time and time lost serving stop. Thus, the right-of-way in the vicinity of a bus stop had obvious influences on the performance of the results. The peak/non-peak period, however, was not a key factor to determine the performance of bus dwell time and time lost estimation. For instance, at the Public Transport Corporation bus stop (Type 3), the value of R-square (0.8331) and MAPE (13.23%) in the non-peak period were better than those (0.8294 and 14.39%, respectively) in the peak period. However, at Beiji Huitang bus stop (Type 2), the results were contrary to those at the Public Transport Corporation stop.

TABLE 4.
Summary Statistics of Bus Dwell Time and Time Lost Serving Stop at Different Types of Bus Stops

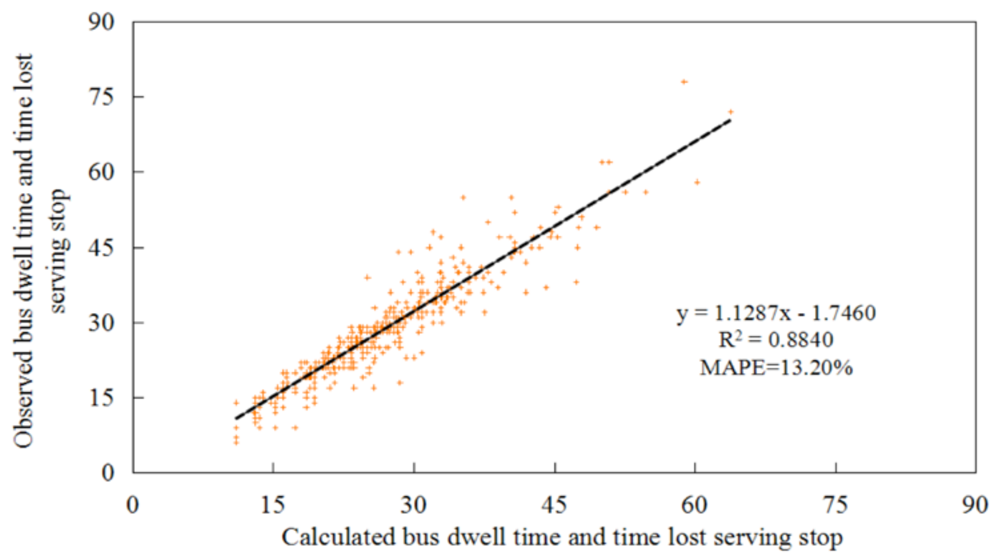
No.	Bus Stop	Type	State	Sample Size	R-square Value	MAPE
1	Gulou North	Type 1	Peak	67	0.8412	12.53%
2			Non-peak	47	0.8341	12.01%
3	Beiji Huitang	Type 2	Peak	113	0.8038	13.42%
4			Non-peak	108	0.7982	14.03%
5	Public Transport Corporation	Type 3	Peak	96	0.8294	14.39%
6			Non-peak	101	0.8331	13.23%
7	Xuanwuhu Park	Type 4	Peak	40	0.8142	13.99%
8			Non-peak	56	0.8066	13.15%
9	Renmin Park	Type 5	Peak	34	0.8744	10.02%
10			Non-peak	40	0.8873	9.54%
11	Gangding	Type 6	Peak	51	0.8534	12.09%
12			Non-peak	52	0.8691	13.05%
13	Danfeng Street	Type 7	Peak	39	0.7829	17.14%
14			Non-peak	41	0.7614	16.14%

To fully evaluate the performance of the proposed method, the values of MAPE and linear regression analysis between calculated and observed bus dwell time and time lost serving stop were graphed, as shown in Figure 8. Scattered data points of peak and non-peak periods were balanced on both sides of the lines of identity, which indicated that the proposed model was not overvalued or undervalued. R-square and MAPE were calculated to be 0.8840 and 13.20% for non-peak and 0.8387 and 13.46% for peak, indicating that the proposed method could estimate bus dwell time and time lost serving stop relatively accurately.

FIGURE 8.
Fitted relationships of bus dwell time and time lost serving stop between calculated and observed data



(*a*) Peak period

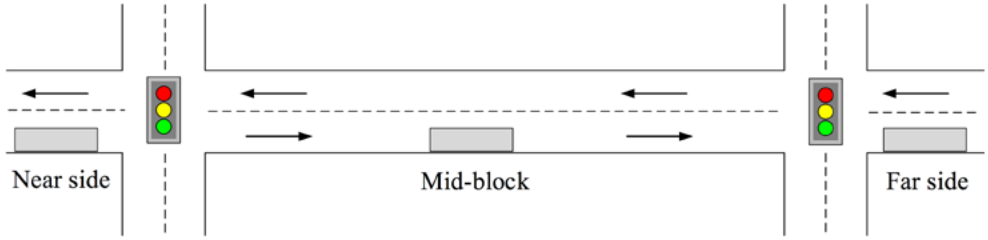


(*b*) Non-peak period

Sensitivity Analysis

Bus stop locations could significantly impact the delay of a bus at a bus stop. In light of this, a sensitivity analysis was conducted to investigate the effects of bus stop locations on bus dwell time and time lost serving stop. As shown in Figure 9, bus stop locations are of three types: near-side, far-side, and mid-block. In this study, Type 3 (Public Transport Corporation) and Type 6 (Gangding) were near-side stops; Type 1 (Gulou North), Type 5 (Renmin Park), and Type 7 (Danfeng Street) were far-side stops; and Type 2 (Beiji Huitang) and Type 4 (Xuanwuhu Park) were mid-block stops.

FIGURE 9.
Schematic drawing of bus stop locations



Analytical results of bus dwell time and time lost serving stop including maximum value, minimum value, mean value, median value, and standard variation are summarized in Table 5. Bus dwell time and time lost serving stop were analyzed based on different bus stop locations (near-side, far-side, and mid-block) and time periods (peak and non-peak). As can be seen, the mean and median values at near-side stops were higher than those at far-side and mid-block stops, indicating that near-side stops had a significant impact on bus dwell time and time lost serving stop. A near-side bus stop is located immediately prior to an intersection and may be influenced by other vehicles in the intersection. Compared with far-side and mid-block bus stops, a near-side bus stop has longer average delay for re-entering the traffic stream, bus stop failure time, and traffic signal delay. For instance, at a near-side bus stop, a bus must wait at the stop until all of the buses have finished serving their passengers and have a green signal enabling them to proceed down the street. Thus, a near-side bus stop creates longer bus dwell time and time lost serving stop. In addition, the mean and median values of near-side, far-side and mid-block stops during the peak period were more than those during the non-peak period.

TABLE 5.
Bus Dwell Time and Time Lost Serving Stop at Different Stop Locations

Bus Stop Location	State	Sample Size	Max (s)	Min (s)	Mean (s)	Median (s)	SD (s)
Near-side stop	Peak	147	69.00	19.00	33.74	32.00	9.16
	Non-peak	153	59.00	12.00	30.43	29.00	8.44
Far-side stop	Peak	140	73.00	13.00	28.22	27.00	9.19
	Non-peak	128	60.00	10.00	28.06	26.00	8.06
Mid-block stop	Peak	153	73.00	10.00	27.52	25.00	11.21
	Non-peak	164	75.00	9.00	27.01	22.00	13.68

Frequency histogram and cumulative distribution curves for bus dwell time and time lost serving stop at different bus stop locations are presented in Figure 10. For the peak period, cumulative curves for dwell time and time lost serving stop at near-side stops were below the curves for far-side and mid-block stops, indicating bus stop location could have an influence on dwell time and time lost serving stop.

T-tests were further conducted to compare bus dwell time and time lost serving stop at near-side, far-side, and mid-block stops. Results showed that the differences in bus dwell time and time lost serving stop taken at near-side and far-side stops and near-side and mid-block stops during peak and non-peak periods were all statistically significant. However, the differences taken at far-side and mid-block stops were not statistically significant. The findings further indicated that near-side stops could result in longer dwell time and time lost serving stop than the other two types of bus stops.

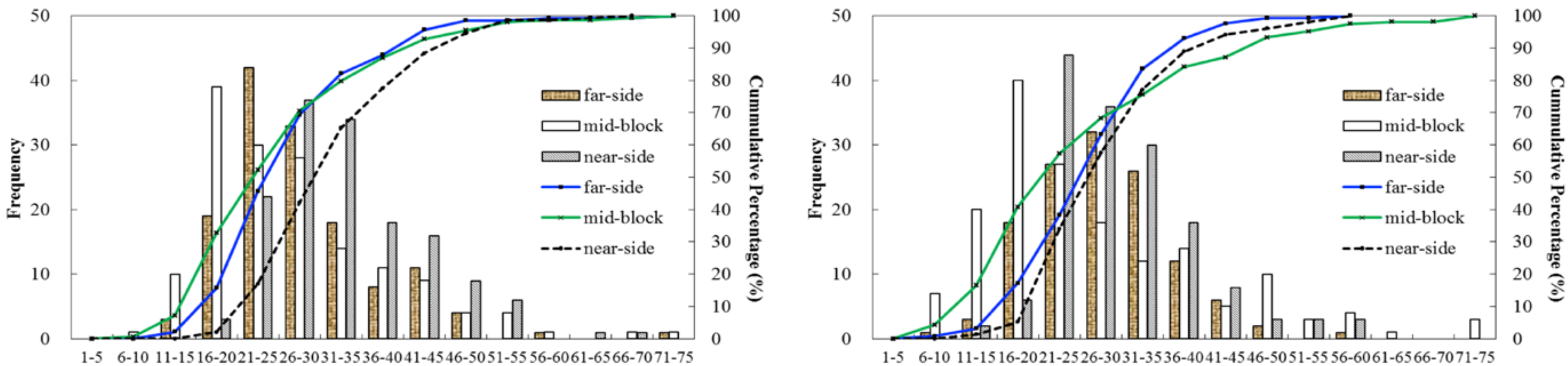
Conclusions

This study proposed a method to estimate bus dwell time and time lost serving stop, which consists of deceleration time, time for serving boarding and alighting passengers, dead time, and acceleration time at the bus stop. A polynomial model incorporating kinematics of a particle was derived for estimating bus acceleration and deceleration times. In addition, descriptive statistics were used to analyze dead time, which involved average delay for re-entering the traffic stream, boarding lost time, bus stop failure time, and traffic signal delay.

A case study was conducted to show the applicability of the proposed model with data collected from the seven common types of bus stops in the cities of Nanjing, Changzhou, and Guangzhou, China. To validate the proposed method, a linear regression analysis was performed to find the correlation between calculated and observed bus dwell time and time lost serving stop. The results of R-square and MAPE (0.8840 and 13.20% for non-peak, 0.8387 and 13.46% for peak) indicated that the proposed method was well validated and could be practically used in China for the analysis and estimation of bus dwell time and time lost serving stop. In addition, sensitivity analyses were conducted to investigate the effects of bus stop locations on bus dwell time and time lost serving stop. The results showed that the differences taken at near-side and far-side stops and near-side and mid-block stops during peak and non-peak periods were all statistically significant. However, the differences taken at far-side and mid-block stops were not statistically significant. The findings further indicated that near-side stops could result in longer dwell time and time lost serving stop than the other two types of bus stops.

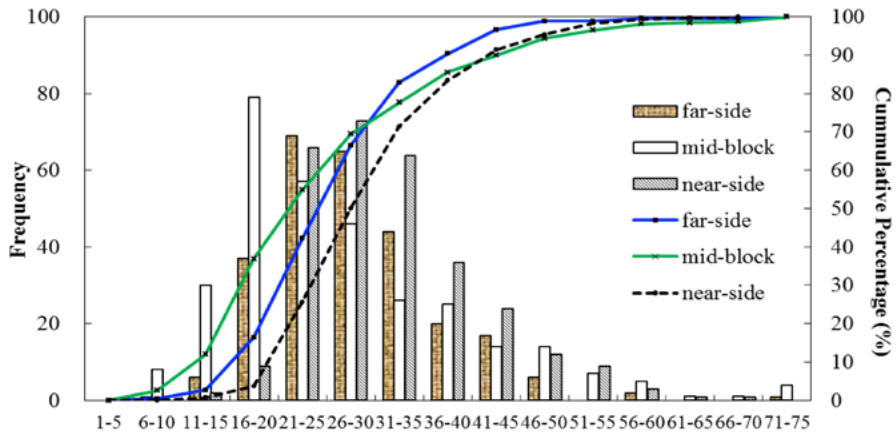
This study explored the bus dwell time and time lost serving stop in urban locations for general weather conditions. Different weather conditions (such as inclement weather conditions) and different locations (such as suburban locations) may have impacts on the performance of the proposed method. Further research can be conducted to investigate their impacts.

In addition, the proposed method can be applied in other locations; however, in different countries, especially in other developing countries, the service time for each passenger and bus dead time at a stop may be different. Thus, to apply the proposed method in other countries, the transit agency will need to collect traffic data to obtain the corresponding characteristics, such as the service time for each passenger.



(a) Peak

(b) Non-peak



(c) Total

t-Test Results

State	Near side vs. Far side	Near side vs. Mid-block	Far side vs. Mid-block
Peak	Yes	Yes	No
Non-peak	Yes	Yes	No
Total	Yes	Yes	No

FIGURE 10. Comparison between bus dwell time and time lost serving stop at near-side, far-side and mid-block stops

Acknowledgments

This study was sponsored by the National Science Foundation of China (No. 51308114), the Scientific Research Foundation for the Returned Overseas Chinese Scholars of State Education Ministry, the Key Project of National Science Foundation of China (No. 51338003), and the Scientific Research Foundation of the Graduate School of Southeast University (No.YBJJ1633).

References

Balasubramanian, P., and K. Rao. 2015. "An Adaptive Long-Term Bus Arrival Time Prediction Model with Cyclic Variations." *Journal of Public Transportation*, 18(1): 1-18.

Bian, B., N. Zhu, S. Ling, and S. Ma. 2015. "Bus Service Time Estimation Model for a Curbside Bus Stop." *Transportation Research Part C*, 57: 103-121.

Ceder, A. 2007. *Public Transit Planning and Operation: Theory, Modeling, and Practice*. Butterworth-Heinemann, Oxford, UK.

Cundill, M., and P. Watts. 1973. "Bus Boarding and Alighting Times." TRRL Report LR 521. Transport and Road Research Laboratory, Wokingham, United Kingdom.

Dueker, K. J., T. J. Kimpel, and J. G. Strathman. 2004. "Determinants of Bus Dwell Time." *Journal of Public Transportation*, 7(1): 21-40.

Federal Highway Administration. 2003. "TSIS/CORSIM User's Manual, Version 5.1." Washington, DC.

Fernandez, R. 2010. "Modelling Public Transport Stops by Microscopic Simulation." *Transportation Research Part C*, 18(6): 856–868.

Fernandez, R., J. Gibson, and M. Mendez. 1995. "Modelacion del Comportamiento en Paraderos Formales." Actas del VII Congreso Chileno de Ingenieria de Transporte, Santiago, Oct. 17-20, 358-368.

Fitzpatrick, K., K. Hall, D. Perkinson, L. Nowlin, and R. Koppa. 1996. "Guidelines for the Location and Design of Bus Stop." TCRP Report 19. Transportation Research Board, Washington, DC.

Furth, P., and T. Muller. 2007. "Part 4: Capacity and Quality of Service—Service Reliability and Hidden Waiting Time: Insights from Automatic Vehicle Location Data." *Transportation Research Record*, 1955: 79-87.

Gu, W., Y. Li, M. J. Cassidy, and J. B. Griswold. 2011. "On the Capacity of Isolated, Curbside Bus Stops." *Transportation Research Part B*, 45: 714-723.

Guenthner, R., and K. Hamat. 1988. "Transit Dwell Time under Complex Fare Structure." *Journal of Transportation Engineering*, 114(3): 367-379.

Hadas, Y., and A. Ceder. 2010. "Optimal Coordination of Public-transit Vehicles Using Operational Tactics Examined by Simulation." *Transportation Research Part C*, 19: 879-895.

Hamdouch, Y., H. W. Ho, A. Sumalee, and G. Wang. 2011. "Schedule-based Transit Assignment Model with Vehicle Capacity and Seat Availability." *Transportation Research Part B*, 45(10): 1805-1830.

Hawas, Y. E. 2013. "Simulation-based Regression Models to Estimate Bus Routes and Network Travel Times." *Journal of Public Transportation*, 16(4): 107-130.

Jacques, K. S., and H. S. Levinson. 1997. "Operational Analysis of Bus Lanes on Arterials." TCRP Report 26. Transportation Research Board, Washington, DC.

Jaiswal, S. 2010. "Busway Platform Bus Capacity Analysis." Ph.D. thesis. Queensland University of Technology, Brisbane, Australia.

Jaiswal, S., J. Bunker, and L. Ferreira. 2010. "Influence of Platform Walking on BRT Station Bus Dwell Time Estimation: Australian Analysis." *Journal of Transportation Engineering*, 136: 1173–1179.

KFH Group. 2013. *Transit Capacity and Quality of Service Manual, Third Edition*. Transportation Research Board, Washington, DC.

Leurent, F., E. Chandakas, and A. Poulhès. 2014. "A Traffic Assignment Model for Passenger Transit on a Capacitated Network: Bi-layer Framework, Line Sub-Models and Large-Scale Application." *Transportation Research Part C*, 47: 3-27.

Levine, J., and G. Torng. 1994. "Dwell Time Effects of Low Floor Bus Design." *Journal of Transportation Engineering*, 120(6): 914-929.

Levinson, H. S. 1983. "Analyzing Transit Travel Time Performance." *Transportation Research Record*, 915: 1-6.

Li, M., F. Zhao, L. Chow, H. Zhang, and S. Li. 2006. "Simulation Model for Estimating Bus Dwell Time by Simultaneously Considering Numbers of Disembarking and Boarding Passengers." *Transportation Research Record*, 1971: 59-65.

Lin, T., and N. H. M. Wilson. 1992. "Dwell Time Relationships for Light Rail Systems." *Transportation Research Record*, 1361: 287-295.

Meng, Q., and X. Qu. 2013. "Bus Dwell Time Estimation at Bus Bays: A Probabilistic Approach." *Transportation Research Part C*, 36: 61-71.

Milkovits, M. N. 2008. "Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data." *Transportation Research Record*, 2072: 125-130.

PTV Group. 2005. VISSIM User Manual, Version 4.10. Karlsruhe, Germany.

Robinson, S. 2013. "Measuring Bus Stop Dwell Time and Time Lost Serving Stop with London iBus Automatic Vehicle Location Data." *Transportation Research Record*, 2352: 68-75.

Szeto, W. Y., M. Solayappan, and Y. Jiang. 2011. "Reliability-based Transit Assignment for Congested Stochastic Transit Networks." *Computer-Aided Civil and Infrastructure Engineering*, 26: 311-326.

Tirachini, A. 2013. "Bus Dwell Time: The Effect of Different Fare Collection Systems, Bus Floor Level and Age of Passengers." *Transportmetrica A*, 9(1): 28-49.

Transportation Research Board. 2000. *Highway Capacity Manual*. Washington, DC.

Wu, Y., J. Tang, Y. Yu, and Z. Pan. 2015. "A Stochastic Optimization Model for Transit Network Timetable Design to Mitigate the Randomness of Traveling Time by Adding Slack Time." *Transportation Research Part C*, 52: 15-31.

Yan, Y., Z. Liu, Q. Meng, and Y. Jiang. 2013. "Robust Optimization Model of Bus Transit Network Design with Stochastic Travel Time." *Journal of Transportation Engineering*, 139(6): 625-634.

Yang, X., Z. Gao, X. Zhao, and B. Si. 2009. "Road Capacity at Bus Stops with Mixed Traffic Flow in China." *Transportation Research Record*, 2111: 18-23.

Ye, Z., C. Wang, Y. Yu, X. Shi, and W. Wang. 2016. "Modeling Level-of-Safety for Bus Stops in China." *Traffic Injury Prevention*, DOI: 10.1080/15389588.2015.1133905.

About the Authors

Chao Wang (*woashiachaoazia@163.com*) is currently a Ph.D. candidate in the School of Transportation, Southeast University. He received his B.E. degree in traffic engineering from Shandong University of Technology, China in 2013. His research interests include public transportation, traffic system modeling and traffic safety.

Zhirui Ye (*yezhirui@seu.edu.cn*) earned his Ph.D. degree in Transportation Engineering from Texas A&M University. He has more than 10 years of experience in transportation engineering and science research and is a professor in the School of Transportation and director of the Institute of Transportation Engineering at Southeast University, China. Previously, he was a research scientist at the Western Transportation Institute at Montana State University.

Yuan Wang (*wangyuan_1990@seu.edu.cn*) received her B.S. in transportation engineering from Southeast University in 2012. She is now a Ph.D. candidate in transportation engineering at Southeast University. Her research interests include public transportation and traffic safety.

Yueru Xu (*xuyr1992@163.com*) received his B.S. in transportation engineering from Southeast University in 2013. He is now a graduate research assistant in transportation engineering at Southeast University. His research interests include public transportation and traffic safety.

Wei Wang (*wangwei@seu.edu.cn*) is a professor in the School of Transportation at Southeast University. During the past decades, he has focused on teaching and conducting research in the areas of transportation system planning and management, traffic flow theory, highway capacity, and intelligent transportation systems.

Public Transport Crowding Valuation: Evidence from College Students in Guangzhou

Jianrong Liu and Huiying Wen
South China University of Technology

Abstract

Overcrowding has grown to be an increasingly important issue for public transit in Guangzhou, China. To capture traveler benefits of reduced crowding from improved public transport, it is necessary to identify the relevant importance of crowding to travelers. This paper analyzes the disutility of crowding in metro car and bus transit with discrete choice models. Based on the stated preference survey data from college students in Guangzhou, the results show that there is non-negligible impact of crowding on passenger travel. The relationship between the disutility of crowding and standee density is not linear; that is, the disutility increases at a modest rate as the standee density increases when it is easy to move around in cars and increases rapidly when it is difficult to move around in cars. Also, there is only a slight difference between the effects of crowding on metro and bus transit.

Keywords: *Crowding; discrete choice; public transit; stated preference*

Introduction

Traditionally, researchers have considered travel time and cost as main attributes that influencing peoples' travel choice behaviors. However, as Tirachini et al. (2013) and Hensher et al. (2013) point out, with the improvement of the understanding of the modal choice problem, there is solid evidence that travelers not only take into account of quantitative attributes such as travel time and cost, but also qualitative aspects that may influence the experience of traveling, such as crowding, reliability, etc. Because of the high density of passengers in carriages of public transit, there may be many effects on passenger well-being, such as anxiety, stress, feelings of exhaustion, reduction of perceived security, and so on.

Because there are so many effects of crowding on traveler well-being, it is necessary to determine how much travelers are willing to pay to reduce the crowding in carriages of public transit. Therefore, this paper attempts to determine the influences of crowding in carriages of public transit and if there is difference between passenger viewpoints on crowding in metro cars and buses.

As pointed by Zhan (2016), in Chinese high-education regions, the university campus is a special community in which the high student density generates a large and significant trip demand. Therefore, exploring and understanding college students' evaluation of the impact of public transit are the basic supports for transportation development strategies policies and planning.

Literature Review

Crowding on public transit reduces the probability that passengers will find a seat in carriages and prevents individuals from using travel time for other activities effectively (reading, rest, etc.). Congestion in public transit also may induce security fears, increase noise levels, and reduce hygiene. All of these effect increase personal stress and dissatisfaction (O'Regan and Buckley 2003; Evans and Wener 2007; Mahudin et al. 2011; Mahudin et al. 2012; Li and Hensher 2013). Theyf also may affect traveler path choice of public transportation (Kim et al. 2016).

Noting widespread dissatisfaction with crowding in bus or metro cars, a considerable number of studies have been carried out to determine the effects of crowding. Most analyzed the valuation of crowding in public transportation with discrete choice models. Generally, there are two discrete choice models, the constant value per trip model and the multiplier value model. The constant value per trip model assumes that the crowding effect is irrespective of the duration of travel; the travel time multiplier value model assumes that the crowding effect is proportional to travel time. In addition to discrete choice models, there are other methods used to analyze the value of crowding.

Constant Value per Trip Model

Cantwell et al. (2009) divided the crowding conditions on trains and buses into five segments—very crowded, somewhat crowded, neither crowded nor uncrowded, somewhat uncrowded, and very uncrowded. It was found that the ratio between the valuation of train crowding and bus crowding was 1.4, which indicates that users would derive a greater benefit from a reduction in crowding. Basu and Hunt (2012) defined five levels of in-vehicle crowding in a qualitative manner and found the in-vehicle valuations (in Indian Rupees) to be 0.32 for light, 0.46 for moderate, 0.54 for heavy, and 0.59 for very heavy, adopting very light crowding as the benchmark.

Multiplier Value Model

Accent (2006) provided multi-level qualitative descriptions to crudely specify in-vehicle crowding, that is, seat flip uncrowded, seat flip crowded, seat perch uncrowded, seat perch crowded, stand uncrowded, stand lean, and stand crowded. The multipliers of these conditions varied from 1.0–2.14. Douglas and Karpouzis (2006) estimated the passenger cost of on-train crowding with Stated Preference (SP) data, in which eight levels of crowding were provided (uncrowded seat, crowded seat, stand up to 10 minutes, stand 15 minutes, stand 20 minutes or longer, crush stand up to 10 minutes, crush stand 15 minutes, crush stand 20 minutes or longer). The relative valuation compared to uncrowded seating varied from 1.17–2.52. Furthermore, gender was found to be an influence; females had a higher cost associated with standing in crushing conditions than males.

The written descriptions of in-vehicle crowding in Mott (2007) were plenty of seats, a few seats available, no seats available and a few standees, and no seats and densely-packed. Also, the paper divided travelers into seven groups—traders only, commuters, non-commuters, car available, non-car available, up to 40 minutes, and over 40 minutes. The multipliers varied from 1.00–3.01 for commuters, and the others were similar.

MVA Consultancy (2008) specified in-vehicle crowding with standee density (standees per square meter) and analyzed seating multipliers and standing multipliers. The seating multipliers and standing multipliers for business travelers varied from 1.00–1.81 and 1.91–2.16, respectively, when the standee density increased from 0 to 6 passengers per square meter (m^2). Non-business travelers tended to have somewhat low multipliers.

Lu et al. (2008) conducted an SP experiment in Greater Manchester in 2005 in which crowding was shown with combinations of probability of standing and length of time (for example, 2 out of 5 times standing for an entire journey). Within the multinomial logit (MNL) model, the value of crowding was estimated at 12.05 pence per person minute, which is more than twice the value of in-vehicle time. Whelan and Crockett (2009) estimated of the value of overcrowding in trains with an SP survey. To describe and present all attributes in an objective and quantifiable way with a minimal scope for differences in interpretation, they developed a combination of verbal and graphical stimulus material for use in the SP study. The results showed that there is a linear relationship between time multipliers and standee density and found that journey purpose, distance, and income had a significant impacts on time multipliers.

Hensher et al. (2011) described crowding attribute levels by mode with seats occupied and number of standees and showed that with the rise in the number of standees, the crowding utility increases with a quadratic function and the crowding valuation of metro is slightly higher than that of bus. Wang and Legaspi (2012) described in-vehicle crowding with a load factor, in which the multipliers were functions of load factor and standing time. For example, the cost of in-vehicle crowding per minute for standing 10–20 minutes was smaller than that for standing 20 minutes or more.

Haywood and Koning (2013, 2015) specified in-vehicle crowding with passenger density, which is different from standee density. The multipliers ranged from 1.00–1.57, and standee density ranged from 0–6 pass/m^2. Kroes et al. (2013) presented in-vehicle crowding levels by mode with load factor, which ranged from 25–250%. Tirachini et al. (2013) studied the relationship between multipliers and load factor and between multipliers and standee density. It was found that there was a linear relationship between multipliers and standee density, and the multipliers reached approximately 3 when the standee density was 4 standees/m^2.

Vovsha et al. (2014) quantified in-vehicle crowding with seven categories associated with the probability of having a seat and the inability to board when crowding reaches an extreme level. Data in that paper shows that trip purpose, age, travel mode, income, and trip length had influence on multipliers, although all these effects were not striking. Batarce et al. (2015) evaluated time multipliers with SP data and RP data; results shows that the time multipliers at 5–6 standees/m^2 is 2.1 times the multipliers at 1–2 standees/m^2.

Other Methods

Cantwell et al. (2009) analyzed the relationship between crowding in public transport and commute satisfaction with a linear regression analysis. Haywood and Koning (2011) investigated the impact of travel comfort on the utility of subway users with an ordered logit model and found that metro passengers were prepared to travel, on average, eight minutes longer per trip to reduce the high peak-hour level of crowding to the substantially lower level of crowding experienced outside the peaks. This is roughly equivalent to a value of about 1.5 euros per trip, which is clearly non-negligible. Also, it was found that certain individual characteristics (age, socioeconomic status, etc.) significantly influence willingness to pay. Prud'homme et al. (2012) estimated the disutility of crowding with the ordered logit model.

Two papers review the literature about crowding on public transit. Li and Hensher (2011) reviewed public transport crowding valuation research using studies conducted in the UK, the U.S., Australia, and Israel and identified three measures to value crowding—a travel time multiplier, a monetary value per time unit, and a monetary value per trip—but they did not provide a comparison between their performances. They also described associated ways to represent crowding in SP experiments and implied that SP research is the preferred way of conducting valuation research for crowding. Despite the highly-different characteristics of the studies reviewed, they noted that all reported that crowding would increase the value of travel time savings, which, according to them, "can be viewed as an additional component of generalized time."

Wardman and Whelan (2011) reviewed evidence from British experience of the valuation of rail crowding obtained over 20 years from 17 studies in a meta-analysis project and found that the seating multiplier averages 1.19 and the standing multiplier averages 2.32, which implies that the disutility of travel in a very crowded situation for standees is more than twice as much as compared with a situation when seats are available.

Although many studies on crowding have been conducted, most have been in developed countries or areas. There is still little research on crowding in China, especially based on passenger perception. Li and Hensher (2013) argued that the benchmarks that define the unacceptable crowding levels vary across different countries or regions. For example, four standees per m^2 is the benchmark for Australia (Diec et al. 2010), a number that increases to five standees per m^2 for the U.S. (Furth et al. 2006).

Furthermore, as Das and Pandit (2013) pointed out, "Since the service delivery environment differs between developed and developing nations, the user perception of service quality varies between these economic regions"; as a result, research results from developed countries or areas not suitable for China.

Experiment Design and Data Collection

In this study, we analyzed the valuation of in-vehicle crowding with multinomial logit model.

Although Turner et al. (2004), Cox et al. (2006), and Li and Hensher. (2013) argued that there is a disconnection or gap between objective and subjective measures of crowding, there are still many debates on the subjective measures of crowding. The objective measures, such as the number of standing passengers per square meter, are still an appropriate representation of passenger subjective measure of crowding.

To estimate the economic value passengers place on crowding in a metro car or bus, this study conducted an SP choice experiment in which a sample of passengers was offered a series of choices between two (or more) hypothetical alternative public transport services. These services differed in some key characteristics.

To ensure that the interviewees could easily understand the scenarios presented to them and to ensure that the key attributes of the scenarios were presented in a quantifiable manner, the experiment was designed with a two-stage process—a pilot survey and a formal survey. In the pilot survey stage, several choice attributes were considered for inclusion within the SP exercises: (1) level of crowding in metro car, (2) waiting time on subway platform, (3) fare, (4) journey time in metro car, (5) walking time from origination to subway platform and from platform to destination, and (6) interchange.

As mentioned, there are many ways to represent in-vehicle crowding, such as load factor, standee density, combinations of probability of standing and length of standing time, and so on. Because the average commuting time in Guangzhou exceeds 45 minutes during rush hour, public transportation can be so overcrowded that the door is blocked by passengers, sometimes making boarding and alighting difficult; thus, it is entirely possible for passengers to stand at the same level of overcrowding for the entire trip. Therefore, in this study, we did not represent in-vehicle crowding with the probability of standing. Since the same load factor may have different levels of crowding across different types of trains with varying amounts of seating and standing space, this study describes crowding with the objective standard measure of number of standing passengers per square meter.

It is difficult for respondents to identify in-vehicle crowdedness when presented only with standee density, e.g., 6 standees/m^2. Therefore, to enable respondents to have a clear and consistent understanding of the levels of crowding, in-vehicle crowding (or standee density) was described using the linguistic notion method. Based on related research achievements by Jiang et al. (2012) and Qin and Jia (2012, 2014), crowding levels were described as shown in Table 1.

TABLE 1.
Standee Density and Crowding Description in Metro Cars and Bus Carriages

Crowding Conditions	Standee Density	Crowding Description
Crowding1	0 person/m^2	No person standing inside car
Crowding2	1 person/m^2	No seat, but can circulate freely
Crowding3	4 persons/m^2	Some restrictions in movement, high probability of physical contact
Crowding4	7 persons/m^2	Impossible movement, difficult to get on/off car

An example of the layout of the SP question is shown in Figure 1. A focus group of 4 people was asked to evaluate the interpretability of the question. All noted that there were too many attributes and that it was easy to get confused. Therefore, after discussion, the number of attributes was decreased. The attributes and level of each attribute are shown in Table 2.

Since the average commuting time in Guangzhou is around 50 minutes, four levels were set for this attribute—30 minutes, 40 minutes, 45 minutes, and 60 minutes. For standee density, four levels were used based on reality, three levels for fare, and three levels for waiting time on platform.

FIGURE 1.
Example SP question of pilot survey

Situation 1	
Metro A	**Metro B**
Some restriction in movement, high probability of physical contact	**No seat, but can circulate freely**
Waiting time is 5 minutes	**Waiting time is 10 minutes**
Journey time is 35 minutes	**Journey time is 40 minutes**
Walking time is 8 minutes	**Walking time is 6 minutes**
Fare is ¥2	**Fare is ¥3**
Don't need to transfer	**Have to transfer for a time**
Q: Which metro do you prefer?	
☐ **Prefer A**	☐ **Prefer B**

TABLE 2.
Levels of Attributes in Formal Investigation

Attribute	Level of Attribute
Journey time in metro car	i) 30 min, ii) 40 min, iii) 45 min, iv) 60min
Standee density	i) 0 person/m^2, ii) 1 person/m^2, iii) 4 persons/m^2, iv) 7 persons/m^2
Fare	i) ¥3, ii) ¥4, iii) ¥5
Waiting time on platform	i) 5 min, ii) 10 min, iii) 15 min

With attributes and levels mentioned in Table 2, a total of 144 (4 × 4 × 3 × 3) profiles (or a virtual transit system) could be formed, but it was unrealistic and unnecessary to ask the respondents to evaluate all the profiles, and orthogonal design was not used because it would produce too many profiles, especially when the goal is to induce interactions between crowding and travel time.

To gain the separate effects and interactions of attributes, the DOE platform in the software JMP was used to create a choice design. To create an effective design, information about all the attributes and their levels was needed. Therefore, a sample survey was created for a pilot study, and prior information was obtained with JMP. The core of the survey was a set of SP questions in which respondents were asked to sort three hypothetical journeys that differed in terms of on-train travel time, waiting time, on-train crowding, and ticket fare according to their preferences. Respondents were asked to make their choice in the context of the trip they were making. Each respondent undertook one comparison. A total of 16 choice sets similar to Appendix II were developed. Times and crowding were varied systematically so that the effect of travel time and crowding could be established statistically. The choice sets were used for metro and bus.

College students were selected as the focus of the study. Because the demographic characteristics of college students is somewhat different from working people, except for the SP choice investigation, some demographic characteristics were also investigated, as shown in Figure 2.

FIGURE 2.
College student characteristic survey

Gender	Woman	
	Man	
Average monthly consumption	≤ ¥1000	
	¥1000–¥1500	
	¥1500–¥2000	
	≥ ¥2000	

Do you have a car?	Yes	
	No	
Frequency of travel by metro	Very often ≥ 3 times/week]	
	Often 1–4 times/week	
	Occasional 1–3 times/month	
	Circumstantial	

Data Analysis

Sample Size and Descriptive Analysis

The surveys were undertaken between April and May 2015 for metro and between July and August 2015 for bus on the main campus of South China University of Technology in downtown Guangzhou. Each respondent was asked to evaluate only one choice set in Appendix II, and each choice set was evaluated 23 times for metro and 13 times for bus, resulting in 368 valid surveys for metro and 208 for bus. Table 3 shows the socioeconomic characteristics of the college students from the data obtained in the SP survey.

TABLE 3.
Distribution of Sample into Different Socio-Economic Groups

Category	Sub-category	Percentages (%)	
		Metro	*Bus*
Gender	Woman	48.90%	40.10%
	Man	51.10%	59.90%
Do you have a car?	Yes	0.00%	0.00%
	No	100.00%	100.00%
Average monthly consumption	≤ ¥1000	18.80%	22.77%
	¥1000–¥1500	32.60%	38.12%
	¥1500–¥2000	39.10%	33.66%
	≥ ¥2000	9.50%	5.45%
Frequency of travel by metro	Very often (≥ 3 times/week)	51.60%	43.56%
	Often (1–4 times/week)	36.70%	48.02%
	Occasional (1–3 times/month)	11.70%	8.42%
	Circumstantial	0.00%	0.00%

In total, 48.90% of metro respondents and 40.10% of bus respondents were women. A total of 88.30% traveled by metro more than once a week, and 91.58% traveled by bus more than once a week. All respondents were familiar with metro and bus.

Modeling and Discussion of Results

The collected SP data were analyzed with the multinomial logit model in which decision-makers are assumed to make choices based on the concept of utility maximization.

Model 1 – Single Constant Value Model

The analysis began with the estimation of the single constant value per trip model, as specified in Equation 1:

$$U_i = \alpha_0 \mathrm{IVT} + \alpha_1 \mathrm{Fare} + \alpha_2 \mathrm{Wait} + \sum_{i=1}^{4} \beta_i D_i + \varepsilon_i \tag{1}$$

Where U_i is the utility of alternative *I*, Fare is the journey ticket price, IVT is the journey time in car (minutes), Wait is the waiting time on the platform, D_i is a vector of four dummy variables representing the four different levels of crowding shown in Table 1, and ε_i is the unobserved part of utility. α_0, α_1, α_2, β_1, β_2, β_3, β_4 are the coefficients to be estimated.

The choice probability that alternative *i* over alternative *j* can be expressed with $P_i = \Pr ob(U_i > U_j,\ \forall j \neq i)$. Since the choice probability that alternative *i* is selected depends only on the difference in utility, but not its absolute level, we normalized β_1 to zero, and β_2, β_3, β_4 can be interpreted as being to β_1.

The results of the single constant value per trip model runs are shown in Table 4.

TABLE 4.
Results of Single Constant Value per Trip Model

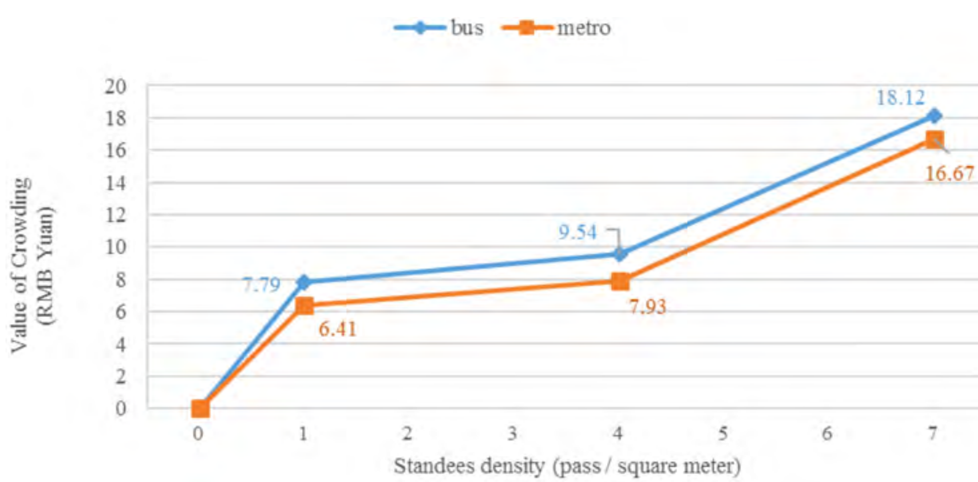
	Parameters	β_2	β_3	β_4	α_0	α_1	α_2
Metro	Coefficient	-1.53515*	-1.89828*	-3.99241*	-0.09653*	-0.23946*	-0.11975*
	Standard Error	0.16314	0.18559	0.27845	0.00982	0.06581	0.01715
	z	-9.41	-10.23	-14.34	-9.83	-3.64	-6.98
	Prob. |z|>Z***	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000
Bus	Coefficient	-1.34293*	-1.64462*	-3.12547*	-.07165*	-.17247**	-.05972*
	Standard Error	0.20071	0.21929	0.29068	0.01114	0.08094	0.01943
	z	-6.69	-7.50	-10.75	-6.43	-2.13	-3.07
	Prob. |z|>Z***	0.0000	0.0000	0.0000	.0000	0.0331	0.0021

**Significant at 10% level*
*** Significant at 5% level*
****Significant at 1% level*
Fit statistics for bus: R^2 = 0.3208, F = 268.3921
Fit statistics for metro: R^2 = 0.3417, F = 419.4775

As shown in Table 4, all the coefficients were significant at the 95% confidence level (Prob.|z|>Z* << 0.05). The estimated coefficients in Table 4 provide information on the value of crowding levels.

Dividing the coefficients in Table 4 except for α_1 by α_1, we obtained the coefficients' value expressed by ticket price (RMB Yuan), as shown in Figure 3, which indicates that the values of crowding in bus are slightly larger than those in metro.

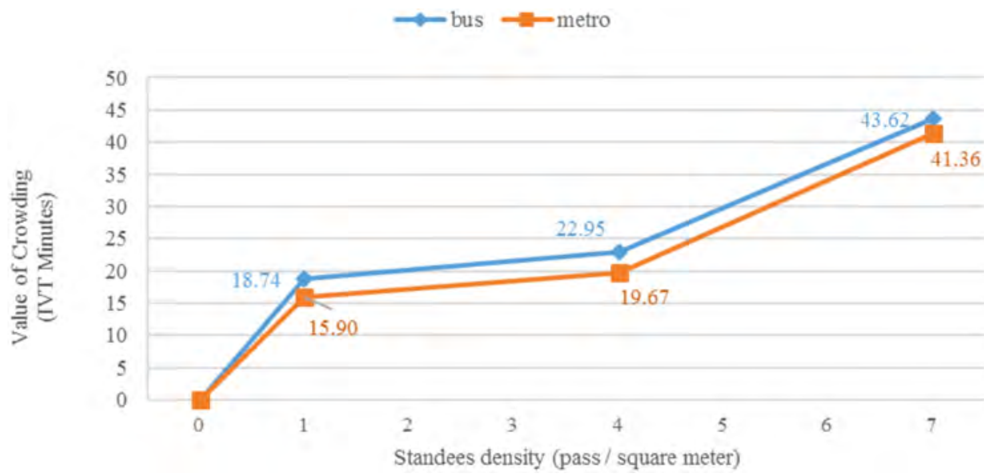
FIGURE 3.
Monetary values of different levels of crowding (RMB Yuan)



Crowding's value in metroincreases to ¥6.41 if passengers have to stand, even though the standee is free to circulate. But the value increases slowly as the standee density increases when it is less than 4 persons/m^2 (no high probability of physical contact). The disutility of crowding increases rapidly as the standee density increases when it is more than 4 persons/m^2—that is, the slope of the line between 4 persons/m^2 and 7 persons/m^2 (7.13) is much larger than that between 1 person/m^2 and 4 persons/m^2 (0.97). Crowding's value for bus is almost the same as that for metro.

Dividing the coefficients in Table 4 except for α_0 by α_0, we obtained the coefficients' value expressed by journey time (in minutes), as shown in Figure 4.

FIGURE 4.
Values of different levels of crowding expressed by IVT (min)



Also as shown in Figure 4, the characteristic of crowding's value (expressed by journey time) in a bus is almost the same as that in a metro, except that crowding's values in a bus are slightly larger than that in a metro. Crowding's value in a metro car increases to 15.90 minutes if passengers have to stand and to 41.36 minutes when standee density increases to 7 standees/m^2. Crowding's value in a bus increases to 18.74 minutes if passengers have to stand and to 43.62 minutes when standee density increases to 7 standees/m^2.

Therefore, we can conclude that passengers dislike crowding strongly, especially when there is a high probability of physical contact.

Model 2. Travel Time Multiplier Model

The single constant value model assumes that the crowding effect is irrespective of the duration of travel. Kroes et al. (2013) argued that the longer the journey, the more important it is to travel comfortably, so the travel time multiplier value model, which assumes that the crowding effect is proportional to the travel time, seems intuitively more appealing. Therefore, we analyzed the effect of crowding in a metro car with the travel time multiplier model. The equation can be expressed as:

$$U_i = \alpha_1 \text{Fare} + \alpha_2 \text{Wait} + \sum_{i=1}^{4} \gamma_i D_i \cdot \text{IVT} + \varepsilon_i \tag{2}$$

Where the meanings of the parameters (U_i, Fare, Wait, IVT, D_i, ε_i) are the same as in Equation 1. α_1, α_2, γ_1, γ_2, γ_3, γ_4 are the coefficients to be estimated. The results of the travel time multiplier value model runs are shown in Table 5.

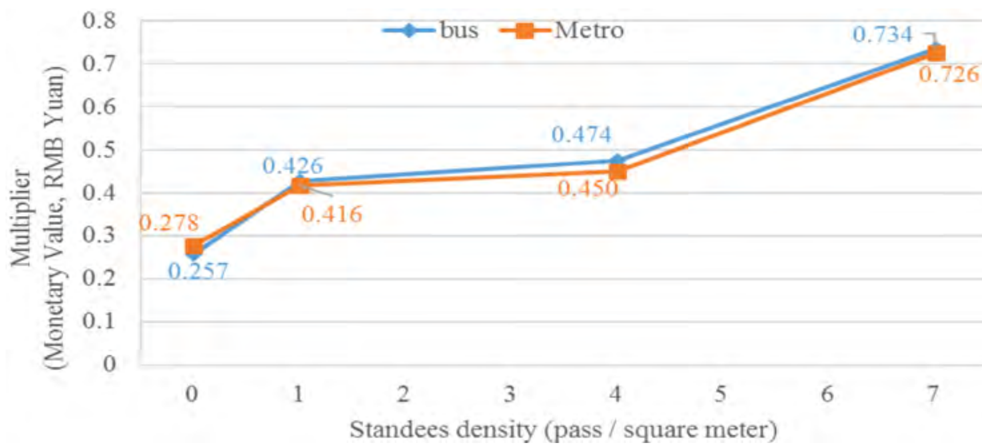
TABLE 5.
Results of Travel Time Multiplier Value Model

	Parameters	γ_1	γ_2	γ_3	γ_4	α_1	α_2
Metro	Coefficient	-0.05682A*	-0.08501*	-0.09200*	-0.14836*	-0.20441*	-0.10619*
	Standard Error	0.00812	0.00923	0.00997	0.01220	0.06483	0.01620
	z	-7.00	-9.21	-9.23	-12.16	-3.15	-6.56
	Prob. |z|>Z***	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000
Bus	Coefficient	-0.03823*	-0.06344*	-0.07051*	-0.10925*	-0.14882***	-0.05493*
	Standard Error	0.00970	0.01081	0.01163	0.01303	0.08080	0.01880
	z	-3.94	-5.87	-6.06	-8.38	-1.84	-2.92
	Prob. |z|>Z***	0.0001	0.0000	0.0000	0.0000	0.0655	0.0035

**Significant at 10% level*
****Significant at 1% level*
Fit statistics for bus: R^2 = 0.3192, F = 270.0541
Fit statistics for metro: R^2 = 0.2913, F = 428.0019

As shown in Table 5, all the coefficients are significant at the 95% confidence level (Prob.|z|>Z* << 0.05), except α_1 of bus, which is significant at the 90% confidence level. Dividing the coefficients in Table 5 except for α_1 by α_1, we obtained the coefficients' value expressed by monetary value (RMB Yuan), as shown in Figure 5.

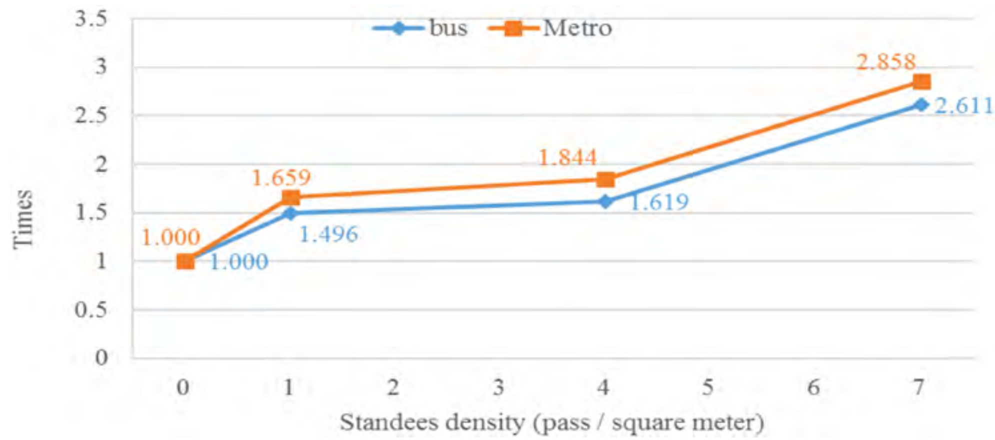
FIGURE 5.
Relationship between value of time multiplier and standee density in metro car



It can be easily determined from Figure 5 that the difference between the bus multiplier and the metro multiplier is extremely small.

To evaluate the effect of crowding more clearly, it was necessary to use relative multipliers. Therefore, we chose a multiplier of bus when the standee density was 0 standees/m^2 as the reference value and divided all multipliers of bus by the reference value to obtain the relative multipliers of bus, and did the same for multipliers of metro. The relative multipliers are shown in Figure 6.

FIGURE 6.
Relative multipliers compared with reference values



The relative multipliers value increases slowly as the standee density increases when it is less than 4 persons/m^2 (no high probability of physical contact) and increases rapidly when the standee density is larger than 4 persons/m^2. The relative multiplier of metro when the standee density is 7 persons/m^2 is 2.858 times that when the standee density is 0 persons/m^2 and is 2.611 for bus.

Conclusions

Using data from a survey of college students in Guangzhou, we proposed individual trade-offs among travel time, cost, waiting time, and passenger density and found that crowding is a non-negligible factor that affecting a traveler's utility and mode choice. For example, crowding's value in a metro car increases to 15.90 minutes if passengers have to stand and to 41.36 minutes when standee density increases to 7 persons/m^2. Since the average one-way commuting time in Guangzhou is about 45 minutes, crowding's value is obviously non-ignorable. Furthermore, there is non-linear relationship between the disutility of crowding and standee density. This disutility increases at a modest rate as the standee density increases when it is no more than 4 persons/m^2 and increases rapidly when standee density is more than 4 persons/m^2. Therefore, 4 persons/m^2 (where there is a high probability of physical contact) is a critical point of disutility. Furthermore, there is only small difference between values of crowding in bus carriages and metro cars.

This conclusion is different from that of other published papers. The ratio that compares the train crowding coefficient with the bus crowding coefficient equals to 1.4 in Cantwell et al. (2009, and the ratios are larger than 1 in Vovsha et al. (2014). However, the ratio in this study fluctuated around 1. In fact, the ratios vary from 1.09 to 1.21 for the single constant value model and 0.92 to 1.05 for the travel time multiplier model. Since the travel time multiplier model seems intuitively more appealing, we can conclude from the data in this study that there is a negligible difference between crowding's valuation in metro and bus in the same crowded situations.

MVA Consultancy (2008), Tirachini et al. (2013), and Whelan and Crockett (2009) concluded that there is a linear relationship between the cost of crowding in a carriage and standee density. However, the results in this study show a high cost for standing relative to sitting (time is valued 1.5–1.65 times higher) but little extra cost for standing in moderately-crowded conditions. Crush standing, however, nearly doubles the time multiplier. The results in this study are quite different from previous studies. When the carriage is not extremely crowded (standee density less than 4 standees/m^2), there is little difference among the multipliers in this study and the multipliers in previous studies, but there are great differences among the multipliers in this study and the multipliers in previous studies. For example, the time multiplier for metro is 2.858 in a crush standing condition, and the time multipliers in MVA Consultancy (2008) and Whelan and Crockett (2009) are only around 2.

Traditional planning practices usually focus on quantitative factors (travel time, cost, etc.). Although some planners in China have recognized the existence of crowding in cars of public transit, they have overlooked and undervalued its impact. The conclusion in this study is particularly important for transit planning because metro's service quality varies greatly and because nearly all transit service quality decisions are made in a formal planning process. Our results can be used during the planning and appraisal stages of public transport projects. For example, in the design of a bus or metro network, planners should focus not only on traditional factors such as traveling time, walking time, ticket price, etc., but also on the impact of crowding in cars. In the analysis of network equilibrium, researchers should also take into account the impact of crowding in public transit.

In this study, survey data were obtained only from college students, and results perhaps can be generalized to others, such as commuters and older adults. However, since demographic characteristics may affect the evaluation of crowding in public transit, it is necessary to obtain more survey data from other groups to analyze the impact of crowding in carriages and determine the differences between the cost of crowding in bus and metro cars.

Acknowledgment

This paper was sponsored by the National Natural Science Foundation of China (Grant No. 51378222) and Guangdong Provincial Science-technology Planning Projects (2013B010401009).

References

Accent. 2006. "Rail Customer Valuations of Sitting, Standing and Crowding." Prepared for Transport for London.

Batarce, Marco, Juan Carlos Muñoz, Juan de Dios Ortuzar, Sebastián Raveau, Carlos Mojica, and Ramiro Alberto Ríos. 2015. "Valuing Crowding in Public Transport Systems Using Mixed Stated/Revealed Preferences Data: The Case of Santiago." *TRB 94th Annual Meeting Compendium of Papers*, Washington DC.

Basu, Debasis, and John Douglas Hunt. 2012. "Valuing of Attributes Influencing the Attractiveness of Suburban Train Service in Mumbai City: A Stated Preference Approach." *Transportation Research Part A: Policy and Practice*, 46(9): 1465-1476.

Cantwell, Mairead, Brian Caulfield, and Margaret O'Mahony. 2009. "Examining the Factors that Impact Public Transport Commuting Satisfaction." *Journal of Public Transportation*, 12(2): 1-21.

Cox, Tom, Jonathan Houdmont, and Amanda Griffiths. 2006. "Rail Passenger Crowding, Stress, Health and Safety in Britain." *Transportation Research Part A: Policy and Practice*, 40(3): 244-258.

Das, Shreya, and Debapratim Pandit. 2013. "Importance of User Perception in Evaluating Level of Service for Bus Transit for a Developing Country like India: A Review." *Transport Reviews*, 33(4): 402-420.

Diec, J., S. Coxon, and A. de Bono. 2010. "Designing a Public Train Station Shelter to Minimise Anti-Social Behaviour and Crime in Melbourne's Metropolitan Rail Environment." 33rd Australasian Transport Research Forum (ATRF), Canberra, ACT, Australia.

Douglas, Neil, and George Karpouzis. 2006. "Estimating the Passenger Cost of Train Overcrowding." 29th Australian Transport Research Forum.

Evans, Gary W., and Richard E. Wener. 2007. "Crowding and Personal Space Invasion on the Train: Please Don't Make Me Sit in the Middle." *Journal of Environmental Psychology*, 27(1): 90-94.

Faber, Maunsell, and Mott MacDonald. 2007. "Rail Overcrowding, Reliability and Frequency Demand Impacts Project." Prepared for Centro.

Furth, Peter G., Brendon Hemily, Theo H. J. Muller, and James G. Strathman. 2006. "Using Archived AVL-APC Data to Improve Transit Performance and Management." Transportation Research Board of the National Academies, Washington, DC.

Haywood, Luke, and Martin Koning. 2011. "Pushy Parisian Elbows: Evidence on Taste for Travel Comfort." Paris School of Economics, Paris.

Haywood, Luke, and Martin Koning. 2013. "Estimating Crowding Costs in Public Transport." DIW Berlin, German Institute for Economic Research.

Haywood, Luke, and Martin Koning. 2015. "The Distribution of Crowding Costs in Public Transport: New Evidence from Paris." *Transportation Research Part A: Policy and Practice*, 77: 182-201.

Hensher, David A., John M. Rose, and Andrew T. Collins. 2011. "Identifying Commuter Preferences for Existing Modes and a Proposed Metro in Sydney, Australia with Special Reference to Crowding." *Public Transport*, 3(2): 109-147.

Hensher, David A., John M. Rose, Waiyan Leong, Alejandro Tirachini, and Zheng Li. 2013. "Choosing Public Transport—Incorporating Richer Behavioural Elements in Modal Choice Models." *Transport Reviews*, 33(1): 92-106.

Jiang, Shengchuan, Sun Yifan, and Du Yuchuan. 2012. "Infuence of In-vehicle Congestion Degree on Choice of Public Transit Mode." *Journal of Tongji University (Natural Science)*, 12: 1831-1835.

Kim, Kyung Min, Sung-Pil Hong, Suk-Joon Ko, and Dowon Kim. 2015. "Does Crowding Affect the Path Choice of Metro Passengers?" *Transportation Research Part A: Policy and Practice*, 77: 292-304.

Kroes, Eric, Marco Kouwenhoven, Laurence Debrincat, and Nicolas Pauget. 2013. "On the Value of Crowding in Public Transport for Île-de-France." International Transport Forum Discussion Paper.

Li, Zheng, and David A. Hensher. 2013. "Crowding in Public Transport: A Review of Objective and Subjective Measures." *Journal of Public Transportation*, 16(2): 107-134.

Lu, Hui, Tony Fowkes, and Mark Wardman. 2008. "Amending the Incentive for Strategic Bias in Stated Preference Studies: Case Study in Users' Valuation of Rolling Stock." *Transportation Research Record*, 2049(1): 128-135.

Mahudin, N. D. Mohd, Tom Cox, and A. Griffiths. 2011. "Modelling the Spillover Effects of Rail Passenger Crowding on Individual Well Being and Organisational Behaviour." *Urban Transport XVII: Urban Transport and the Environment in the 21st Century*: 227-238.

Mahudin, N. D. Mohd, Tom Cox, and Amanda Griffiths. 2012. "Measuring Rail Passenger Crowding: Scale Development and Psychometric Properties." *Transportation Research Part F: Traffic Psychology and Behaviour,* 15(1): 38-51.

MVA Consultancy. 2008. "Valuation of Overcrowding on Rail Services." Prepared for Department for Transport.

O'Regan, Brendan, and Finian Buckley. 2003. "The Psychological Effects of Commuting in Dublin." Centre for Research in Management Learning and Development Working Paper Series.

Prud'homme, Rémy, Martin Koning, Luc Lenormand, and Anne Fehr. 2012. "Public Transport Congestion Costs: The Case of the Paris Subway." *Transport Policy*, 21(C): 101-109.

Qin, Feifei. 2014. "Investigating the In-Vehicle Crowding Cost Functions for Public Transit Modes." *Mathematical Problems in Engineering*, 2014: 1-13.

Qin, Feifei, and Haicheng Jia. 2012. "Remodeling In-Vehicle Crowding Cost Functions for Public Transit." Transportation Research Board 91st Annual Meeting.

Tirachini, Alejandro, David A. Hensher, and John M. Rose. 2013. "Crowding in Public Transport Systems: Effects on Users, Operation and Implications for the Estimation of Demand." *Transportation Research Part A: Policy and Practice*, 53: 36-52.

Turner, S, E. Corbett, R. O'Hara, and J. White. 2004. "Health and Safety Effects of Rail Crowding: Hazard Identification." Rail Safety and Standards Board.

Vovsha, Peter, G. S. O. Marcelo, D. William, et al. 2014. "Statistical Analysis of Transit User Preferences including In-Vehicle Crowding and Service Reliability." TRB 2014 Annual Meeting.

Wang, B, and J. Legaspi. 2012. "Developing a Train Crowding Economic Costing Model and Estimating Passenger Crowding Cost of Sydney CityRail network." 35th Australasian Transport Research Forum (ATRF), Perth, Australia.

Wardman, Mark, and Gerard Whelan. 2011. "Twenty Years of Rail Crowding Valuation Studies: Evidence and Lessons from British Experience." *Transport Reviews*, 31(3): 379-398.

Whelan, G., and J. Crockett. 2009. "An Investigation of the Willingness to Pay to Reduce Rail Overcrowding." *Proceedings of the First International Conference on Choice Modelling*, Harrogate, England.

Zhan, Guangjun, Xuedong Yan, Shanjiang Zhu, and Yun Wang. 2016. "Using Hierarchical Tree-Based Regression Model to Examine University Student Travel Frequency and Mode Choice Patterns in China." *Transport Policy*, 45(C): 55-65.

About the Authors

Jianrong Liu (*212021@163.com*) is a lecturer in the Department of Transportation Engineering, School of Civil Engineering and Transportation, South China University of Technology. His interests are in public transport services, stated preference modeling, and travel behavior.

Huiying Wen (*hywen@scut.edu.cn*) is a professor in the Department of Transportation Engineering, School of Civil Engineering and Transportation, South China University of Technology. She leads several interdisciplinary research projects focusing on transport policy, transport planning, road safety, and public transportation.

APPENDIX I: Summary of Reviewed Crowding Valuation Studies

Author	Methods	Mode	Way of Representing Crowding	Measurement	Value	Classification
Accent (2006)	Discrete choice model	Rail	Qualitative description	Multiplier	When crowding varied from "seat uncrowded" to "stand crowded," multipliers increased from 1 to 2.14.	None
Basu and Hunt (2012)	Discrete choice model	Train	Qualitative description	Constant value	Valuations of in-vehicle were 0.32, 0.46, 0.46, 0.54, 0.59 Indian Rupees for light crowding, moderate crowding, heavy crowding, and very heavy crowding, respectively, adopting very light crowding as benchmark.	None
Batarce et al. (2015)	Discrete choice model	Bus, train	Qualitative description	Multiplier	Value of in-vehicle travel time varied from \$4.60 to \$10.40 when standee density varied from 1–2 standees/m^2 to 5–6 standees/m^2.	None
Cantwell et al. (2009)	Discrete choice model, linear regression	Train, bus	Qualitative description	Constant value	Ratio between valuation of train crowding and bus crowding is 1.4.	Train, Bus
Douglas and Karpouzis (2006)	Discrete choice model	train	Combinations of seating time, standing time, degree of crowdedness on train	Multiplier	When crowding on train varied from "crowded seat" to "crush stand 20 minutes or longer," time multiplier varied from 1.17 to 2.52.	Gender, Age, Trip Purpose
Faber and MacDonald (2007)	Discrete choice model	Rail	Qualitative description	Multiplier	When in-vehicle crowding varied from "plenty of seats" to "standees packed," multipliers increased from 1 to 3.01 for commuters, 2.73 for commuters.	Commuter or Not, Car Availability, Over 40 Min or Not
Haywood and Koning (2011)	Ordered logit Model	Subway	Additional minutes Willingness to wait for more comfortable subway	Constant value	Travelers in Paris willing to increase trip durations by 5.7–8.1 minutes to enjoy off-peaks comfort conditions during rush hours.	Age, Socioeconomic Status
Haywood and Koning (2013)	Discrete choice model	Metro	Standee density	Multiplier	Multiplier ranged from 1.00 to 1.57 when standee density ranged from 0 to 6 pass/m^2.	None
Hensher et al. (2011)	Discrete choice model	Metro, bus	Seats occupied, number of standees	Multiplier	With rise of number of standees, crowding utility increased with a quadratic function.	None
Kroes et al. (2013)	Discrete choice model	Metro, bus, train	Load factor	Multiplier	When load factor were 25–250%, multipliers were 1–1.363 for seated train passengers, 1.261–1.553 for standing train passengers, 1–1.511 for seated bus passengers, 1.342–1.718 for standing passengers.	None

APPENDIX I (cont'd): Summary of Reviewed Crowding Valuation Studies

Author	Methods	Mode	Way of Representing Crowding	Measurement	Value	Classification
Lu et al. (2008)	Discrete choice model	Rolling stock	Combinations of probability of standing and length of time	Multiplier	Value of crowding estimated at 12.05 pence per person minute, more than twice value of in-vehicle time.	Complex Design, Cheap Talk
MVA Consultancy (2008)	Discrete choice model	Rail	Standee density	Multiplier	When standees density varied from 0–6 pass/m^2, 1–1.81 (business, seating), 1.91–2.16 (business, standing), 1–1.62 (non-business, seating), 1–2.06 (non-business, standing).	Business, Non-Business, Sit, Stand, Regional, Interurban
Prud'homme et al. (2012)	Linear regression	Subway	Standee density	Constant	WTP (€/trip) equals to standee density × 0.68.	None
Tirachini et al. (2013)	Discrete choice model	Metro	Load factor, standee density	Multiplier	Linear relationship between multipliers and standee density.	None
Vovsha et al. (2014)	Discrete choice model	Bus, LRT, rail	Qualitative descriptions	Multiplier	Non-linear relationship between multipliers and standees density.	Trip Purpose, Age, Travel Mode, Income, Trip Length
Wang and Legaspi (2012)	Discrete choice model	Train	Load factor	Multiplier	Multiplier was function of load factor and standing time.	None
Whelan and Crockett (2009)	Discrete choice model	Train	Load factor, standee density	Multiplier	When standee densities increases from 0 to 6 pass/m^2, time multipliers of seated passengers and standees increase from 1 to 1.63 and 1.53 to 2.04, respectively.	Trip Purpose, Trip Length, Income

APPENDIX II. Survey for Bus and Metro

Choice Set	Choice ID	Journey Time	In-vehicle Crowding	Fare	Waiting Time
1	1	40 min	Some restrictions in movement, high probability of physical contact	¥5	10 min
	2	60 min	No seat, but can circulate freely	¥3	5 min
	3	45 min	No person standing inside car	¥4	15 min
2	1	40 min	No person standing inside car	¥4	15 min
	2	30 min	No seat, but can circulate freely	¥3	10 min
	3	45 min	Impossible movement, difficult to get on/off metro car	¥5	5 min
3	1	40 min	Impossible movement, difficult to get on/off metro car	¥4	10 min
	2	45 min	No person standing inside car	¥5	15 min
	3	30 min	Some restrictions in movement, high probability of physical contact	¥3	5 min
4	1	45 min	Some restrictions in movement, high probability of physical contact	¥4	5 min
	2	40 min	No seat, but can circulate freely	¥5	15 min
	3	30 min	Impossible movement, difficult to get on/off metro car	¥3	10 min
5	1	45 min	Impossible movement, difficult to get on/off metro car	¥4	10 min
	2	60 min	No person standing inside car	¥5	5 min
	3	40 min	Some restrictions in movement, high probability of physical contact	¥3	15 min
6	1	45 min	Some restrictions in movement, high probability of physical contact	¥5	10 min
	2	60 min	No person standing inside car	¥3	5 min
	3	60 min	No seat, but can circulate freely	¥4	5 min
7	1	30 min	Some restrictions in movement, high probability of physical contact	¥4	15 min
	2	45 min	No seat, but can circulate freely	¥3	10 min
	3	60 min	Impossible movement, difficult to get on/off metro car	¥5	10 min
8	1	30 min	No seat, but can circulate freely	¥4	5 min
	2	40 min	No person standing inside car	¥3	10 min
	3	45 min	Some restrictions in movement, high probability of physical contact	¥5	15 min
9	1	60 min	Impossible movement, difficult to get on/off metro car	¥3	5 min
	2	30 min	No seat, but can circulate freely	¥5	15 min
	3	40 min	Some restrictions in movement, high probability of physical contact	¥4	10 min
10	1	45 min	Some restrictions in movement, high probability of physical contact	¥5	5 min
	2	40 min	No seat, but can circulate freely	¥3	10 min
	3	30 min	Impossible movement, difficult to get on/off metro car	¥4	15 min
11	1	45 min	No seat, but can circulate freely	¥4	15 min
	2	40 min	No person standing inside car	¥5	5 min
	3	30 min	Some restrictions in movement, high probability of physical contact	¥3	10 min
12	1	45 min	No person standing inside car	¥3	10 min
	2	40 min	No seat, but can circulate freely	¥4	5 min
	3	30 min	Impossible movement, difficult to get on/off metro car	¥5	15 min

APPENDIX II (cont'd). Survey for Bus and Metro

Choice Set	Choice ID	Journey Time	In-vehicle Crowding	Fare	Waiting Time
13	1	45 min	No seat, but can circulate freely	¥3	15 min
	2	60 min	Some restrictions in movement, high probability of physical contact	¥4	5 min
	3	60 min	No person standing inside car	¥5	10 min
14	1	45 min	Some restrictions in movement, high probability of physical contact	¥3	15 min
	2	40 min	No seat, but can circulate freely	¥5	10 min
	3	60 min	No person standing inside car	¥4	10 min
15	1	30 min	No person standing inside car	¥4	10 min
	2	40 min	Impossible movement, difficult to get on/off metro car	¥3	15 min
	3	45 min	Some restrictions in movement, high probability of physical contact	¥3	5 min
16	1	45 min	No seat, but can circulate freely	¥4	10 min
	2	30 min	Some restrictions in movement, high probability of physical contact	¥5	10 min
	3	40 min	Impossible movement, difficult to get on/off metro car	¥3	5 min

Modeling Transit User Stop Choice Behavior: Do Travelers Strategize?

Mohammad Nurul Hassan, Taha Hossein Rashidi, and S. Travis Waller
University of New South Wales, Australia

Neema Nassir and Mark Hickman
University of Queensland, Australia

Abstract

Transit choice research focuses predominantly on mode choice and route choice, whereas very few studies on stop choice are conducted. To fill this gap, this research aimed to study transit stop choice behavior with a focus on how people strategize when making their choices. It is hypothesized that travelers treat stops differently based on various schemes (strategies); minimizing travel time, access time, and the number of transfers are the schemes considered in this study, and the effectiveness of several discrete choice model specifications was examined. The study found that path attributes and stop attributes have significant impacts on stop selection behavior. Furthermore, users' socioeconomic characteristics along with trip timing play important roles in choosing transit stops. The outcomes of this study could facilitate the recent move toward development of behavioral route choice models using smart card data, which can then assist travel demand estimation models with a focus on public transport.

Keywords: *Transit stop choice, transit path choice, travel scheme, nested logit, mixed logit*

Introduction

In transit demand modeling literature, two areas have been discussed: 1) transit mode choice (or general transit ridership) and 2) transit assignment or path choice. Recently, researchers have started using smart card data to develop transit path choice models (Schmöcker, Shimamoto, and Kurauchi 2013; Jánošíková, Slavík, and Koháni 2014). As smart card datasets can detect repetitive observations, path identification and estimation become much easier. By using a smart card dataset, Schmöcker, Shimamoto, and Kurauchi (2013) proposed a bi-level discrete choice model in which the upper level considers the choice preference of users and the lower level deals with the deterministic probabilities of boarding paths. However, as smart card datasets usually lack information about the actual origin and destination, these models can determine path choice from only the departure stop. Consequently, these models miss the link between the trip origin and departure transit stops.

This gap was addressed by Nassir et al. (2015) by developing a transit stop choice model. They assumed that transit users select their route by selecting a stop (bus stop, train station, or ferry terminal) from a desirable choice set. They argue that modeling the path choice behavior at the stop level is more appropriate, as the observed data are consistent with the choice actually made by the users. They proposed a nested structure in which an acceptable model fit is gained by considering a bi-level train and no-train nesting structure. Moreover, the study found that the choice of stop depends not only on the attributes of the paths (fastest travel time, number of transfers, etc.), but also on the attributes of the stops. They showed that the presence of shelter at stops, walk time from the origin location to the stop, travel time, number of transfers, and number of routes significantly affect the choice of stops. These findings add to the body of knowledge on the behavioral aspect of transit mode choice, but their work cannot be treated as a comprehensive stop choice study due to three major shortcomings: 1) they did not consider users' socioeconomic and demographic characteristics; 2) attributes related to the trip were missing; and 3) their modeling specification was quite limited and restricting.

Other stop choice studies are found in the literature, but they focused on other issues. Debrezion, Pels, and Rietveld (2009) conducted a railway station choice model for Dutch railway users. The main focus of their study was to determine a measure of station accessibility. They proposed a nested logit model in which access modes are modeled at the upper level and stations are modeled at the lower level. They found that access distance has a negative effect on the accessibility indicator, and parking availability, frequency of public transport, and railway station quality have a positive effect on station choice. Chakour and Eluru (2013) modeled access modes and station choice using a different approach. They found that a latent segmentation technique delivers better results than the nested logit approach proposed by Debrezion, Pels, and Rietveld (2009). Mahmoud, Habib, and Shalaby (2014) investigated the choice of park-and-ride stations for cross-regional commuter trips in the greater Toronto and Hamilton area. The study aimed to find aspects important to the design of more sustainable and attractive transit stations. They developed several multinomial logit models by using data on parking facilities, surrounding land use, and station amenities.

The work presented in this paper aimed to develop a stop choice model by addressing the shortcomings of the model developed by Nassir et al. (2015) and also to introduce a strategy-based (scheme-based) decision-making mechanism for transit users, which is a unique contribution from this paper. As such, we considered a total of 28 variables containing users' socioeconomic and demographic attributes and 9 variables addressing trip attributes, along with path attributes, stop attributes, and correction attributes. We also considered three strategy attributes. This study investigated appropriate modeling structures by testing different discrete choice models from the Household Travel Survey (HTS) of 2009 in Southeast Queensland (SEQ), Australia. The detailed description of the model is presented in the next section, followed by model results, discussions, and conclusions.

Description of the Model

In this study, it was assumed that when a transit user wants to make a trip, he/she decides what type of travel scheme is suitable for his/her current situation. In this study, we considered three basic schemes: minimize the time of travel (MTT scheme), minimize the access time (MAT scheme) to reach the boarding stop, and minimize the number of transfers (MTr scheme). Combinations of these three basic schemes (four combinations) also were considered. We assumed that users choose the alternative (access stop) that best matches their desired scheme and maximizes their utility. For example, if a user wants to minimize travel time (an MTT user), he/she chooses an alternative that falls under the MTT scheme. Similarly, an MAT-MTr user chooses a stop that takes less time to access and has the most direct connection to the destination (MAT-MTr scheme). The detailed descriptions of the models are discussed later in this section.

Model Structure

We considered four types of model structures: Multinomial Logit (MNL), Mixed MNL, Nested Logit (NL), and Mixed NL. In the MNL structure, the restricting Independence of Irrelevant Alternatives (IIA) property holds. This model forms the base case scenario. The form of MNL can be described by Equation (1):

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_i e^{\beta' x_{ni}}} \tag{1}$$

where, P_{ni} is the probability of selecting the alternative i by an individual n, x_{ni} is the column vector associated with attributes influencing the choice, and β' is the vector of parameters to be estimated.

A Mixed MNL model also was tested to determine if it could capture random taste variations among individuals. In the Mixed MNL formulation, β' is treated as a random parameter to be estimated, having a probability density function of $f(\beta)$. The choice probability of the Mixed MNL form can be written by the form provided in Equation (2). To capture the effects of the three basic schemes in MNL and Mixed MNL models, dummy variables (whether or not the option offers the scheme) were considered, because no nesting structure can be included in these models.

$$P_{ni} = \int \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} f(\beta) d\beta \tag{2}$$

The third type, NL, was chosen to capture the correlation between alternatives belonging to different travel schemes. We assumed that alternatives falling under the same scheme have some unobserved similarities among them, and a nested structure might be able to capture them. Here, the schemes were considered to form the nests and the stops associated with the schemes were included under that nest. In the NL formulation, the choice probability for alternative $i \in B_k$ can be written as in Equation (3):

$$P_{n\,i} = \frac{e^{\beta' x_{ni}/\lambda_k} \left(\sum_{j \in B_k} e^{\beta' x_{nj}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} e^{\beta' x_{nj}/\lambda_l}\right)^{\lambda_l}} \tag{3}$$

The fourth model, Mixed NL, can capture both random taste variations and correlation among the alternatives. Recently, some researchers (Hess, Bierlaire, and Polak 2005; Antonini, Bierlaire, and Weber 2004; Bajwa et al. 2008; Hammadou et al. 2008) reported a technique in which the β' coefficients inside the nests are treated as random parameters with a function of $f(\beta)$. The nest coefficients were not assumed to have any distribution. The model can be written as in Equation (4):

$$P_{n\,i} = \int \frac{e^{\beta' x_{ni}/\lambda_k} \left(\sum_{j \in B_k} e^{\beta' x_{nj}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{l=1}^{K} \left(\sum_{j \in B_l} e^{\beta' x_{nj}/\lambda_l}\right)^{\lambda_l}} f(\beta) d\beta \tag{4}$$

In the mixed models, randomness was captured assuming a log-normal distribution for the variables that show negative signs in MNL models, a uniform distribution for dummy variables, and a normal distribution for all the other variables (Hensher and Greene 2002).

Several studies focusing on the optimal choice of transit users combine all costs into a unified generalized cost to be considered in the objective function. Unlike this approach, this study attempted to introduce a "behavioral" stop selection model that reflects the process of decision-making by travelers. This behavioral model assumes that travelers maximize their utility based on the attributes of alternatives as well as a random error component capturing what is not known to the modeler. The proposed behavioral model is unique in a sense that it takes into account different ways to capture the unobserved error component in the utility function. It also examines mixed formulations to capture complicated taste variation structures.

Nest Structures

In this study, we considered three schemes (MTT, MAT, and MTr) individually and their combinations. Therefore, seven nesting groups were analyzed (see Table 1). These nesting structures also were used in Mixed NL estimation models. Thus, each group consisted of two models: NL and Mixed NL. The idea of considering different schemes as nests derived from the findings of other researchers (Nassir et al., 2015; Kurauchi et al., 2012; Fonzone and Bell 2010; Fonzone et al. 2010). Nassir et al. (2015) showed that transit users tend to choose stops that minimize travel time, minimize access time, and minimize the number of transfers. Kurauchi et al. (2012) found that London Oyster Card users might use different schemes (strategies) for their regular commute because they do not use fixed routes. Fonzone and Bell (2010) and Fonzone et al. (2010) also reported similar findings.

TABLE 1.
Nest Structures for Proposed NL and Mixed NL Models

Group	Model Name	Number of Nests	Nest Structure
1	TT, TT[M]*	2	MTT, NoMTT
2	AT, AT[M]	2	MAT, NoMAT
3	Tr, Tr[M]	2	MTr, NoMTr
4	TT-AT, TT-AT[M]	4	MTT, MAT, MTT&MAT, None
5	TT-Tr, TT-Tr[M]	4	MTT, MTr, MTT&MTr, None
6	AT-Tr, AT-Tr[M]	4	MAT, MTr, MAT&MTr, None
7	TT-AT-Tr, TT-AT-Tr[M]	8	MTT, MAT, MTr, MTT&MAT, MTT&MTr, MAT&MTr, MTT&MAT&MTr, None

** [M] = Mixed NL model*

In Table 1, the first nesting group is for the MTT scheme. Here, we considered two nests: 1) stops that are fastest (fastest routes from the stop) were grouped in the MTT nest, and 2) the rest of the stops were grouped in NoMTT nest. The next two groups considered the MAT and MTr schemes, similar to the first nesting group. The next three groups (4, 5, and 6) coupled two schemes; for example, in the fourth structure, both MTT and MAT were coupled. Here, there were four probable combinations of these two schemes: 1) minimizing travel time only (MTT), 2) minimizing access time only (MAT), 3) considering both (MTT and MAT), and 4) considering none of them (None). The last structure considered all three schemes, with all the probable combinations (eight nests).

Data Preparation

Descriptive Analysis

The dataset used in this research was taken from the Household Travel Survey (HTS) of May 2009 conducted in Southeast Queensland, Australia. All travel records (1,693 journeys) using public transport (which includes three modes: bus, train, and ferry), with walking legs of access, egress, and transfer(s), were extracted from the HTS data for this research. These 1,693 journeys included 1,435 transit trips with no transfers, 229 trips with a single transfer, 26 trips with 2 transfers, and 3 trips with 3 transfers. Regarding the mode of the access stop, 1,176 travelers had chosen bus stops, 492 travelers had chosen train stations, and 25 had chosen ferry terminals. The Queensland Department of Transport and Main Roads (DTMR) provided another dataset containing information about stop facilities such as shelter, lighting, access walkways, boarding slabs, etc. The SEQ transit authority Translink shared transit network data and service schedules for May 2009. The transit network included 14,442 stops, 767 paths, and 33,897 scheduled trips. The walk network data, consisting of local streets, sidewalks, crosswalk connections, walking ramps, footways, and stairways for SEQ, were obtained from OpenStreetMap (http://www.openstreetmap.org/). This included about 250,000 nodes and 340,000 links. ArcGIS was used to calculate the shortest walking paths. The average walking speed of a traveler was assumed to be 1.2 m/s to calculate walking times.

At the end of the choice set generation process, 1,238 observations were finalized. The scheme preferences of users for selecting their access stops were revealed from these data. A "reasonably minimum" travel time and access time were fixed for each choice set to account for the fact that users' perception of time does not exactly match reality. It was considered likely that an alternative stop yielding a travel time that was reasonably close to the minimum travel time of that choice set would be considered by an MTT user (who chooses a minimizing travel time scheme). To calculate the "reasonably minimum" travel/access time for a choice set, 10% of the difference between the maximum and minimum travel/access times was added to the minimum travel/access time. Stops that yielded less than this "reasonably minimum" travel/access time threshold were flagged as MTT or MAT stops. For the MTr scheme, only the minimum number of transfers was considered. Finally, to be consistent with the relevant nesting group, separate data files were generated for each model. The revealed choice of schemes for each nesting group is presented in Figure 1.

FIGURE 1.
User preference of schemes

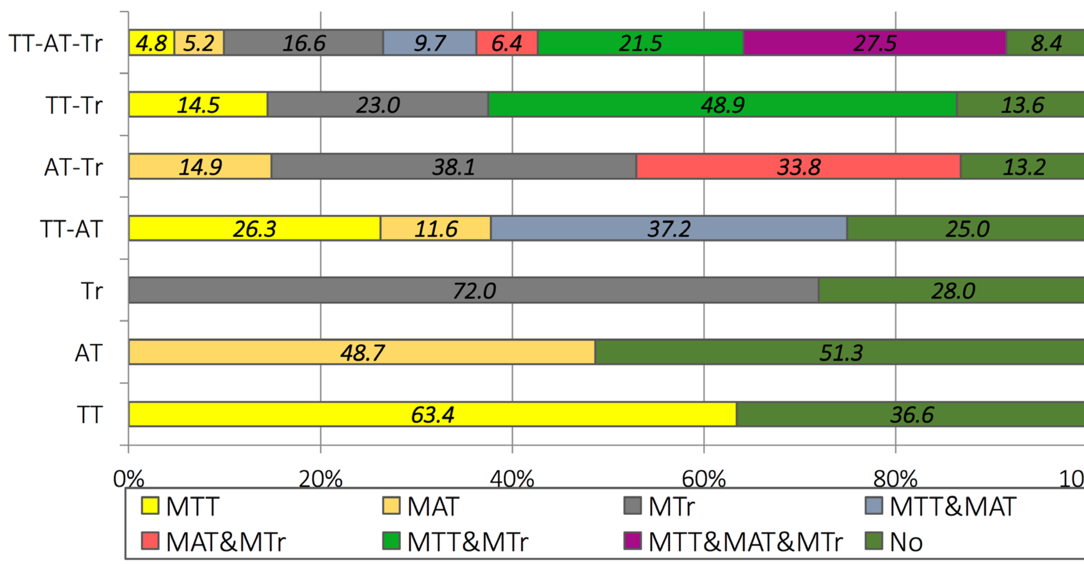


Figure 1 shows that most travelers choose access stops that contain some schemes. In the three-single-scheme situation, MTT and MTr schemes seem to be more popular (63% of users choose MTT and 71% choose MTr) than MAT schemes (only 49% of users choose MAT schemes). If there are multiple schemes, users seem to prefer combined schemes rather than single schemes or none. For example, in TT-AT and TT-Tr, the share of combined schemes are dominant (MTT&MAT=37%, MTT&MTr=49%) compared to single schemes or none. Contrastingly, in the AT-Tr combination, the share of MTr (38%) is more than the combined schemes of MAT&MTr (34%). Finally, in the TT-AT-Tr combination, users seem to prefer combined schemes. Very few (8%) users seem to have no preference for schemes.

Explanatory Variables

Several stop choice works were studied to develop the explanatory variables. Debrezion, Pels, and Rietveld (2009) mainly considered station facility attributes to construct their model. Chakour and Eluru (2013) considered socio-demographic attributes, trip characteristics, facility attributes, and land-use and built-environment factors. Mahmoud, Habib, and Shalaby (2014) studied facility attributes and land use variables. Nassir et al. (2015) considered facility attributes, impedance attributes, and correction attributes. In this study, we considered a total of 61 explanatory variables, which could be classified in 6 classes: 1) facility attributes, 2) impedance attributes, 3) user attributes, 4) trip attributes, 5) strategy attributes, and 6) correction attributes. Brief descriptions of the variables are provided in Table 2.

TABLE 2. Explanatory Variables of Models

Variable	Mean	SD	Description
Facility			
AccessWalk	11.33	7.11	Walk time from origin location to stop (min)
Shelter	0.41	0.49	Binary variable indicating sheltered stop
StopLight	0.34	0.47	Binary variable indicating illuminated stop
StreetLight	0.31	0.46	Binary variable indicating illuminated street
BoardingSlab	0.88	0.32	Binary variable indicating existence of boarding slab
FootPath	0.87	0.34	Binary variable indicating existence of foot path
Map	1.65	2.74	Total number of printed map/schedule at stop
Impedance			
FastestTT	46.95	19.85	Travel time (min) of fastest path to destination from stop (excluding AccessWalk)
MinTransfer	0.83	0.84	Minimum number of transfers among paths from stop to destination
MinWalk	19.05	8.88	Minimum walk time (min) among paths from stop to destination (excluding AccessWalk)
MinFare	1.15	1.10	Minimum fare among paths from stop to destination
MinWait	10.56	14.34	Minimum wait time (min) among paths from stop to destination
NumRoutes	1.74	1.96	Number of available paths from stop to destination
TotalFreq	4.55	7.46	Summation of frequency for all paths from stop to destination
AveTT	48.50	20.33	Average travel time of all paths from stop to destination (excluding AccessWalk)
AveTransfer	0.95	0.83	Average number of required transfers for all paths from stop to destination
AveWalk	19.70	8.83	Average walking time (min) for all paths from stop to destination (excluding AccessWalk)
AveFare	1.17	1.10	Average fare for all paths from stop to destination
AveWait	12.37	15.17	Average waiting time (min) for all paths from stop to destination
User			
Age	35.55	19.20	Age of user
Male	0.44	0.50	Binary variable indicating user is male
HHSize	3.02	1.35	Total number of members in HH (Household)
CoupleKids	0.36	0.48	Binary variable indicating user H/H type is couple with kids
OneParent	0.08	0.27	Binary variable indicating user H/H type is one parent with kids

Variable	Mean	SD	Description
Sole	0.13	0.33	Binary variable indicating user H/H type is sole
Couple	0.20	0.40	Binary variable indicating user H/H type is couple
OtherHHType	0.23	0.42	Binary variable indicating user H/H type is other
House	0.81	0.40	Binary variable indicating user lives in a house
Flat	0.15	0.35	Binary variable indicating user lives in a flat
Townhouse	0.05	0.21	Binary variable indicating user lives in a townhouse
Bedrooms	3.13	0.98	Number of bedrooms in accommodation
OwnedProp	0.57	0.50	Binary variable indicating user lives in owned property
LivedInTheProp	99.38	127.87	Total number of months lived on accommodation
HHIncome	1,850.28	1,340.09	Weekly income of H/H
HighPerIncome	0.11	0.31	Binary variable indicating user falls in high income group
MedPerIncome	0.38	0.49	Binary variable indicating user falls in medium income group
LowPerIncome	0.51	0.50	Binary variable indicating user falls in low income group
FullTimeWork	0.37	0.48	Binary variable indicating user is full time worker
AnyWork	0.58	0.49	Binary variable indicating user works
Student	0.00	0.06	Binary variable indicating user is student
AustralianBorn	0.72	0.45	Binary variable indicating user born in Australia
CarLicence	0.51	0.50	Binary variable indicating user has car license
BikeLicence	0.02	0.15	Binary variable indicating user has motorbike license
NoLicence	0.39	0.49	Binary variable indicating user has no license
TotalVehs	1.37	0.99	Total number of vehicles in HH
PersonalVeh	0.75	0.43	Binary variable indicating user has personal vehicle
Bicycles	1.39	1.52	Total number of bicycles in HH
Trip			
Train	0.05	0.22	Binary variable indicating trip access stop is train station
AMPeakDep	0.28	0.45	Binary variable indicating trip starts in AM peak Hour
PMPeakDep	0.17	0.38	Binary variable indicating trip starts in PM peak Hour
PeakHourDep	0.45	0.50	Binary variable indicating trip starts in a peak Hour
AMPeakArv	0.25	0.44	Binary variable indicating trip ends in AM peak Hour
PMPeakArv	0.22	0.42	Binary variable indicating trip ends in PM peak Hour
PeakHourArv	0.48	0.50	Binary variable indicating trip ends in a peak Hour
Weekday	0.90	0.30	Binary variable indicating trip was on weekday
PurposeWork	0.67	0.47	Binary variable indicating trip was made for work purpose
Strategy (used only for MNL and Mixed MNL models)			
MTTStr	0.23	0.42	Binary variable indicating option offers minimum travel time
MTransferStr	0.45	0.50	Binary variable indicating option offers minimum number of transfers
MAccessStr	0.17	0.37	Binary variable indicating option offers minimum walking access time
Correction for Correlation			
CfC1	1.09	0.79	Correction for correlation, basic definition
CfC2	1.09	0.79	Correction for correlation, weighted by path frequency
CfC3	1.09	0.79	Correction for correlation, weighted by path travel time

Facility attributes included seven variables related to the transit stop. Two types of impedance attributes, direct and aggregate, were calculated from a path enumeration process. The path enumeration process refers to the procedure of generating a set of reasonable paths from a given origin and destination at the given departure time. Direct impedance attributes (the measures of best paths from different points of view) included five variables: fastest travel time, minimum number of transfers, minimum walking time, minimum fare, and minimum waiting time among all the reasonable paths from the origin to the destination. These, in fact, represented the best reasonable path in these five aspects from each stop. For example, for a particular stop, the fastest travel time variable indicated the fastest travel time of all reasonable paths from that stop. Similarly, the minimum number of transfers of all reasonable paths from the stop was recorded for the minimum transfer variable, and so on. Aggregate impedance attributes (including averages among all reasonable paths) included seven variables, among which five included the average measure (travel time, number of transfers, walking time, fare, and waiting time) among all reasonable paths. The other two contained the total number of possible paths from the access stop to destination and the total frequency of all these paths.

User attributes contained a variety of socio-economic attributes of the user. Trip attributes contained trip mode, timing, and trip purpose. Strategy attributes were used only for the MNL and Mixed MNL models. Corrections for correlation attributes were developed to deal with path commonalities (overlapping routes, which have strong correlations) among the stops. Path commonalities breach the IID (independent and identically-distributed) property of the MNL models to some extent and can lead to inaccurate estimations. The correction factors (CfC1, CfC2, CfC3) proposed in this research were defined based on the Path Size Correction Logit (PSCL) formulation (Nassir et al. 2014). To meet the specifications of the access stop choice model, these factors were adjusted as follows (equations 5, 6, and 7). For an observation from origin location *o* at departure time τ to destination location *d*, three definitions of correction for correlation were defined for every stop *s* in the choice set $C_o^{d,\tau}$:

$$CfC1_s^{d,\tau} = -\sum_{i \in \Gamma_s^{d,\tau}} \frac{1}{\left|\Gamma_s^{d,\tau}\right|} \ln \sum_{t \in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \tag{5}$$

$$CfC2_s^{d,\tau} = -\sum_{i \in \Gamma_s^{d,\tau}} \frac{f_{i,s}^{\tau}}{\sum_{j \in \Gamma_s^{d,\tau}} f_{j,s}^{\tau}} \ln \sum_{t \in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \tag{6}$$

$$CfC3_s^{d,\tau} = -\sum_{i \in \Gamma_s^{d,\tau}} \frac{\left(T_{j,d}^{\tau}\right)^{-1}}{\sum_{j \in \Gamma_s^{d,\tau}} \left(T_{j,d}^{\tau}\right)^{-1}} \ln \sum_{t \in C_o^{d,\tau}} \delta_{i,t}^{d,\tau} \tag{7}$$

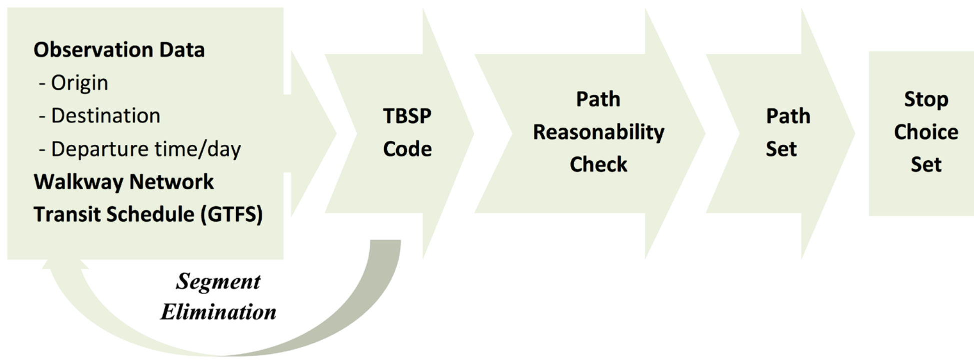
Where *i*, *j* are the indices of the routes; *s*, *t* are the indices of stops; $\Gamma_s^{d,\tau}$ is the set of all routes at stop s with reasonable paths to destination *d* at time τ; $f_{i,s}^{\tau}$ is the frequency of route *i* at stop *s* at time τ; $T_{j,d}^{\tau}$ is the travel time of the fastest path from stop *s* boarding on route *i* to destination *d* at time τ; and $\delta_{i,t}^{d,\tau}$ is the top-route incidence parameter,

$$\delta_{i,t}^{d,\tau} = \begin{cases} 1, \; if \; i \in \Gamma_s^{d,\tau} \\ o, \; if \; i \notin \Gamma_s^{d,\tau} \end{cases}$$

Choice Set Generation

Stop choice sets were generated by the algorithm in Nassir et al. (2015) in four steps (Figure 2). Initially, observed origin-destination and departure information (day and time) data were collected along with the walkway network and transit schedule. This information was used in the second step as an input. A version of a transit Trip-Based Shortest Path (TBSP) algorithm was used in this step (Khani et al. 2012; Nassir et al. 2012; Khani, Hickman, and Noh 2014; Khani 2013). This version is a transit time-dependent K-shortest path algorithm that aims to minimize the arrival time to the destination and was modified to terminate after the destination was marked for computational efficiency.

FIGURE 2.
Choice set generation framework



This algorithm has a "segment elimination" module that was executed after each iteration of the TBSP code. A segment is a combination of three elements: boarding stop, alighting stop, and the path connecting these two stops. In each iteration, after the TBSP generates a path, the segment elimination module eliminates all the segments used in that path from the schedule data and, thus, updates the schedule for the next iteration. This was done to create diversity among the generated paths.

In the third step, reasonable paths were sorted out. The TBSP code contained three reasonability conditions for path generation: 1) transfer walking distance cannot exceed 1km, 2) access and egress walks cannot exceed 2km, and 3) waiting time before a boarding cannot exceed 1 hour. Two other reasonability checks also were set after the TBSP path generation: 1) path travel time does not exceed the shortest path travel time plus a threshold factor known as off-optimality, and 2) number of transfers does not exceed 3. The maximum off-optimality threshold was set as 20 minutes, as suggested in Nassir, Hickman, and Ma (2015).

The TBSP code also had an embedded maximum walking range of 2 km to generate the locations of the access stops from which the paths are generated. This 2km threshold range was taken from the preliminary analysis of access walk from the SEQ HTS data, in which about 17% of the observations were found to walk more than 1km to access to a transit stop (Nassir et al. 2015). At the end, the maximum number of stop choices in a set was found to be 70 stops, although the majority of observations had fewer than 20 stop choices in the set. Finally, based on the set of reasonable paths, impedance attributes and correction factors for each stop choice were calculated.

It was found that the TBSP algorithm could select about 94.5% of the chosen access stops (1,599 out of 1,693) successfully. The unsuccessful choices of stops were added in the choice sets manually. The impedance attributes of these stops were calculated by restricting the K-shortest path generation algorithm to start from these stops. However, some observations were not matched to the exact stop location. We inferred these locations by applying three matching keys: whether the distance is within a 100m threshold, the mode of the stops, and the path serving that stop. Ultimately, we had to exclude some of the observations (about 26.8%), as we failed to locate the chosen access stop or observed ambiguity between the HTS data and generated paths.

Model Results and Discussions

The models were estimated using the discrete choice estimation package BIOGEME (Bierlaire 1998). Initially, all the models were estimated separately by one of the correction factors. Finally, the correction factors had to be dropped because these seemed to be insignificant, even at the 10% significance level. Table 3 provides a comparison between the models (MNL, NL, Mixed MNL, and Mixed NL) estimated in this study.

From Table 3, we can see that the MNL and NL models show similar adjusted ρ^2 values compared to the Mixed MNL and Mixed NL models. However, the Bayesian Information Criteria (BIC) values seem to be better in the MNL and NL models compared to the Mixed MNL and Mixed NL models. The model results indicate that two of the single-scheme NL models (AT model and TT model) result in significant nest structures. Nonetheless, in the single scheme Mixed NL models, the nest coefficients are insignificant. Furthermore, among the dual scheme models, TT-AT models show better nest structures and TT-Tr models show better BIC values than the other two groups. In contrast, most of the nest coefficients of the only tri-scheme model are insignificant, although their model fit (adjusted ρ^2) is better than all the other models. Therefore, from Table 3 we can conclude that travel schemes such as MTT and MAT have an influence on the users' choice of access stops; users generally follow MTT or MAT schemes or a combination of these two schemes (MTT-MAT).

From the comparisons shown in Table 3, we selected the best models according to three criteria: BIC, adjusted ρ^2, and significance of the nest coefficients. The MNL model shows the best BIC value among all the models; the adjusted ρ^2 value also is better than some of the models. The Mixed MNL model has a low BIC value compared to the MNL model, but the adjusted ρ^2 value is slightly better than the MNL model. Among the nested and mixed nested models, the TT-Tr and TT-Tr[M] models show the best BIC values (4012.04 and 4014.21, respectively). Moreover, the adjusted ρ^2 values also are higher than most of the other models in this group. Nevertheless, two of the nest coefficients of these two models seem to be insignificant (nest coefficient "None" was highly insignificant). On the other hand, TT and AT models have significant nest coefficients, but BIC and adjusted ρ^2 values seem to be worse than the other models in this group. However, if we want to balance the three criteria for model selection (BIC, adjusted ρ^2, and nesting coefficients), the TT-AT model can be considered as the best model among the nested and mixed nested models. The estimates of the MNL model and the TT-AT model are shown in Table 4.

TABLE 3. Comparisons of Models*

	MNL	Nested Logit Models						
		TT	*AT*	*Tr*	*TT-AT*	*TT-Tr*	*AT-Tr*	*TT-AT-Tr*
No. of parameters	9	11	13	15	17	21	23	26
Final log-likelihood	-1970.858	-1980.199	-1985.941	-1962.492	-1951.951	-1931.246	-1943.24	-1917.642
Likelihood ratio test	1939.051	1915.459	1903.974	1950.872	1971.955	2013.364	1989.377	2040.369
ρ^2	0.329	0.326	0.324	0.332	0.336	0.343	0.339	0.347
Adjusted ρ^2	0.326	0.322	0.32	0.327	0.33	0.336	0.331	0.338
BIC	4005.81	4038.73	4064.46	4031.80	4024.96	4012.04	4050.27	4020.44
Nest Coefficients (λ)	Not Applicable	MTT=0.81 NoMTT=0.82	MAT=0.78 NoMAT=0.75	MTr=0.79 NoMTr=1.00 (0.02, 0.97)	MTT=0.67 MAT=0.81 (1.32, 0.19) MTT&MAT= 0.63 None=0.78	MTT=0.83 (1.43, 0.15) MTr=0.66 MTT&MTr= 0.73 None=0.99 (0.13, 0.9)	MAT=0.90 (0.78, 0.44) MTr=0.69 MAT&MTr= 0.93 (0.36, 0.72) None=0.96 (0.52, 0.61)	MTT=0.71 (1.35, 0.18) MAT=0.95 (0.32, 0.75) MTr=0.63 MTT&MAT=0.68 (1.21, 0.23) MTT&MTr=1.00 MAT&MTr=0.38 (1.03, 0.3) MTT&MAT&MTr=1 None=0.98 (0.31, 0.76)
	Mixed MNL	**Mixed Nested Logit Models**						
		TT[M]	*AT[M]*	*Tr[M]*	*TT-AT[M]*	*TT-Tr[M]*	*AT-Tr[M]*	*TT-AT-Tr[M]*
No. of parameters	11	14	14	17	18	22	23	27
Final log-likelihood	-1966.73	-1982.25	-1974.53	-1960.11	-1976.32	-1928.77	-1938.57	-1916.69
Likelihood ratio test	1942.397	1905.092	1926.789	1955.643	1923.224	2018.315	1998.724	2042.266
ρ^2	0.331	0.325	0.328	0.333	0.327	0.343	0.34	0.348
Adjusted ρ^2	0.327	0.32	0.323	0.327	0.321	0.336	0.332	0.338
BIC	4011.79	4064.19	4048.77	4041.28	4081.28	4014.21	4040.92	4025.66
Nest Coefficients (λ)	Not Applicable	MTT=0.89 (1.2, 0.23) NoMTT=0.91 (1.24, 0.21)	MAT=0.78 (1.78, 0.08) NoMAT=0.76	MTr=0.81 NoMTr=1 (0.01, 1.00)	MTT=0.74 MAT=0.79 (1.44, 0.15) MTT&MAT= 0.63 None=0.81	MTT=0.85 (1.23, 0.22) MTr=0.65 MTT&MTr= 0.75 None=1 (0.06, 0.95)	MAT=0.96 (0.3, 0.76) MTr=0.66 MAT&MTr= 0.93 (0.33, 0.74) None=0.95 (0.58, 0.56)	MTT=0.73 (1.27, 0.2) MAT=1 (.01, 1.00) MTr=0.63 MTT&MAT=0.74 (0.97, 0.33) MTT&MTr=0.54 AT Tr=0.3 (0.97, 0.33) MTT&MAT&MTr=1 None=0.94 (0.8, 0.42)

**t-test value and p-value are provided in parentheses for coefficients that are not significant at 5% level.*

TABLE 4.
Estimation Results of Best Models

	MNL Model			TT-AT Model		
Explanatory Variables (β)	*Coefficient*	*Robust Std. Error*	*Robust t-test*	*Coefficient*	*Robust Std. Error*	*Robust t-test*
MinTransfer	-0.311	0.13	-2.39	-0.855	0.0772	-11.07
MinWalk	-0.0329	0.0105	-3.14	-0.026	0.0091	-2.85
NumRoutes	0.0572	0.0141	4.07	0.048	0.0124	3.85
AccessWalk	-0.164	0.0133	-12.39	-0.124	0.0134	-9.24
StopLight	0.388	0.0951	4.08	0.292	0.0799	3.65
Train	2.3	0.123	18.64	2.510	0.3110	8.06
MTTStr	0.341	0.151	2.25	N/A		
MTransferStr	1.030	0.176	5.83	N/A		
AustralianBorn_TT	0.435	0.177	2.46	0.825	0.1170	7.04
Male_TT_AT	N/A			-0.363	0.1620	-2.25
Student_TT_AT	N/A			9.730	0.7460	13.04
Flat_TT_AT	N/A			0.569	0.1950	2.92
HHSize_TT_AT	N/A			0.256	0.0343	7.47
PMPeakDep_TT_AT	N/A			-0.491	0.2390	-2.05
Nest Coefficients (λ)*						
TT	N/A			0.813	0.177	1.32+
AT	N/A			0.671	0.152	3.21
TT AT	N/A			0.633	0.237	2.43
None	N/A			0.781	0.079	3.58

** Robust t-test is estimated for the hypothesis, H_0=1*
+ Significant at 0.20 level

From Table 4, the two direct impedance attributes MinTransfers and MinWalk were found to be significant. The signs of these coefficients were negative, as expected; this means that transit users prefer to start their trip from a stop that had a more direct connection to their destination and involved less walking. One of the aggregate impedance attributes, NumofRoutes, was found to be significant in the models; this means that transit users tend to choose access stops that have multiple path options. Facility attributes AccessWalk and StopLight also were found to be significant. The negative sign of AccessWalk means users perceives more disutility if they have to walk more to the access stop. The positive sign of the StopLight attribute implies that users prefer to choose stops that have lighting. The sign of the coefficient of Train is positive, which means that transit users in SEQ are much more willing to travel by train than by other modes.

Generally, the coefficients of the common variables of these two models (presented in Table 4) seem to be quite similar, except for MinTransfer; the coefficient of MinTransfer was smaller in the MNL model. This probably happened because some of the effects of this parameter might have been captured by MTransferStr, which is a dummy variable for the presence of the MTr scheme. These models identify that users consider every minute of walking to the access stop to be about five minutes of other types of walking (e.g., for transfers or walking to the destination) involved in the travel path. This indicates that users do not perceive/evaluate walking in a consistent way. Somehow, walking to access stops poses a much higher disutility than other walks in the travel path. This might support theories about the myopic behavior of transit users by other researchers (Nassir et al. 2015; Fonzone and Bell 2010).

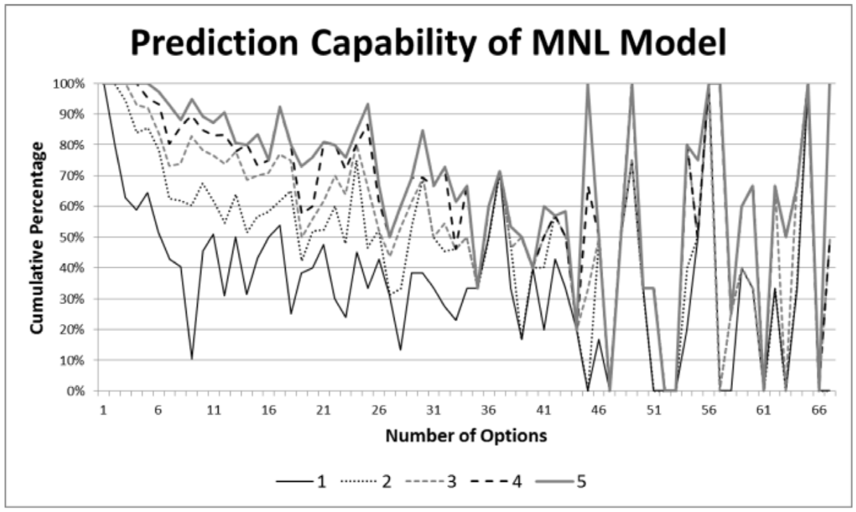
Compared to previous studies, in a nutshell, this study considered 61 attributes, compared to 21 attributes considered in Nassir et al. (2015). In analyzing the same dataset, the current study found 8 significant attributes in the MNL model and 12 significant attributes in the TT-AT model compared to 6 significant attributes in Nassir et al. (2015). Furthermore, the model fit (adjusted ρ^2: MNL model 0.326, TT-AT model 0.336) in this study seems to outperform the model fit (adjusted ρ^2: 0.287) developed by Nassir et al. (2015).

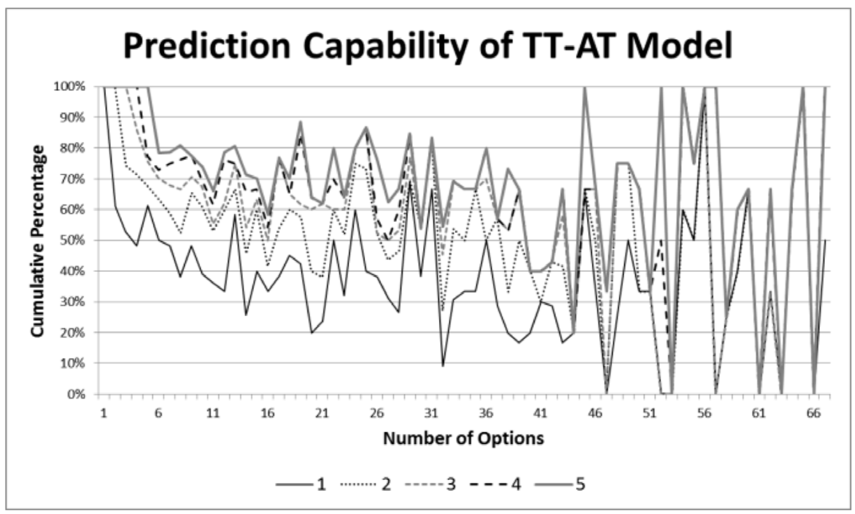
Some of the socio-economic attributes also were found to be significant. As reported in Table 4, both the models show that Australia-born users are more likely to select MTT schemes for choosing transit stops. In the TT-AT model, female students are more likely to use the combination of MTT and MAT schemes when choosing their preferred transit stop. Moreover, users from larger households and users living in a flat tend to prefer the combination of MTT and MAT schemes when choosing transit stops. Trip attribute PMPeakDep was found to be significant, indicating that users making a trip other than at the PM peak hour are inclined to follow the combined scheme of MTT and MAT when choosing their transit stop. Another interesting finding is that of the three strategy attributes used in the MNL model, two (MTT and MTr) became significant, which indicates that users consider either MTT scheme or MTr scheme. The NL model presented in Table 4 (TT-AT) shows significance (5% significance level) for the AT, TT-AT, and None schemes. The TT scheme is significant at the 20% level.

Model Predictability and Sensitivity

The choice probabilities of all the options were calculated for the MNL and TT-AT model. It was found that the models could correctly predict the users' chosen alternatives in 46% (MNL) and 44% (TT-AT) of cases. It also can be interpreted that, according to the MNL model, 46% of users choose the stop with the highest probability. Again, 84% of users (MNL model) seem to choose the access stop from a set of five stops with the highest probabilities; for TT-AT model, this is about 79%. The predictive capabilities of these models are shown in Figure 3, which presents the cumulative percentage of successful prediction, with an increasing pattern for the number of options considered to include the actual selected option. In other words, if a set of predicted options is considered to include the observed option, the chance of having the observed option increases. Obviously, as the choice set (as defined previously in the methodology section) size increases, the chance of including the observed option in the set of predicted options decreases. In Figure 3, five curves are fitted, representing the prediction capabilities for having the observed choice in the set of predicted options where the highest probability is for curve 5. This shows that the models can predict the choices better if the choice set size is relatively small, and vice versa. However, when the choice set size is larger than 40, the predictability is uncertain.

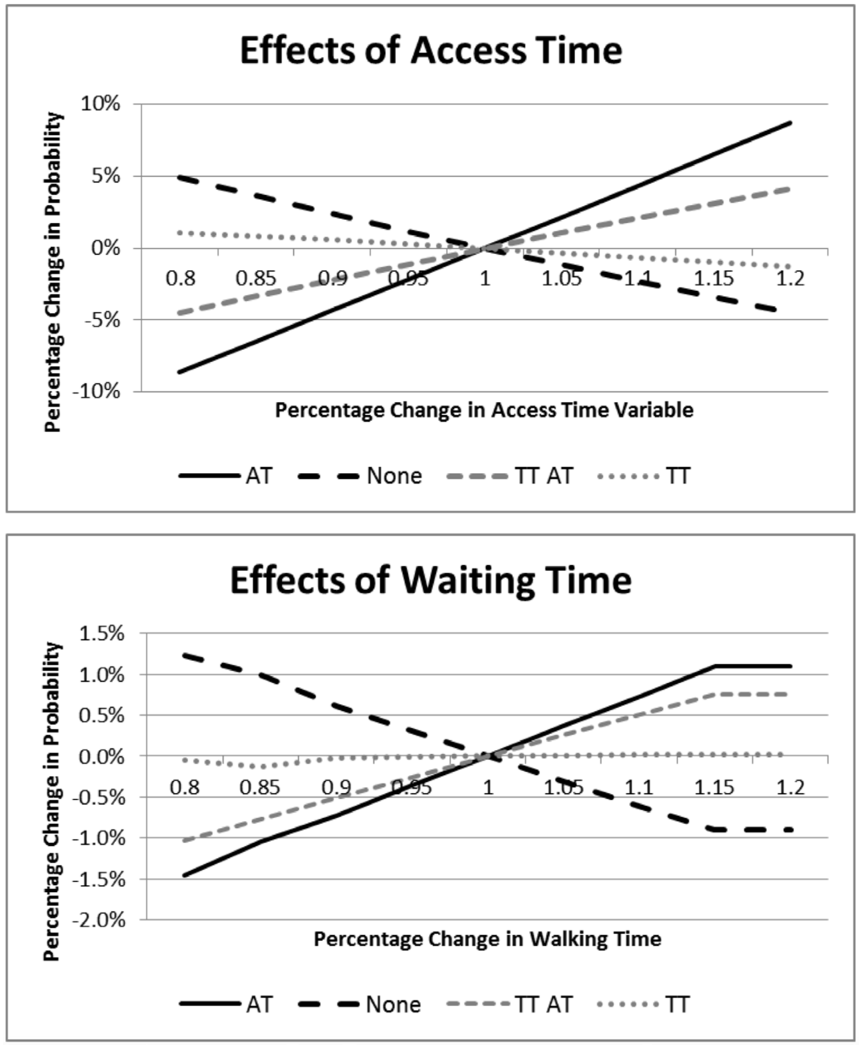
FIGURE 3.
Prediction capabilities of stop choice models





The TT-AT model was tested to observe the sensitivity of the nests with a change of access time and walking time; the results are shown in Figure 4. Here, the effects of waiting time seem to be almost similar to the effects of access time on the nests. However, the difference is in the magnitude, which seems to be much higher for the access time change. Figure 4 shows that by increasing the access time and waiting time, the probability of choosing from the AT and TT AT nests (strategies) increases; however, the TT nest seems to be relatively insensitive. This can be interpreted as follows: if the access time or waiting time is increased, the probability of selecting a stop that follows the MAT or MTT-MAT scheme will be increased, and if the access time or waiting time is decreased, the probability of selecting a stop that follows the MAT or MTT-MAT scheme will be decreased.

FIGURE 4.
Effects of different variables on nests



Conclusions

One of the contributions of this study is to improve the stop choice model developed by Nassir et al. (2015) by adding socioeconomic, trip, and strategy variables. Furthermore, this study considered different nesting structures and developed several types of discrete choice models. Relating the nesting structures to the schemes/strategies people consider when selecting stops is a unique contribution of this paper.

This study provides a deeper understanding about stop choice behavior compared to the existing literature. It was found that transit users can use different travel schemes/strategies when selecting access stops. The most appropriate scheme seems to be the combination of minimizing travel time and minimizing access time. From the behavioral point of view, it can be concluded that SEQ transit users perceive alternatives that are either faster (MTT nest) or more easily accessible from the origin of the trip (MAT nest), or both (fast and nearby) in a similar way.

This study shows that the choice of access stop is not only affected by impedance factors of the paths (number of transfers, walking time, travel time), but also by the attributes of the stop (such as walking time to access the stop and the presence of lighting at the stop). Moreover, the presence of multiple paths from a stop shows a positive influence on the utility of stop choices. Again, some socioeconomic attributes, such as gender, studentship, place of birth, household size, and dwelling type (flat), affect the choice of stop. Furthermore, transit users also take into account the transit mode and time of the day of the trip. One interesting point is that the developed models relate some of the impedance factors associated with paths linked to the origin and destination stops. Therefore, the proposed approach of this study married the stop and path selection themes in a straightforward manner, and further analysis is required to examine the opposite direction when stop attributes are includes in a route choice model. This work is underway by the authors.

The main contribution of this research is that it can be used to develop a behavior-based transit path choice model from trip origin to destination. For this, the suggested access stop choice model can be developed from the trip origin to the departure stop. Again, from the departure stop to the destination stop, other boarding strategy-based models (from smart card data) can be developed. Eventually, the combination of these two models can effectively estimate and evaluate future transit demand from any given origin to destination. Thus, the presented study can be extremely beneficial for the policy-makers, as this eventually affects the evaluation process of transit policies considered for the target year.

Further investigations can be conducted to determine the impacts of travel schemes when paths are considered to be selected by travelers rather than stops. Other model structures, such as cross-nested logits, mixed cross-nested logits, and nested logits with multiple levels and combinations (e.g., scheme-mode-stop, scheme-mode-path, mode-scheme-path etc.), also can be tested. Results from such models can provide a clearer understanding about transit choice research.

References

Antonini, G., M. Bierlaire, and M. Weber. 2004. "Simulation of Pedestrian Behaviour Using a Discrete Choice Model Calibrated on Actual Motion Data." 4th Swiss Transport Research Conference.

Bajwa, Shamas, Shlomo Bekhor, Masao Kuwahara, and Edward Chung. 2008. "Discrete Choice Modeling of Combined Mode and Departure Time." *Transportmetrica*, 4(2): 155-77.

Bierlaire, Michel. 1998. "BIOGEME: A Free Package for the Estimation of Discrete Choice Models."

Chakour, Vincent, and Naveen Eluru. 2013. "Analyzing Commuter Train User Behavior: A Decision Framework for Access Mode and Station Choice." *Transportation*, 41(1): 211-28.

Debrezion, Ghebreegziabiher, Eric Pels, and Piet Rietveld. 2009. "Modelling the Joint Access Mode and Railway Station Choice." *Transportation Research Part E: Logistics and Transportation Review*, 45(1): 270–83. doi:10.1016/j.tre.2008.07.001.

Fonzone, Achille, and Michael G. H. Bell. 2010. "Bounded Rationality in Hyperpath Assignment: The Locally Rational Traveller Model." Paper presented at the 89th Annual TRB Meeting, Washington, DC. http://researchrepository.napier.ac.uk/4238/.

Hammadou, Hakim, Isabelle Thomas, Ann Verhetsel, and Frank Witlox. 2008. "How to Incorporate the Spatial Dimension in Destination Choice Models: The Case of Antwerp." *Transportation Planning and Technology*, 31(2): 153-81. doi:10.1080/03081060801948126.

Hensher, D. A., and William H. Greene. 2002. "The Mixed Logit Model : The State of Practice and Warnings for the Unwary." Working Paper, Institute of Transport Studies, Australia, 01-02. Institute of Transport Studies, the University of Sydney and Monash University.

Hess, Stephane, Michel Bierlaire, and John W. Polak. 2005. "Mixed GEV Modelling of Mode-Choice." Monte Verità/Ascona.

Jánošíková, Ľudmila, Jiří Slavík, and Michal Koháni. 2014. "Estimation of a Route Choice Model for Urban Public Transport Using Smart Card Data." *Transportation Planning and Technology*, 37(7): 638-48. doi:10.1080/03081060.2014.935570.

Khani, Alireza. 2013. "Models and Solution Algorithms for Transit and Intermodal Passenger Assignment (Development of FAST-TrIPs Model)." University of Arizona.

Khani, Alireza, Mark Hickman, and Hyunsoo Noh. 2014. "Trip-Based Path Algorithms Using the Transit Network Hierarchy." *Networks and Spatial Economics*, 15(3): 635-53.

Khani, Alireza, Sanggu Lee, Mark Hickman, Hyunsoo Noh, and Neema Nassir. 2012. "Intermodal Path Algorithm for Time-Dependent Auto Network and Scheduled Transit Service." *Transportation Research Record*, 2284: 40-46.

Kurauchi, Fumitaka, Jan-Dirk Schmöcker, Achille Fonzone, Seham Mohamed Hassan Hemdan, Hiroshi Shimamoto, and Michael G. H. Bell. 2012. "Estimating Weights of Times and Transfers for Hyperpath Travelers." *Transportation Research Record*, 2284 (-1): 89-99. doi:10.3141/2284-11.

Mahmoud, Mohamed, Khandker Habib, and Amer Shalaby. 2014. "Park-and-Ride Access Station Choice Model for Cross-Regional Commuting: Case Study of Greater Toronto and Hamilton Area, Canada." *Transportation Research Record*, 2419: 92-100. doi:10.3141/2419-09.

Nassir, Neema, Mark Hickman, Ali Malekzadeh, and Elnaz Irannezhad. 2015. "Modeling Transit Access Stop Choices." http://trid.trb.org/view.aspx?id=1338262.

Nassir, Neema, Mark Hickman, and Zhen-Liang Ma. 2015. "Activity Detection and Transfer Identification for Public Transit Fare Card Data." *Transportation*, 42(4): 683-705.

Nassir, Neema, Alireza Khani, Mark Hickman, and Hyunsoo Noh. 2012. "Algorithm for Intermodal Optimal Multidestination Tour with Dynamic Travel Times." *Transportation Research Record*, 2283: 57-66. doi:10.3141/2283-06.

Nassir, Neema, Jennifer Ziebarth, Elizabeth Sall, and Lisa Zorn. 2014. "Choice Set Generation Algorithm Suitable for Measuring Route Choice Accessibility." *Transportation Research Record*, 2430 (December): 170-81. doi:10.3141/2430-18.

Schmöcker, Jan-Dirk, Hiroshi Shimamoto, and Fumitaka Kurauchi. 2013. "Generation and Calibration of Transit Hyperpaths." *Procedia—Social and Behavioral Sciences*, 80: 211-30.

About the Authors

Mohammad Nurul Hassan (*m.n.hassan@student.unsw.edu.au*) is a Ph.D. candidate at the University of New South Wales (UNSW) in Australia.

Taha Hossein Rashidi (*Rashidi@unsw.edu.au*) is a Senior Lecturer at UNSW.

S. Travis Waller (*s.waller@unsw.edu.au*) is a Professor and rCITI Director at UNSW.

Neema Nassir (*n.nassir@uq.edu.au*) is a Postdoctoral Research Fellow at the University of Queensland in Australia.

Mark Hickman (*m.hickman1@uq.edu.au*) is a Professor and ASTRA Chair of Transport at the University of Queensland in Australia.

Cross-Elasticities in Frequencies and Ridership for Urban Local Routes

Joseph C. Totten and David M. Levinson, Ph.D.
University of Minnesota–Twin Cities

Abstract

Observational data from the Minneapolis-Saint Paul region's Metro Transit were analyzed to determine the effects of service levels on ridership levels at different intervals. The research compares changes in service levels and ridership in several service intervals and includes elasticities and cross elasticities, or the influence that these service levels have on different service intervals' ridership. These cross-elasticities were found to have little effect during the week; however, weekend ridership was found to be influenced by rush-hour and overnight frequencies.

Keywords: *Bus transit, scheduling, elasticity*

Introduction

Most people in the U.S. do not ride public transportation, specifically local buses. It has been posited that one factor is due to flexibility: although services for rush hour may be adequate, there is little flexibility for return trips at non-standard times (Jaffe 2014; Dutch 2015). This study investigated these assertions, with the hypothesis that if a common reason for not riding transit is a lack of flexibility, an increase in midday and/or evening services would increase rush-hour ridership. This was done by determining elasticities of ridership with respect to frequencies of bus routes. Elasticities signify the percent change in ridership that results from a 1% change in frequency; a cross-elasticity is the elasticity of a service interval's ridership with respect to another interval's frequency. This research is important because it informs transit providers about how they can best use their limited resources to garner ridership. The routes examined in this study were local routes, primarily within the Minneapolis and St. Paul city limits, with pre-existing midday and evening services. The routes examined and their general changes in frequency are shown in Figure 1.

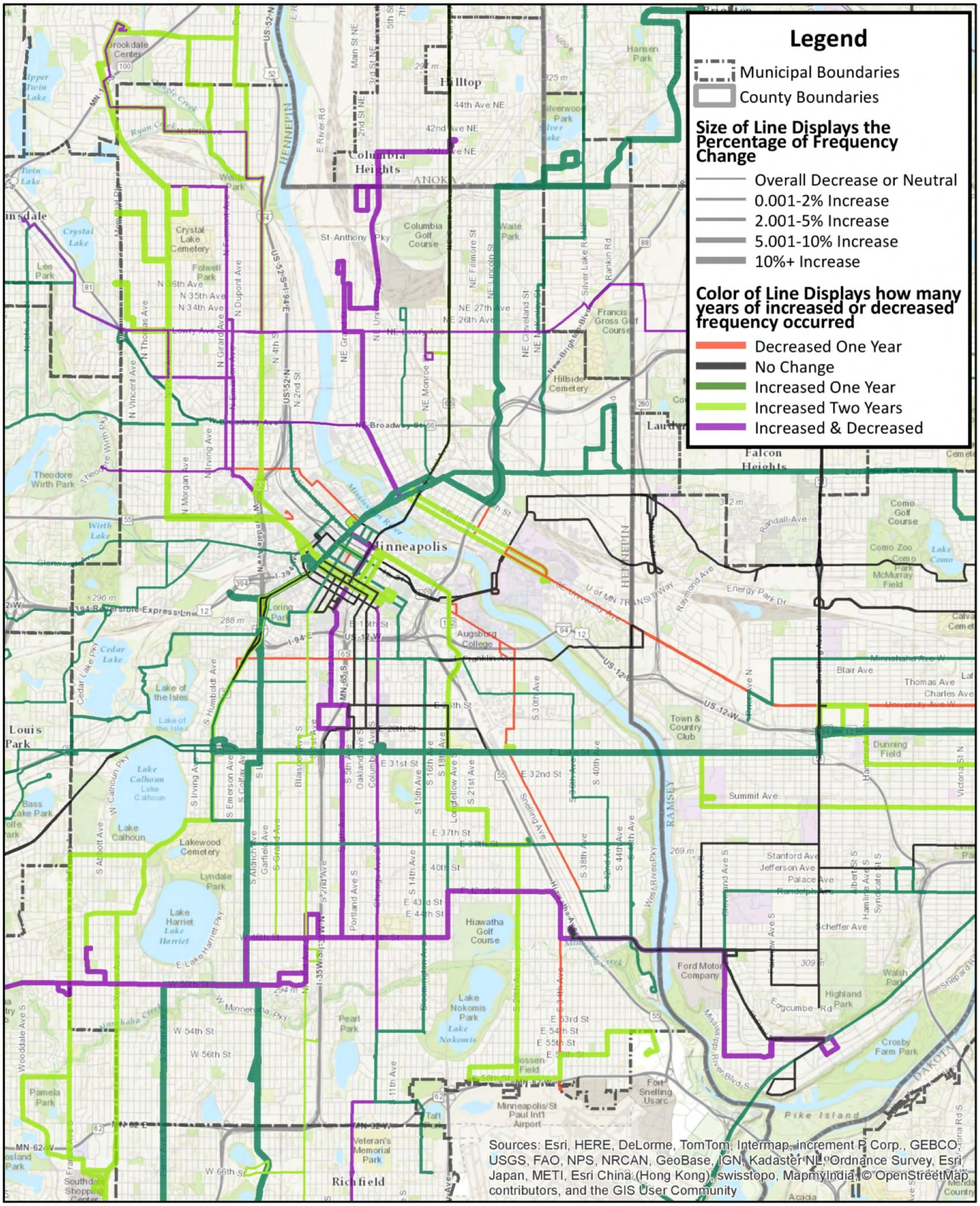


FIGURE 1. Map of urban-local bus routes and frequency change, Minneapolis

Literature Review

The studies shown in Table 1 are primarily literature reviews and analysis of existing studies. The values shown and discussed in this study focus on short-term elasticities, with year-over-year changes in ridership and service levels. Previous works on the effect of frequency on ridership have found that frequency has an elasticity between 0.30 and 1.03 (Evans 2004). The lower value is a better representation of urban systems, the higher value is more related to suburban systems with infrequent service. Furthermore, on weekends, when there is less-frequent service in metropolitan transit, higher elasticities are observed than on weekdays (Paulley et al. 2006). As a proxy for the influence of increasing service levels, service expansion or increasing the hours that a service is offered also has been studied (Simmons 2014), with findings that expanding evening service had an elasticity of 0.30 to 0.50 while equivalent increases occur during the day (Currie and Loader 2009). Studies regarding the frequency of off-peak service and its effect on ridership during other service periods were not found by the author.

TABLE 1.
Previous Study Results

Study Author	Year(s)	Range	Locations Studied
Evans	2004	0.30–1.03	North America, Europe
Currie and Loader	2009	0.17–0.38 weekday 0.80+ weekends	Melbourne, Australia,
Litman	2015	0.50–0.70	North America, Western Europe
Paulley et al.	2006	0.38	Europe
Brown and Neog	2012	0.76–0.91	United States
Koonce et al.	2006	0.30–1.11	Portland, Oregon
Lago et al.	1981	0.30–0.85	North America, London

Methods

Data were collected by Metro Transit of Minneapolis-St. Paul, Minnesota, for the fall quarters of three years (2011, 2012, 2013) and include the number of runs started each hour and ridership figures for weekday, Saturday, and Sunday service, with weekday ridership divided into rush-hour ridership and non-rush-hour ridership. Only data from local and limited-stop routes were used, as these routes were less susceptible to changes in routing while still providing changes in scheduling. Making the raw data usable for this analysis required taking the runs started each hour and averaging them for each service interval to get each service interval's average runs per hour in each year. Additionally, the percent change of every service interval's data needed to be taken for 2011 to 2012 and 2012 to 2013. The equation used for percent change in frequency is:

$$\Delta_F = \left(\frac{F_t - F_{t-1}}{F_{t-1}}\right) * 100\%$$

Where Δ_F is the percent change of hourly frequency for the service interval from one year to the next and F_t is the hourly frequency for the service interval in year t.

The equation used for percent change in ridership is:

$$\Delta_R = \left(\frac{R_t - R_{t-1}}{R_{t-1}}\right) * 100\%$$

Where Δ_R is the percent change of ridership from one year to the next and R_t is the ridership in year t.

To investigate the hypothesis, elasticities and cross-elasticities were studied. Elasticity is used when both the dependent and independent variables vary over time and can be expressed in percent changes. The value of elasticity is the coefficient of percent change of the independent variable to produce the dependent variable, as seen in the following equation:

$$\Delta_R = \Delta_F * E$$

Where Δ_R is the percent change of ridership, Δ_F is the percent change of frequency, and E is the elasticity.

As this study aimed to determine elasticities not only during the same hours, but also across hours, both own-elasticities and cross-elasticities were evaluated. An own-elasticity is when the dependent variable of ridership and the independent variable of frequency are represented in the same time period; a cross-elasticity has variables representing different time periods. Because elasticities were considered as a coefficient in a linear relationship, the regression used was a Robust Standard Error Linear regression, to minimize the effect of outliers.

Table 2 shows the times of each service interval and how ridership data were compiled.

TABLE 2.
Hours of Ridership and Service Interval Data

Hours	Ridership Data	Service Data
01:00–05:00[1]	Non-Rush Hour	Owl
06:00–09:00	Rush Hour	Rush Hour
09:00–15:00	Non-Rush Hour	Midday
15:00–18:30[2]	Rush Hour	Rush Hour
18:30–01:00	Non-Rush Hour	Evening
Saturday	Saturday	Saturday
Sunday[3]	Sunday	Sunday

[1] *05:00 was not used in any service interval and was ignored for this analysis.*

[2] *8:00 is split between rush hour and evening service; therefore, any runs starting between 18:00 and 18:59 were considered half a run in rush hour and half a run in evening service.*

[3] *Weekend frequencies consist of runs from 08:00-21:00 to isolate changes in frequency, as opposed to service-hour expansion.*

Results

Whereas 120 route-years are displayed, only 80 elasticity measurements (including zeroes) were included due to needing two route-years to get one elasticity measurement. The lack of data points for owl service levels, as seen in Table 3, make it difficult to make a strong claim about any significance using this service interval. Table 3 shows there are high standard deviations for frequencies, as compared to average frequencies; this indicates the diversity of local bus routes in the Minneapolis-Saint Paul metropolitan area. Some routes require many buses per hour, such as Route 5, with a frequency of 8.75 buses per hour or 7-minute headways during rush hour; some require a much lower level of service, such as Route 62 with a frequency of 1.08 per hour and nearly 1-hour headway during rush hour.

TABLE 3.
Descriptive Statistics

Frequency Time Frame	Number of Route-Years with Any Service	Number of Route-Years with at Least Hourly Service	Number of Changes in Frequency[1]	Average Frequency of Routes with Service	Standard Deviation of Frequency of Routes with Service
Rush Hour	120	114	35	3.91	2.10
Midday	111	102	19	3.48	2.02
Evening	99	76	20	1.87	1.00
Owl	78	3	4	0.42	0.31
Saturday	96	82	18	2.94	1.62
Sunday	90	75	21	2.30	1.19

[1] *If a route's frequency changed from one year to the next for the service period shown, then that would be one change in frequency. Thus, this represents the number of data points actually used for determining elasticity.*

As seen in Table 4, the percent change of ridership is very highly-correlated between Saturday and Sunday ridership, with a lesser correlation in scheduling. As shown, Saturday and Sunday are similar, but are still different enough that they should be considered separately, as they are in the analysis. In Table 5, all ridership correlations are positive, indicating that if ridership increases in one service period, it generally increases in other periods.

TABLE 4.
Correlation Matrix of Percent Change in Ridership

	Saturday	Sunday	Off Peak	Peak	Weekday Total
Saturday	1	0.8334	0.0851	0.0478	0.1240
Sunday		1	0.0998	0.0835	0.1318
Off Peak			1	0.4261	0.5850
Peak				1	0.9261
Weekday Total					1

TABLE 5.
Correlation Matrix of Percent Change in Frequency

	Rush Hour	Midday	Evening	Owl	Saturday	Sunday
Rush Hour	1	0.4725	-0.0111	-0.0344	-0.0233	-0.0557
Midday		1	0.0585	-0.0316	0.0066	0.0347
Evening			1	0.57694	-0.0835	0.0987
Owl				1	0.0485	0.0160
Saturday					1	0.7339
Sunday						1

For rush-hour ridership, as shown in Table 6, it can be seen that rush hour is the only service level that has an elasticity significant at $p<0.10$. Rush-hour frequency has a strong positive elasticity with ridership. The found elasticity of 0.39 falls in the normal range, as shown in the literature review, for short-term elasticity. The influences of the frequencies of other schedule periods were not seen to be significant in this study. No service period had an effect significant at $p<0.05$ on rush hour ridership.

TABLE 6.
Results

			Percent Change in Ridership			
			Rush Hour	*Non-Rush Hour Weekday*	*Saturday*	*Sunday*
Percent Change in Frequency	Rush Hour	Elasticity	0.385[a]	0.003	0.056	0.273[c]
		RSE	0.195	0.132	0.107	0.073
	Midday	Elasticity	0.349	0.391[b]	0.169	-0.225
		RSE	0.248	0.159	0.132	0.141
	Evening	Elasticity	0.004	0.070	0.036	0.158
		RSE	0.046	0.051	0.054	0.122
	Owl	Elasticity	-0.081	-0.035	0.075[c]	0.011
		RSE	0.077	0.026	0.022	0.025
	Saturday	Elasticity	-0.042	0.026	0.257[c]	0.123[a]
		RSE	0.028	0.026	0.043	0.070
	Sunday	Elasticity	0.013	0.009	0.100[c]	0.496[c]
		RSE	0.019	0.020	0.032	0.050
Constant		Elasticity	0.021[b]	-0.023	-0.020[c]	-0.027[c]
		RSE	0.008	0.019	0.007	0.009

[a] *$|p|<0.10$*
[b] *$|p|<0.05$*
[c] *$|p|<0.01$*

For non-rush hour weekday ridership, as shown in Table 6, midday frequency has an elasticity of 0.39, which is significant at $p<0.05$. Whereas non-rush hour weekday ridership contains midday, evening, and owl service within its defined times, midday frequencies had an effect that would put it in line with the own-elasticities found in previous studies. No other service intervals were seen as being significant at $p<0.10$ for non-rush hour weekday ridership. Further research with ridership data for each service interval would allow for more accurate and useful results for all service intervals.

As shown in Table 6, weekend and owl service intervals have elasticities significant at $p<0.10$ with Saturday ridership, whereas Saturday and owl service are significant at $p<0.01$ and Sunday service is significant at $p<0.05$. This is likely associated with Saturday ridership comprising riders using both Saturday service and owl service on Friday night after midnight. The own-elasticity seen for Saturday service of 0.26 is lower than expected compared to previous studies. The effect of Sunday service on Saturday ridership is posited as due to the weekend being observed as one entity to most of the traveling public and possibly the correlation of 0.7339 between Saturday and Sunday frequencies. The magnitude of the Sunday elasticity is not great, at 0.10. The low elasticity value of owl frequency, at 0.08, and the small number of changes in owl frequency, as seen in Table 3, make this result questionable, as there are not enough data to make a strong claim.

Significant elasticities for Sunday ridership at $p<0.10$, as shown in Table 6, were seen with rush hour, Saturday, and Sunday service intervals. Sunday and rush-hour frequencies are significant at $p<0.01$. Sunday's own-elasticity was seen as 0.50, and rush hour's services had an elasticity of 0.27 on Sunday ridership. A possible explanation for why rush hour frequency appears to have a significant effect on Sunday ridership may be due simply to a growing transit mode share along a route, as people may become less averse to using transit for weekend travel if they use it for their daily commuting needs. Saturday frequency had a smaller effect on Sunday ridership, with an elasticity of only 0.12. As with Saturday ridership, the correlation between Saturday and Sunday changes in frequency are a possible factor in these elasticities; more data are needed with changes in these service intervals to know if they are truly affecting one another or simply changing together.

Conclusion

This research established that the ridership of weekday service depends on the frequencies of rush hour and midday and refutes the hypothesis that changes in midday and evening frequencies would have a noticeable effect on rush-hour ridership. During the week, rush-hour ridership is seen as being affected by changes of only rush-hour frequency, with an elasticity of 0.39; likewise, non-peak ridership was seen as affected only by changes in midday frequency, with an elasticity of 0.39. The weekends are far more interconnected, with service levels during rush hour, owl, and the entire weekend being significant for the ridership on one or both days of the weekend. Saturday ridership was affected by changes in Saturday frequency with an elasticity of 0.26 and Sunday frequency with an elastic of 0.10; owl frequency also was seen as a contributor in this analysis, but with so few changes in owl frequency, this cannot be certain. Sunday ridership was affected by changes in Sunday frequencies with an elasticity of 0.50, Saturday frequencies with an elasticity of 0.12, and rush-hour frequency with an elasticity of 0.27. It is intuitive that all own-elasticities and cross-elasticities would be positive and cross-elasticities would overall be smaller than own-elasticities. Additionally, the hypothesis of this research failed to be corroborated; if the goal of a transit agency is to provide as many rush-hour trips as possible, this research has established that using driver hours at other times is not shown to have any effect, whereas using those driver hours during rush hours will increase ridership.

This research should be expanded to include a larger data set, including express and suburban local routes, and should be replicated in other metropolitan areas. The additional research also would allow for a better determination of significance, as there would be more data to solidify significance or non-significance. Express routes, in particular, should be investigated, as midday and evening service usually is not provided on these routes; thus, adding these services would allow for investigation of new services and elasticities at much lower frequencies.

References

Brown, J., and D. Neog. 2012. "Central Business Districts and Transit Ridership: A Reexamination of the Relationship in the United States." *Journal of Public Transportation*, 15(4): 1-22.

Carrel, A., A. Halvorsen, and J. Walker. 2013. "Passengers' Perception of and Behavioral Adaptation to Unreliability in Public Transportation." *Transportation Research Record*, 2351: 153-62.

Currie, G., and C. Loader. 2009 "High Ridership Growth from Extended Transit Service Hours: An Exploration of the Causes." *Transportation Research Record*, 2110: 120-127

Dutch, S. 2013. "Why People Don't Use Mass Transit." http://www.uwgb.edu/dutchs/pseudosc/masstransit.htm, accessed Sep 3, 2015.

Evans, J. E., IV. 2004. "TCRP Report 95: Traveler Response to Transportation System Changes Chapter 9: Transit Scheduling and Frequency." Transportation Research Board of the National Academies, Washington, DC.

Federal Transit Administration. 1998. "Research Results Digest; Continuing Examination of Successful Transit Ridership Initiatives" Transit Cooperative Research Program, Washington, DC.

Jaffe, E. 2014. "If So Many People Support Mass Transit, Why Do So Few Ride?" *The Atlantic*, 22.

Koonce, Peter, P. Ryus, D. Zagel, Y. Park, and J. Parks. 2006. "An Evaluation of Comprehensive Transit Improvements—TriMet's Streamline Program." *Journal of Public Transportation*, 9(3): 103-115.

Lago, A., P. Maywork, and J. McEnroe. 1981. "Transit Service Elasticities, Evidence from Demonstration and Demand Models." *Journal of Transport Economics and Policy*, May: 99-119.

Litman, T. 2014. "Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior." Victoria Transport Policy Institute, http://www.vtpi.org/tdm/tdm11.htm#_Toc161022588, accessed April 15, 2015.

Litman, T. 2015. "Transit Price Elasticities and Cross-Elasticities." Victoria Transport Policy Institute, http://www.vtpi.org/tranelas.pdf, accessed September 1, 2015.

McMahon, J. 2013. "Top Eight Reasons People Give Up On Public Transit." *Forbes*, May 6.

Metropolitan Council. 2015. Data Finder, "Transit Boardings and Alightings." http://www.datafinder.org/metadata/TransitStopsBoardingsAndAlightings.html, accessed August 7, 2015.

Paulley, N., R. Balcombe, R. Mackett, H. Titheridge, J. M. Preston, M. R. Wardman, J. D. Shires, J. D. and P. White. 2006. "The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership." *Transport Policy*, 13(4): 295-306.

Simmons, J. 2014. "Bus Route Span of Service Changes: Ridership Impacts on Unaltered Hours." Master's thesis, San Jose State University.

About the Authors

Joseph Totten (*totte011@umn.edu*) has a BSCE from the University of Minnesota–Twin Cities with an emphasis in transportation and a minor in Urban Studies. He currently works for the City of Edina, Minnesota, in traffic and traffic safety.

David Levinson (*dlevinson@umn.edu*) is the Richard P. Braun/CTS Chair in Transportation in the Department of Civil, Environmental, and Geo-Engineering at the University of Minnesota and director of the Networks, Economics and Urban Systems (NEXUS) research group. He holds a Ph.D. in Transportation Engineering from the University of California at Berkeley.

Effects of Speed, Curves, and Driver Behavior on Passive Securement Systems on Large Transit Buses

Andrea Mather and Katharine Hunter-Zaworski, Ph.D., P.E.
Oregon State University

Abstract

Wheeled mobility devices that are not secured properly on large transit vehicles pose risks to all passengers. The purpose of this study was to increase the understanding of the effects of horizontal and vertical curves, speed, and driver behavior on the safety and security of people using wheeled mobility devices in rear-facing passive containment systems on large transit buses. Testing included the use of manual wheelchairs and lightweight scooters on an articulated low-floor transit bus. The project conclusions were derived from data produced by accelerometers placed on the bus as well as visual observations of wheeled mobility device movement. The data showed a clear difference in the amount of movement of the wheeled mobility devices and the comfort of the seated passenger when the bus traveled on a combination of horizontal and vertical curves at different driving speeds.

Keywords: *Wheeled mobility devices, rear facing containment, bus dynamics*

Introduction

The securement of wheeled mobility devices (WhMDs) on transit buses is required under the transportation regulations associated with the Americans with Disabilities Act (ADA) (ADA 1998). Since the enactment of the ADA, securement systems have been studied, designed, and deployed to increase passenger safety, security, and comfort. Large transit buses are equipped with two types of securement systems: active and passive. Common active securement systems include auto docking systems or belt-type tie-downs. Active systems that have belts or straps usually require a second person to attach them to the wheeled mobility device. This often increases dwell time at bus stops and encroachment on the personal space of the passenger.

WhMDs on large transit buses that have a gross vehicle weight greater than 26,000 pounds are required to be equipped with one forward-facing belt-type securement in addition to any rear-facing containment systems. The belt-type securement systems usually require another person, often the driver, to secure the WhMD appropriately. This often increases the vehicle dwell time at stops and can influence the transit schedule. Rear-facing passive systems are designed to allow the passenger to secure himself or herself without the assistance of another person. These containment systems have widespread use in Europe and Canada (Hunter-Zaworski and Rutenberg 2014).

This study focused on rear-facing passive containment systems that are deployed on transit buses that travel on mixed right-of-way streets with both horizontal and vertical curvature.

Background

In 2001, a survey conducted by the University of South Florida found that all 94 transit agencies included in the study used a belt securement system (Foreman and Hardin 2002). In 2013, Frost et al. found that for the past 20 years, forward-facing belt-type securement systems were the most common securement system in the U.S. on large transit vehicles. The researchers also found that only 7.5% of trips made by people in manual chairs used securement systems (Frost et al. 2013).

Intersections that are designed for large transit vehicles have recommended geometric design dimensions set forth by the American Association of State Highway and Transportation Officials (AASHTO). The AASHTO *Guide for Geometric Design of Transit Facilities on Highway and Streets* states that the maximum grade for roadways on which transit vehicles operate is 10%, but it recommends a lower grade (AASHTO 2014). Tables 1 and 2 show AASHTO's standard bus design characteristics and bus performance characteristics.

TABLE 1.
AASHTO Standard Bus Design Characteristics

Item	Regular Bus		Articulated Bus
	40 ft	*45 ft*	*60 ft*
Gross Weight	36,900–40,000 lbs	55,200 lbs	66,600 lbs
Turning Radius Inside	24.5-30 ft	24.5-30 ft	27.3 ft
Turning Radius Outside	42.0 ft–47 ft	42.0–47 ft	39.8–42 ft

Source: AASHTO, Guide for Geometric Design of Transit Facilities on Highways and Streets, 2014

TABLE 2.
AASHTO Bus Performance Characteristics

	MPH/Sec	Ft/Sec^2	g's
Acceleration			
0–10 sec	3.33	4.9	0.15
10–30 sec	2.22	3.3	0.10
30–50 sec	0.95	1.4	0.04
Deceleration			
Normal	2-3	2.9–4.4	0.09–0.14
Maximum	6-12	8.8–17.6	0.27–0.54
Maximum Grade (Sustained Roadway)	6%		
Maximum Grade (Short Upgrade)	10-12%		

Source: AASHTO, Guide for Geometric Design of Transit Facilities on Highways and Streets, 2014

Researchers developed guidelines for transit operations at standard operating speeds around corners. This includes guidelines from transit districts and departments of education (school buses) (Kentucky Department of Education 2008). These recommendations are 10 miles per hour (mph) for turns and 15 mph for evasive maneuvers (MUTD 2011).

Objectives and Motivation

Lane Transit District (LTD) in Eugene, Oregon, approached the research team with questions concerning several major intersections in its operating system and the performance of rear-facing passive containment systems. The primary objective of the research was to determine the relationship between horizontal and vertical curves and speed and the effect on passive containment for WhMDs on large transit vehicles. This relationship is very complex, with multiple factors interacting with each other. The study was designed to isolate several key factors in the field tests.

Description of Testing

Testing was conducted in partnership with LTD using LTD buses. LTD operates vehicles in demand-responsive paratransit, fixed-route, and bus rapid transit (BRT) services. The project focused on buses operating in fixed-route and BRT operating modes. Vehicle testing occurred over two days, the first in February 2015 and the second in October 2015. Testing included driving trials at the maintenance facility and roadway tests on regular transit routes that included steep hills and sharp turns. The purpose of testing in the yard was a controlled study of horizontal turning maneuvers. Testing conducted in the maintenance yard calibrated the data acquisition equipment and validated testing assumptions related to horizontal curves. The test drives on the roadway included sharp horizontal and steep vertical curves.

Horizontal Curve Testing

To study the acceleration and WhMD behavior in horizontal curves, tests were conducted in LTD's parking lot in Springfield (Figure 1). This provided the research team with the opportunity to conduct sharp horizontal turning maneuvers on a level grade. The bus made sharp left turns at the places indicated by the number 2 on Figure 1 and slalom turns through the parking lot down the lanes indicated by the number 1. The parking lot was mostly empty during the testing and was similar to the configuration shown in Figure 1. This allowed the driver to make sharp turns to demonstrate the worst-case scenario.

FIGURE 1.
Aerial view of flat parking lot used to test horizontal curves

1 = location of S turns, 2 = sharp left turns
Source: Google Maps

Testing on Horizontal and Vertical Curves

The vertical and horizontal curve driving tests were conducted at a highway interchange in Eugene that has a mix of steep vertical and sharp horizontal curvature and a signalized intersection. The section of roadway is at the end of a highway overpass that includes a signalized intersection followed by a left turn onto a downgrade ramp. This intersection was of particular interest because of the combination of vertical and horizontal curvature and a signal-controlled intersection. This intersection is the location of a prior incident involving LTD passengers seated in WhMDs who were secured in an active forward-facing securement systems that resulted in the WhMD tipping over. The bus traveled on the overpass westbound on Goodpasture Island Road, followed by a downgrade to the signal. The intersection has one through/left lane (no right turn).

Test Methodology

The accelerometers were placed in a longitudinal orientation on the floor of the bus to collect three-dimensional acceleration data. The acceleration data collection was independent of the type of WhMD. During the bus testing, two different WhMDs were occupied by a 50-percentile male anthropometric test dummy (TED) sitting in the seat. The test dummy was used in these data collection activities to minimize human subject risk. The WhMD types included a standard manual chair and a three-wheeled scooter. The scooter used in the testing was similar to models that can be bought without a prescription at a non-medical supply store and is representative of WhMDs that many passengers use when riding LTD vehicles. The center of gravity of the scooter was higher off the ground than the manual chair and more prone to tipping over; the majority of the tests used the scooter for this reason. Some of the initial tests in the maintenance yard used the manual chair with the test dummy sitting in the wheelchair. Both WhMDs were in good working condition.

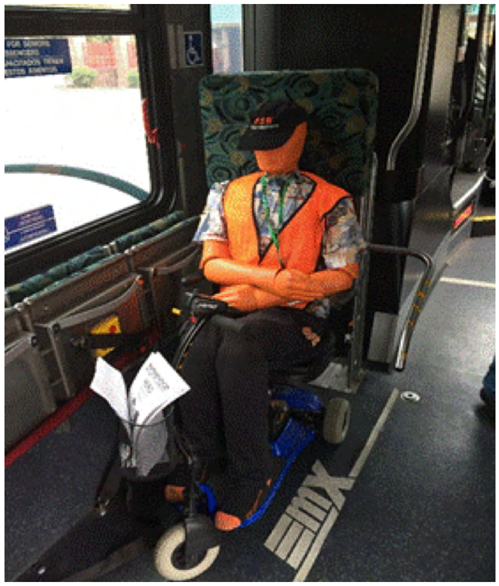
In all tests, the WhMDs had the brakes set on the device or powered down. Research has shown that during revenue service, passengers do not consistently set the brake on their devices. The research team conducted previous research on other transit vehicles that showed that setting the brake has a significant impact on the movement of WhMDs. For the safety of the research team in this study, the brakes were set. The mobility of TED also was restricted to folding his arms in his lap. Prior testing showed that TED is much more stable when he puts an arm on the folded-up seat. The position of TED's arms was intentionally included to evaluate a passenger who has no upper body strength or control. Figure 2 illustrates the placement of TED's arms during testing and shows a manual wheelchair in the rear-facing containment with the aisle side-arm lowered. Passengers have the potential to increase their stabilization if they have mobility and strength in their upper body.

All the testing used a rear-facing passive containment system that is located directly behind the driver. The passenger is rear-facing, with the back of his WhMD touching the backboard of the system. The system also features containment on three sides, with a bar that extends from the back on the aisle side and a folded seat on the window side. Figure 2 shows TED in the rear-facing containment location and sitting in a wheelchair.

FIGURE 2.
TED in wheelchair in passive rear-facing containment

To increase stability, the passenger may use the back of the folded seat. Figure 3 shows TED in the rear-facing containment location and sitting in a scooter.

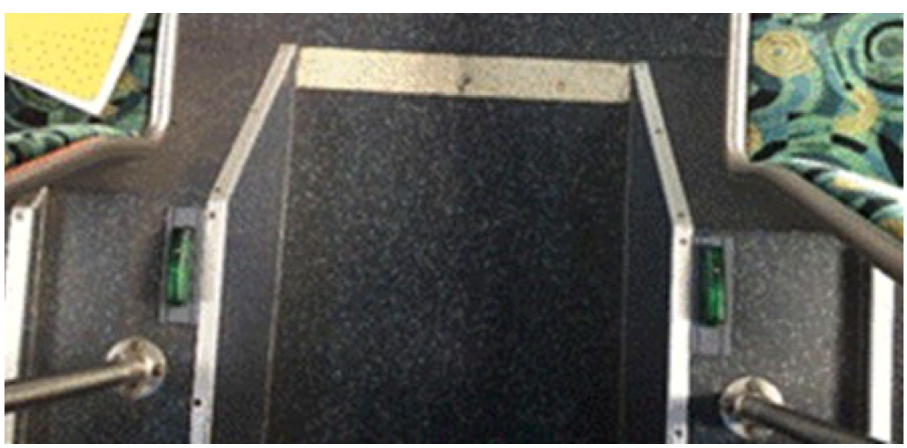
FIGURE 3.
TED in scooter in passive rear-facing containment system



The study included two forms of data collection: observations and accelerometers. Each of the researchers and officials from LTD conducted observations. One researcher was located next to the securement system and one in the middle of the bus to allow for multiple viewing angles during testing. Taking photos occurred only before and after testing for reference of orientation and experimental design.

Data were collected for this study using Gulf Coast Data Concepts Model X2-2 USB Accelerometers, shown in Figure 4. The placement of the accelerometers included locations before the vehicle articulation point and over the wheel well. The accelerometers recorded acceleration in three axis directions (axial, longitudinal, vertical) with a 32-Hz sample rate. For redundancy in data, data were collected from two accelerometers. Also used during data collection were time stamps on the accelerometers and GPS tracking. Figure 4 shows the location of the accelerometers.

FIGURE 4.
Accelerometer placement on longitudinal axis of bus



Consistent weather conditions prevailed during both days of testing—clear with no rain or moisture on the roadway. During each day of testing, the same operator drove for all tests, but there were different operators in February and October. The operator during the February testing was from the LTD Maintenance Department and was very familiar with the performance of the vehicle. The operator in the October testing was a veteran driver who was also an instructor and operator trainer.

The study used an articulated low-floor bus designed for the BRT system. The only people on the bus during the time of testing were researchers and LTD Risk Management staff. The crash dummy occupied the WhMD during the entirety of the testing. Severe cornering test runs were conducted only at the LTD maintenance facility. Figure 5 shows an LTD Emerald Express Bus used for BRT service (EmX) and is similar to the one used in the study.

FIGURE 5.
Example of type of bus used for tests

Photo courtesy of Lane Transit District

Table 3 summarizes the experimental conditions, showing information for both days of testing and data collection locations.

TABLE 3.
Summary of Variables Used in Testing

Equipment	Variable	Description
Bus	Constant	Low-floor articulated BRT bus
Wheeled Mobility Device	Variable	Lightweight three-wheel scooter (powered off) and standard wheelchair with brakes applied
Data Collection System	Constant	Accelerometers placed in same location and collection rate.
Test Location	Variable	Flat maintenance yard to isolate horizontal curves and Goodpasture Island Road intersection to study both vertical and horizontal curves
Driver	Constant/Variable	Driver stayed constant for day, but different drivers used in February and October tests
Speed of Curves	Variable	Curve speed changed to show difference between recommended speed and extreme speed

Study Limitations

LTD has only rear-facing passive containment on the large articulated buses used in its BRT service. Rear-facing containment is very popular with passengers who use wheeled mobility devices, and LTD is considering installing rear-facing containment systems on its new non-articulated buses. Limitations to the study included using only one type of bus and only regular or moderately-severe driving conditions. Future testing should consider using non-articulated transit buses to expand the applicability of the results.

The nature of the data collection process in the field limits the isolation of all contributing factors and conditions. Different tests were used to isolate some factors, but not all factors could be limited in the field.

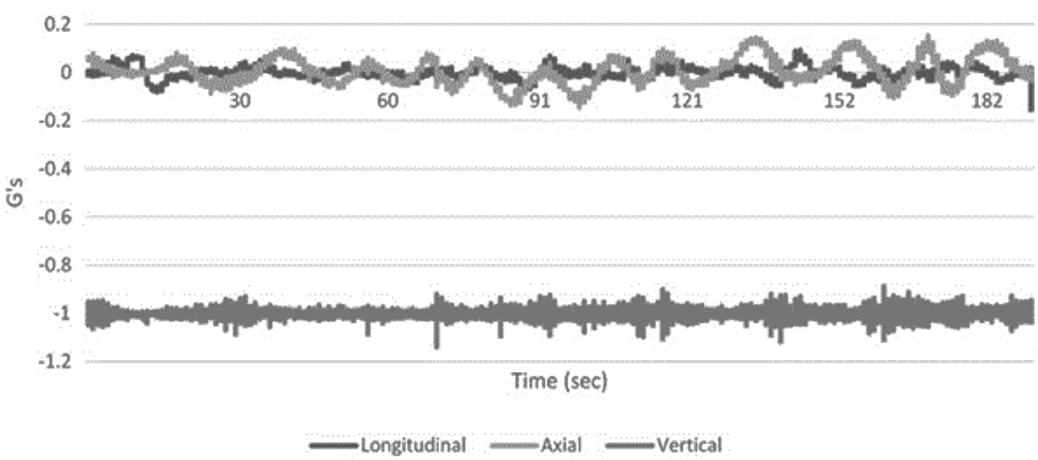
Results

The results of this study were divided into three segments: isolated horizontal curves, combination of horizontal and vertical curves, and driver behavior. Calibration tests for the accelerometers were conducted before the start of the testing. The results of the study were derived from the accelerometer data from the bus and observations made by research team.

Horizontal Curves

The graph in Figure 6 is from the tests conducted at the bus parking lot at the LTD maintenance facility. The data from the three axis accelerometers show the very low acceleration rates during slow speed and increasing to the maximum safe speed on horizontal curves. The lower speeds were 5 mph and increased to approximately 15 mph. The researchers observed no movement during the test of the manual wheelchair that was occupied with TED. The testing was completed in a single session.

FIGURE 6.
Results of low-speed (5–15 mph) S-curve tests conducted at LTD maintenance facility



Since acceleration is the rate of change of velocity, as the speeds changed during cornering, this was reflected in the accelerations. Figure 6 shows the lateral acceleration resulting from the "S" cornering. The vertical acceleration measured the "bumps in the road," and the forward or longitudinal acceleration measured the changes in speed until the bus came to a complete stop (183 sec).

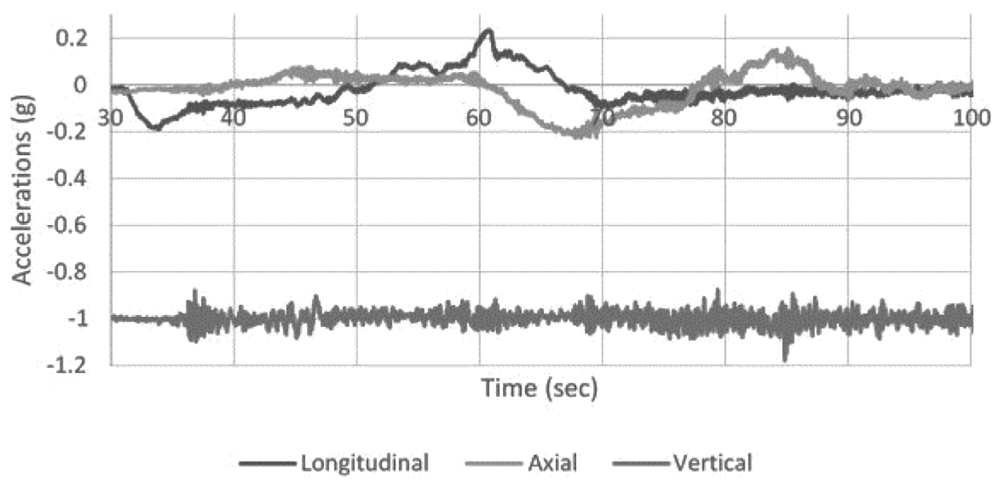
Observations of TED showed very little to no movement throughout the testing of the isolated horizontal curvature. The test dummy's movement was very limited to within the containment system and did not cause any alarm for safety.

Vertical and Horizontal Curves

The second group of tests conducted included a vertical curve and a horizontal curve at the interchange of Goodpasture Island Road and Delta Highway in Eugene. Three data collection tests were conducted under the conditions of low speed, high speed, and excess speed on cornering that caused the WhMD to tip within the containment system. Each of the speed tests was conducted only once due to time limitations.

Accelerometer data, as shown in Figure 7, illustrates the accelerations of the bus at a low speed (5 mph) while navigating the horizontal and vertical curvature. The change in acceleration was the smallest of any of three tests. The slower speed has the smallest amount of acceleration. This test also had the lowest difference in maximum longitudinal and axial acceleration. Observations of the TED and the WhMD within the containment system were limited to little to no movement.

FIGURE 7.
Low-speed (5 mph) no-movement acceleration data



The higher-speed (14 mph) test—the highest speed a professional driver would drive—showed minimal movement of the WhMD. This movement would typically occur in regular revenue service operations and likely would not cause injury to a passenger. When compared to the low-speed test, the higher-speed test had much larger changes in the maximum longitudinal and minimum axial acceleration. The changes in acceleration also produced a larger jerk during the turning maneuver. The accelerations of the vehicle are shown in Figure 8.

FIGURE 8.
Higher-speed (14 mph) slight-movement acceleration data

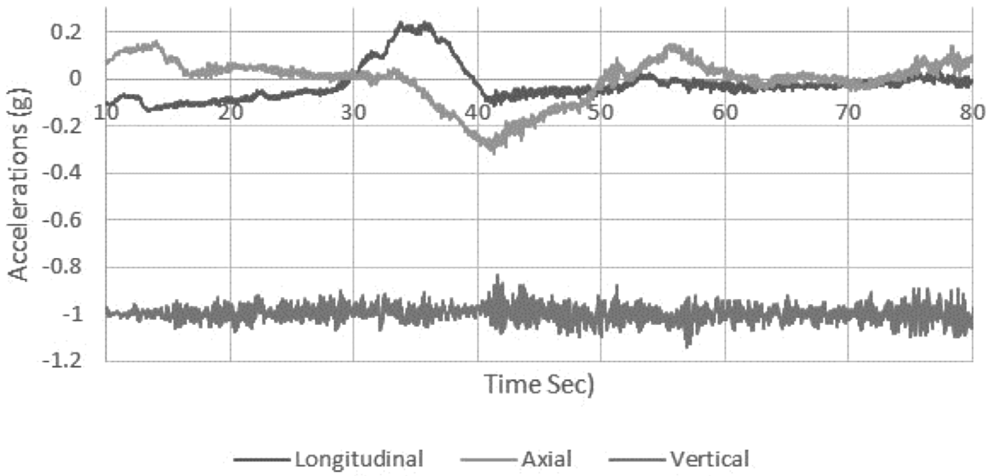
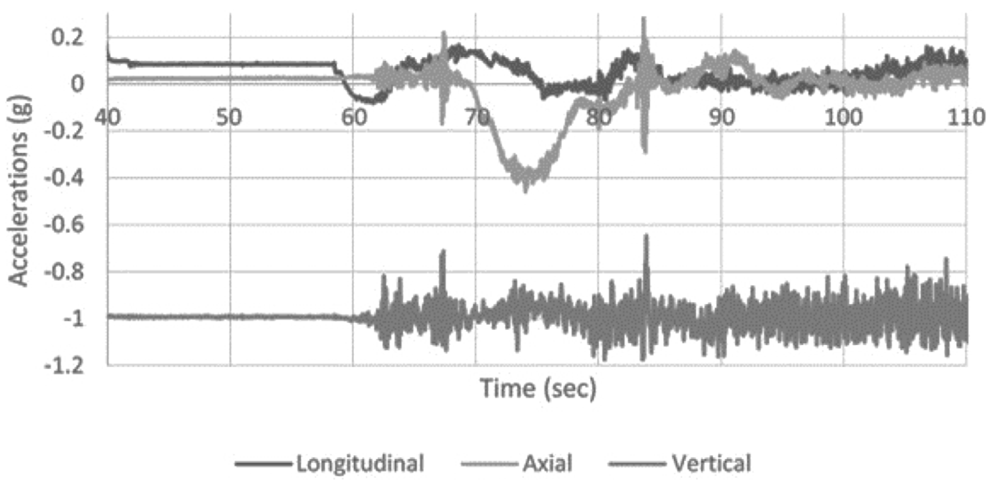


Figure 9 shows the accelerations when the wheeled mobility device tipped over and also illustrates the higher levels of acceleration. The jagged lines show that the changes in accelerations were sudden. At approximately the 70-sec mark, a spike in the acceleration occurred. This was when the bus started from the stop line at the intersection and also is when the wheels at the front of the WhMDs moved in the direction of the tipping. The maximum acceleration occurred in the middle of the turn. The side-to-side motion of the test dummy induced some of the motion of the WhMD, which caused the test dummy to shift weight off center and start to tip over. The tipping also was due to the high center of gravity of the scooter with a 50% test dummy.

FIGURE 9.
High-speed test that tipped WhMD accelerations data



Driver Performance

Different drivers drove the bus on each day of testing. On the first day, the driver was from the LTD Maintenance Department and was very experienced with performance of the bus used in testing. On the second test day, the driver was very experienced with the bus and was a professional operator with more than 20 years' experience as a commercial vehicle operator and also was a bus operator trainer. The differences in how each driver completed turns were shown in the accelerometer data. The first day of testing was designed to look at the maximum or most severe driving conditions. The operator drove close to the top level of vehicle performance to simulate severe driving operations. At the intersection of interest, the driver drove through the corner at a high speed. Both the high speed and sudden changes in direction caused the WhMD to become unstable and tip. On the second day of testing, the professional driver completed all the driving trials within the standard driving parameters. In addition, he called out the speed that he took the corners. The testing began at the low speed, and no movement of the WhMD or TED was observed. During the higher-speed tests, there was still very little movement of WhMD or TED. The data also showed that the driver still drove through the curves very smoothly. The research team observed a higher level of passenger comfort (less motion sickness) when the professional driver drove the corners at the suggested speeds that are used in operator training.

Conclusions and Recommendations

This study showed that passive rear-facing containment systems for WhMDs are adequate for preventing users from tipping when the bus is operated within normal driving parameters. This also assumes that the passenger and the WhMD have the brakes applied or are powered off and that the WhMD fits in the containment space. The WhMD also must be constrained, with the back of the WhMD near or touching the backboard of the passive containment area. Information about proper use of the rear-facing containment area should be placed on placards on board so users understand correct use and the consequences for using the system improperly.

Transit operators need to understand the implications of driver behavior on the safety and comfort of all passengers. The acceleration data showed the influence of the driving style of the operator. Driver style during turns was found to be a contributing factor to tipping. This was an unexpected factor. On the first day of testing, a driver from the LTD Maintenance Department operated the bus with the intent to simulate severe driving. On the second day of testing, a professional driver and operator trainer drove the bus with the intent to study normal operations. The difference in the smoothness of the curves was obvious, as shown in the accelerometer data and visual observations.

In the 5 mph and 14 mph tests, the rate of change of acceleration was more gradual; in the tipping test, the rate of change of acceleration was much more rapid and showed greater changes in acceleration in all of the directions. The severe driving was more erratic. Even though speed data were not collected in the tipping, a post-testing interview with the driver led the researchers to believe that the speed was about 20 mph during the tipping test.

In summary, passive rear-facing containment systems are adequate for most roadway geometries, with the assumption that drivers operate the vehicle at the prescribed speeds for the roadway geometrics.

Future Research

The results of this study were shared with LTD, but additional research should be conducted on this topic. The impact of driving style was a surprising and unintended outcome of this study. Targeted research to isolate the characteristics of an "expert" driver and the impact on accelerations would produce better training and best practices for operators. In this study, using only one intersection limited the conclusions. Additional roadway geometry types, intersection types, and types of vehicles are needed to determine the extent of the effects of the combination of vertical and horizontal curves on passive securement systems on large transit buses.

References

American Association of State Highway and Transportation Officials (AASHTO). 2014. *Guide for Geometric Design of Transit Facilities on Highways and Streets*. Washington, DC.

Americans with Disabilities Act (ADA). 1998. "Accessibility Specifications for Transportation Vehicles." 49 CFR Part 38.

Federal Transit Administration. 2013. "Questions and Answers Concerning Wheelchairs and Bus and Rail Service." http://www.fta.dot.gov/12325_15055.html.

Foreman, C., and J. Hardin. 2002. "The Challenges of Wheelchair Securement: Searching for Solutions." *Bus and Paratransit Conference Proceedings*, 3-17, http://www.nctr.usf.edu/pdf/Wheelchair%20Securement.pdf.

Frost, K. L., G. Bertocci, and S. Zdravko. 2013. "Wheelchair Securement and Occupant Restraint System (WTORS) Practices in Public Transit Buses." *Assistive Technology (RESNA)*, 25(1): 16-23. doi:10.1080/10400435.2012.680660.

Hunter-Zaworski, K. M., and J. R. Zaworski. 2005. "TCRP IDEA Report 38: Assessment of Rear Facing Securement on Bus Rapid Transit." Transit Cooperative Research Program, Washington, DC.

Hunter-Zaworski, K. M., and U. Rutenberg. 2014. "TCRP Report 171: Use of Mobility Devices on Paratransit Vehicles and Buses." Transit Cooperative Research Program, Washington, DC.

Kentucky Department of Education, Pupil Transportation Branch. 2008. *Driver Instructor Training Manual*.

Missoula Urban Transportation District (MUTD). 2011. *Transit Guidelines in Project Development*.

About the Authors

Andrea Mather, EIT (*andrea.j.mather@gmail.com*) received an M.S. in Civil Engineering (2016) and a B.S Civil Engineering in (2014) from Oregon State University.

Katharine Hunter-Zaworski, Ph.D., P.E. (*hunterz@engr.orst.edu*) is an Associate Professor of Civil Engineering at Oregon State University and an internationally-respected expert in accessible public transportation.

Trends in Mobile Transit Information Utilization: An Exploratory Analysis of Transit App in New York City

Niloofar Ghahramani and Candace Brakewood, Ph.D.
The City College of New York

Abstract

Smartphone applications that provide transit information are now very popular. However, there is limited research that examines when and where passengers use mobile transit information. The objective of this research was to perform an exploratory analysis of the use of a smartphone application known as Transit App, which provides real-time transit information and trip planning (schedule) functionality. Backend data from Transit App were examined by time of day and day of week in the New York City metropolitan area. The results show that the pattern of both the trip planning feature and overall real-time information usage follow the typical pattern of transit ridership, which has morning and evening peaks. Additionally, self-reported household locations of Transit App users in the New York City area were compared with household socioeconomic characteristics (specifically, income, ethnicity, and age) from census data using GIS visualizations and the Pearson correlation coefficient, but they do not appear to be correlated. This implies that passengers use Transit App regardless of household income, race, or age trends in their neighborhood. This exploratory study examined a rich new data source—backend data from a transit information smartphone application—that could be used in many future analyses to help transit agencies better understand how transit riders use information and plan their trips.

Introduction

The emergence of smartphones and other mobile-based technologies has revolutionized the way travelers' access both static and real-time transit information. As adoption of these new devices has grown rapidly among transit riders, public transportation agencies have explored the best ways to deliver this information to their passengers. Some transit agencies have developed their own official web or mobile applications, others have released their data openly and encouraged the private sector to develop applications using their data, and some have pursued both strategies. By opening their transit data to third parties, agencies have spawned innovative and cost effective applications ("apps") for cities all over the world (Schweiger 2011; Barbeau et al. 2014).

For both transit riders and agencies, easily-accessible real-time information has been one of the main benefits of these applications. When riders know the approximate arrival time of their vehicle, the burden of waiting for transit can be significantly reduced (Watkins et al. 2011; Brakewood et al. 2014; Brakewood, Rojas et al. 2015). For example, bus riders in Seattle, Washington, who used mobile real-time information before arriving at a stop waited approximately two minutes less than other riders; similarly, their perceived wait times were approximately 30% less than riders who did not use real-time information (Watkins et al. 2011). Additionally, access to real-time information can be influential on an individual's decision to use the transit system. Indeed, prior research has shown that it can increase ridership by approximately 2% (Tang and Thakuriah 2012; Brakewood, Macfarlane, and Watkins 2015). Considering the constrained budgets of many transit agencies, providing real-time information can be a cost-effective way to increase ridership.

Despite these documented benefits, there has been little prior research examining when and where transit passengers use mobile transit information. Moreover, many of these new information and communication technologies collect detailed data on the backend about when and where this information is being accessed. Therefore, this study aimed to conduct an exploratory analysis of usage of mobile transit information and focuses specifically on Transit App, one of the most popular multi-regional real-time transit information apps. The objective of this research was to analyze trends of Transit App usage by time of day and day of week and to examine the relationship of users' household locations with socioeconomic characteristics in the New York metropolitan area.

Literature Review

This section provides a brief review of prior research pertaining to real-time transit information. Before the widespread availability of mobile phones, real-time transit information was provided primarily via signage at transit stops or in stations. Many early studies focused on the effects of at-stop signage on transit riders' perceptions and behavior (e.g., Hickman and Wilson 1995; Dziekan and Vermeulen 2006; Dziekan and Kottenhoff 2007; Tang and Thakuriah 2011). More recently, the literature pertains primarily to the passenger and transit agency benefits of providing real-time information via mobile and web-based devices (Zhang et al. 2008; Ferris et al. 2010; Watkins et al. 2011; Tang and Thakuriah 2012; Tang, Ross, and Ha 2012; Carrel et al. 2013; Gooze et al. 2013; Brakewood et al. 2014; Brakewood, Macfarlane, and Watkins 2015). Only two prior references have specifically examined backend data from real-time information transit applications, and these are briefly summarized in the following paragraphs.

The first study using backend data from a real-time transit information smartphone application is an unpublished master's thesis that examined two smartphone applications known as "AnyStop" and "TreKing" (Feakins 2013). The author examined usage patterns in Chicago, Illinois, using a two-week sample from December 2010 from

AnyStop and a three -month sample from 2011 from TreKing. By counting the number of sessions recorded in the AnyStop backend database by time of day, the author concluded that the pattern of using AnyStop followed the classic pattern of transit ridership: on weekdays, there are two significant peaks in the morning and evening and one smaller peak around noon, and on weekends, there are multiple peaks distributed relatively equally throughout the day. The author also compared the utilization of both apps to route-level Chicago Transit Authority ridership data and found correlation between the usage of these transit apps and ridership levels (Feakins 2013).

The second and more recent study used backend data from a real-time information transit application called Transit App, which is also the focus of this paper (Davidson 2016). Davidson (2016) examined similarities and differences of origin-destination patterns between two datasets. One dataset was the trip planning feature of Transit App, which provides a-to-b directions based on transit schedules, and the other was the most recent (2010/2011) Regional Household Travel Survey conducted by the New York Metropolitan Transportation Council. The trip planning feature of Transit App provides origins and destinations of the trips that app users are interested in making, whereas the Regional Household Travel Survey data provides the stated origins and destinations of actual trips. The two datasets were compared at the community board level, and the results suggest that they have very similar origin-destination patterns (Davidson 2016).

This brief literature review demonstrates that there has been limited research using the backend data from transit information apps. The most relevant prior study looked at the same data source and location as this study (Transit App backend data in New York City), but it considered only the trip planning feature of the app, which provides scheduled transit information. The analysis in Davidson's study consists of a small subset of the data; real-time information and temporal differences were not studied. The other relevant prior study used Chicago data from 2010 and 2011; however, adoption of smartphones has rapidly grown since then, which could lead to different trends. Moreover, there has been little analysis of who is actually using these apps. Therefore, this study sought to fill these gaps in the literature by examining a recent real-time information dataset and assessing socioeconomic trends associated with usage.

Objective

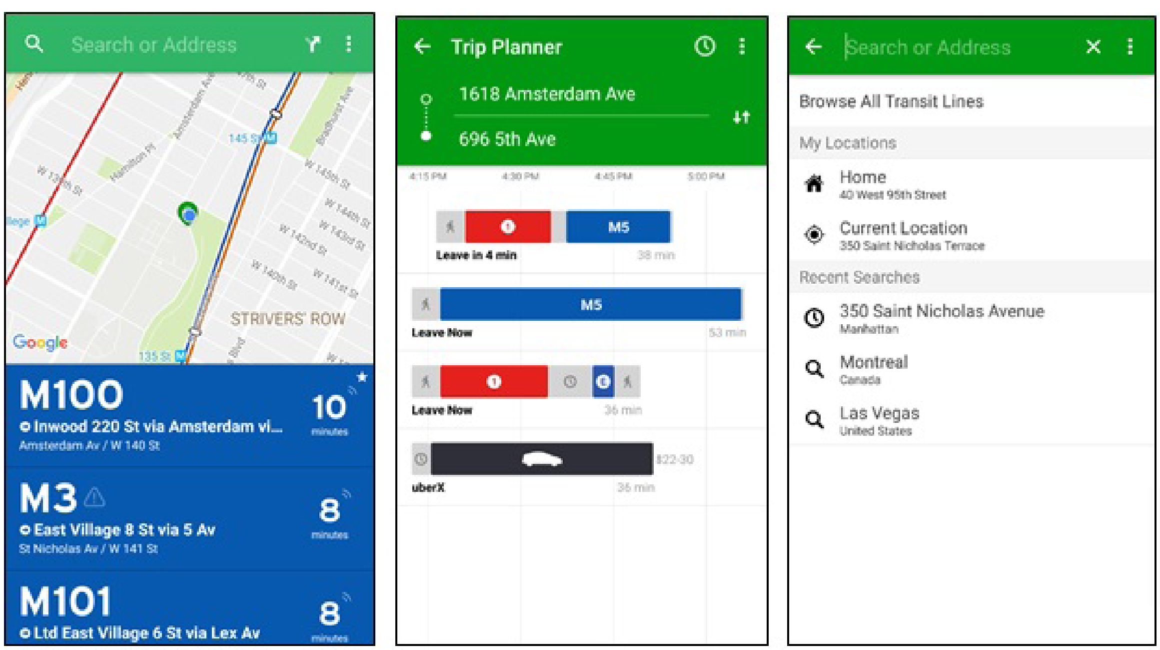
The objective of this study was to perform an exploratory analysis of Transit App usage among transit riders in the New York metropolitan region. The specific topics addressed in this study fall into two categories: general Transit App utilization patterns and usage among different socioeconomic groups. The first section explores overall Transit App usage by time of day and day of week and analyzes whether individual users can be categorized by their daily frequency of app usage. The second part examines whether Transit App may be used more frequently in areas with residents of certain socioeconomic characteristics.

Dataset

This section provides a brief description of the data used in this analysis. First, background information is provided about Transit App, and next, the geographic area of analysis is defined. Last, a detailed description of the data files used in the analysis is provided.

Overview of Transit App

Transit App is a company based in Montreal, Canada, that has developed a freely-available smartphone application providing urban transportation information. In 2012, the company released the first version of its application for iPhone. In the initial version, the app provided transit schedule information for Montreal, Toronto, and Quebec City. Since then, Transit App launched an Android version of its application and has expanded to more than 100 cities in 9 countries, including widespread coverage in the United States. Transit App also has added many features, including real-time transit information, trip planning using schedule information, service alerts, and multimodal support (including bike sharing, car sharing, and Uber). The most heavily-used features of the app are those providing real-time transit information, and Transit App uses real-time information to display transit vehicle departure times when the transit agency makes it available; otherwise, it displays schedule information (Transit App 2015). Additionally, users can store their favorite locations in the app, such as home or work, to facilitate quickly finding information that they commonly use. The app includes a combination of map and list view interfaces. Figure 1 shows the Transit App Android interface displaying real-time transit information for nearby routes (left), trip planning (center), and a stored home location (right), respectively.



a) Nearby routes *b) Trip planning* *c) a stored home location*

FIGURE 1. Transit App screenshots

Area of Analysis

The New York metropolitan area was selected as the geographic area for this analysis because it has the highest concentration of transit trips in the United States (McKenzie and Rapino 2011) and also has the highest Transit App usage in the United States. Because smartphones are mobile devices and some people used the app in regions other than New York, a small percentage of Transit App sessions in this dataset took place in other regions. Usage outside the New York region was not considered in this analysis and was removed from the dataset before conducting the following analysis. After removing the records from outside the New York region, these datafiles, which are discussed in the following section, were imported into ArcGIS 10-2.

Data Files and Description

The dataset for this study was obtained directly from Transit App and contains data for any user that opened Transit App at least once in October 2014 in the New York City region. The dataset includes the user location (latitude/longitude), which is recorded whenever the application is opened. For privacy purposes, all geographic coordinates contained in these files were offset by Transit App developers by a random number up to 300 meters per position. By anonymizing the data, Transit App ensured that none of the data used in this analysis contain personally identifiable information. Also, locations mentioned herein refer to the anonymized version of the data point (e.g., a reference to "home locations" refers to the anonymized home locations).

The raw dataset contained multiple files in a Comma Separated Values (CSV) format, which were as follows:

- *Locations file*: Every time users open Transit App, regardless of what feature they are using, their location is sent to the Transit App server based on the coordinates from the location services in their smartphone. Date, time, accuracy of their location, and speed (e.g., if they are in a vehicle) are recorded in what is referred to as the "locations" file. Also, a unique session ID is created each time a user opens the app. For October 2014, a total of 10,875,013 records were sent to the Transit App server for the New York metropolitan area. This file was imported into GIS based on the users' start coordinates (i.e., where they were when opening Transit App).
- *Trips file*: This file contained information about usage of the trip planning feature in Transit App and is referred to as the "trips" file. Specifically, it included start and end coordinates (latitude/longitude), date, and timestamps of all the trip planning requests. It should be noted that this is a subset of the locations file because anytime a user opens the app, including using the trip planning feature, his/her coordinates are stored in the locations file. For October 2014, the trips file had a total of 399,831 records for the New York metropolitan area. This file was imported into GIS based on the users' start coordinates (i.e., where they were when opening Transit App).

- *Placemarks file*: This file included coordinates of home and work locations that users have stored in Transit App and is referred to as the "placemarks" file. This represents data from an optional function in Transit App where users can store places that they often go (e.g., home or work) to easily access relevant transit information for that specific location. This file contains the coordinates of users' home or work locations, of which there were a total of 11,782 in New York metropolitan area. Of these, only the home locations were imported into GIS based on the user's defined coordinate.

Analysis of General Utilization Trends

For this analysis, nine counties in New York and nine counties in New Jersey were included in the area of analysis; counties farther than Somerset and Morris counties in New Jersey had few Transit App users and were excluded. North of New York City, Westchester and Rockland counties were selected as the New York boundaries since there were very few Transit App users in counties farther north and in counties located in Connecticut. From the east, Suffolk County was set as the boundary.

For this analysis of general trends, Transit App usage was first examined by time of day and then by day of week. Next, the frequency of usage in a day by individual app users was examined. For each of these analyses, the overall usage of Transit App (which is predominantly checking real-time arrival information) and the utilization of only the trip-planning feature (for a-to-b directions) were considered separately

Time of Day Analysis

First, the data were categorized by date and hour. Using the open source statistical program RStudio (RStudio Team 2015), the number of unique session IDs were counted in each hour for the two datasets (all records from the locations file and the trip planning feature only); the results are shown in Figure 2. It should be noted that the scales on the y-axis of Figure 2 are different for the graph displaying all usage from the locations file and the trip planning feature because the number of unique sessions is much larger for all usage.

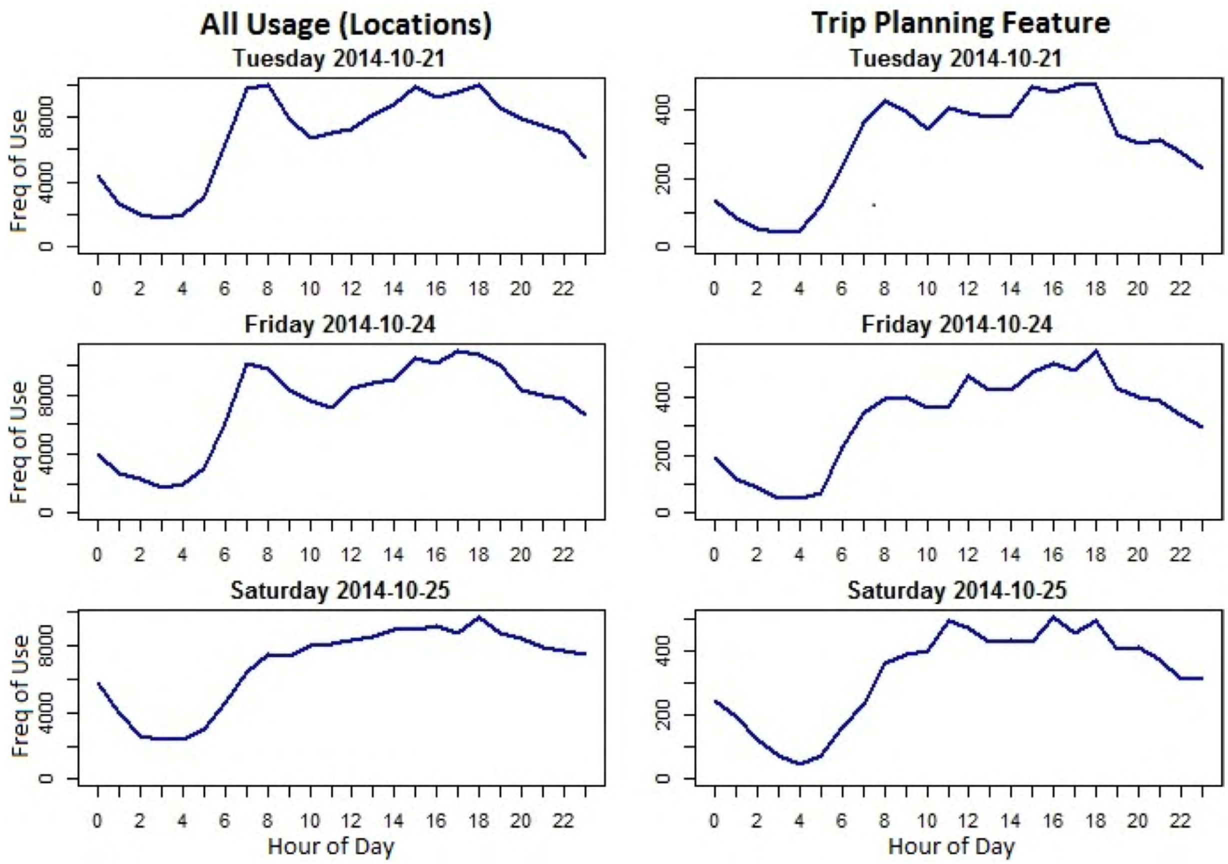


FIGURE 2. Frequency of using Transit App by time of day

On Tuesday, October 21, 2014, there were approximately 178,000 unique sessions in the locations file and only approximately 7,000 unique session IDs in the trips file. Although Tuesday was selected for presentation, this pattern was typical of Mondays, Tuesdays, Wednesdays, and Thursdays. Both October 21 graphs have two significant peaks: one in the morning from 6:00–8:00 AM and another in the evening from 3:00–6:00 PM, which likely represent commuting trips. There is also a smaller peak around 12:00 noon, which may represent trips for lunch or personal business. Another interesting finding is the slightly higher and wider range of Transit App usage in the evening peak period compared to the morning peak. This disparity may be because users make more recreational trips after work or chain errand/shopping trips in the evening. It also may imply that users do not use the app as frequently in the morning, perhaps because they are more familiar with their morning commutes.

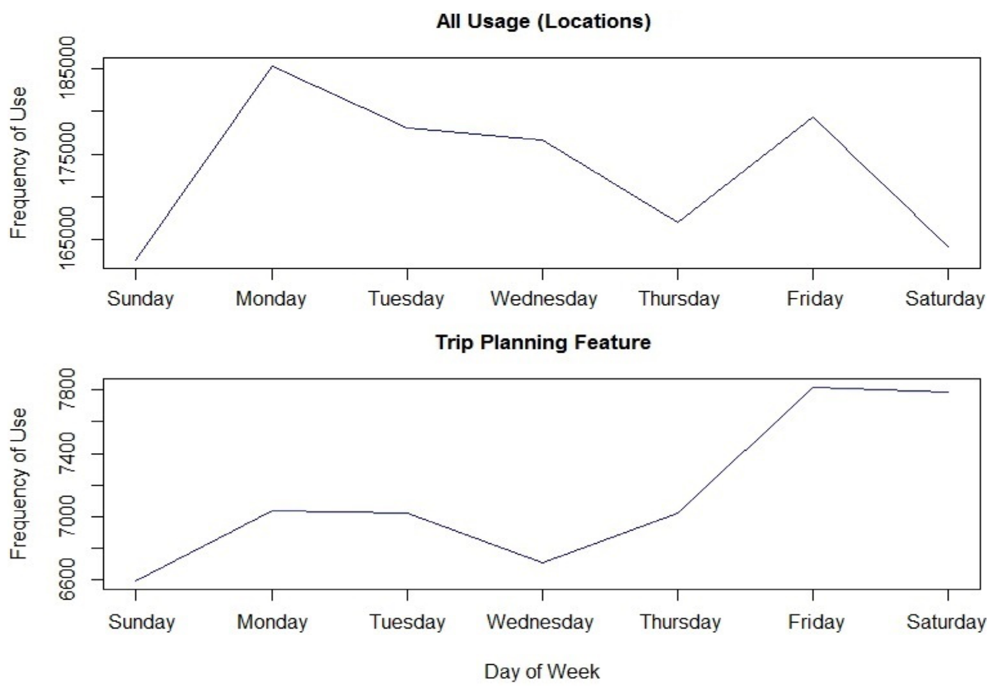
For Friday, October 24, 2014, the pattern of Transit App usage shows overall usage of approximately 179,000 unique sessions and use of the trip planning feature of approximately 7,800 unique sessions. Both Friday graphs reveal morning and evening peaks similar to the Tuesday image. However, the evening peak on Fridays is slightly higher and wider (from 3:00–7:00 PM) than the evening peak on Tuesdays. This larger peak may represent additional leisure trips or people leaving work earlier on Friday afternoons.

For Saturday, October 25, 2014, the pattern of Transit App usage for all features includes approximately 164,000 unique sessions and the trip planning feature includes approximately 7,700 unique sessions. The Saturday figures do not have large peaks; instead, multiple small peaks are distributed nearly equally throughout the day, possibly for recreational and leisure trips. Additionally, usage on Saturday was lower than on weekdays, which is in line with lower levels of transit ridership generally seen on weekends.

Day of the Week Analysis

To compare usage frequency of Transit App on different days of the week, the total number of unique sessions for each day were counted for overall usage of Transit App as well as for the trip planning feature. Figure 3 shows total usage and trip planning utilization for Sunday, October 19, 2014, to Saturday, October 25, 2014. Total usage ranged from 165,000 to 185,000 unique sessions per day for the New York City region, whereas there were only 6,600 to 7,800 unique trip planning sessions per day. The peak for all usage occurred on Monday, whereas trip planning utilization was highest on Friday; the high value on Friday may be because of additional non-commute trips (e.g., recreational trips) for which travelers seek trip planning information. On Sunday, usage (both overall and trip planning specifically) was slightly lower, which likely reflects day-of-the-week trends in transit ridership.

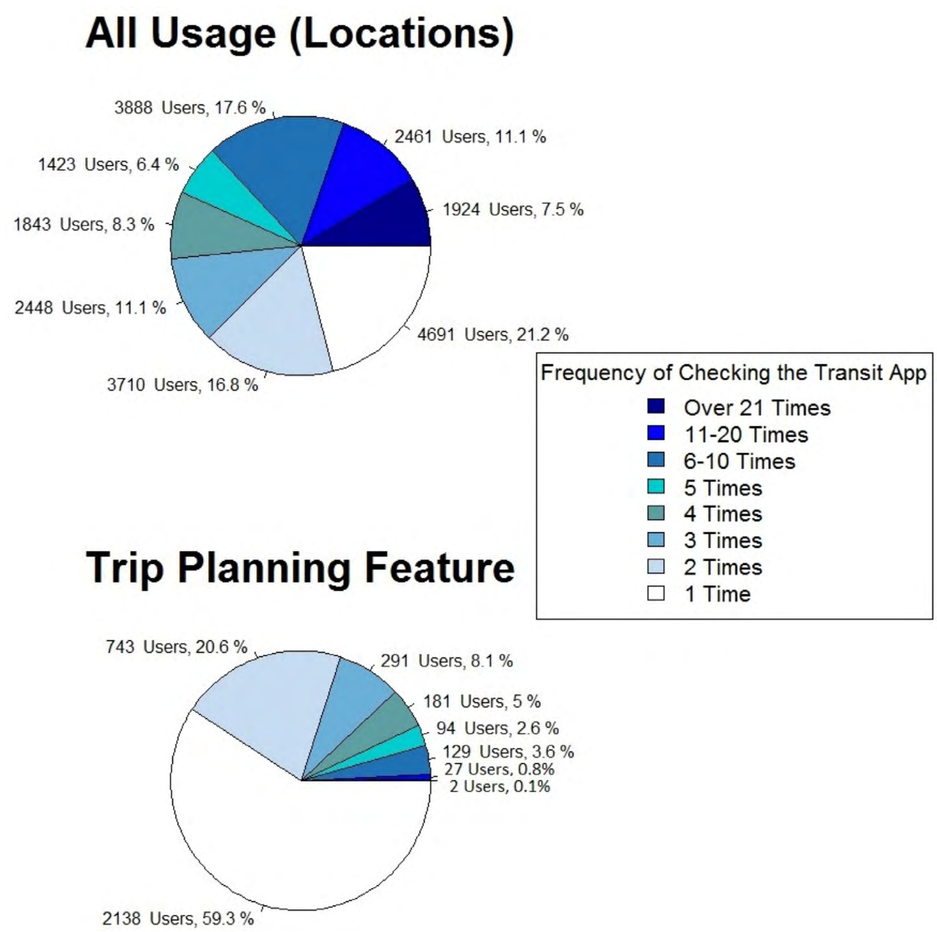
FIGURE 3.
Use of Transit App by day of week, October 19–25, 2014



Individuals' Frequency-of-Use Analysis

This analysis examined how often individual Transit App users typically check the app in a single day. The number of sessions associated with each user defined by their unique device ID was counted, and the results are shown for a single day (Tuesday, October 21) in Figure 4. Results for all usage from the locations file indicate approximately 22,000 users, and trip planning usage had approximately 3,600 users. As can be seen in Figure 4, frequency of usage from the locations file shows that almost 80% of users checked the Transit App two times or more in one day. This may imply that many Transit App users check the app for their commute to and from work and may be accustomed to checking the app for most, if not all, of their daily trips.

FIGURE 4.
Frequency of Transit App usage by individuals on Tuesday, October 21, 2014



The percentage of users who checked Transit App exactly once per day is almost three times higher for the trip planning feature (59.3%) than for the overall utilization (21.1%). Infrequent users of the trip planning feature may represent either infrequent users of the transit system, travelers making irregular trips, or those who use the app for only one way of a commute trip.

Notably, there was a small number of heavy users (i.e., more than 21 times in a day), which may have been the result of experiencing delays on the transit system. These sessions most likely represent "simulated" sessions, meaning that the user moved the GPS point on the map interface of the app to a location other than where they actually were to search for transit information there. Alternatively, these heavy users may not have exited the app, so it was running in the background on their phones and sending signals to the server. Further investigation of these heavy users is recommended for future research.

This analysis was repeated for other days in October 2014, which showed similar patterns.

Census Analysis

The next set of analyses assessed whether Transit App is used more frequently in areas with residents of certain socioeconomic characteristics (specifically, income, race, and age). For the analysis in this part, nine counties in New Jersey and five counties in New York (specifically, the five boroughs of New York City) were considered. The geographic unit chosen for this analysis was the census tract, and tract geometry was obtained from the US Census Bureau website (United States Census Bureau 2015). Socioeconomic information was obtained from the 2010 census through the American Fact Finder website (United States Census Bureau 2015). Because census data are based on home locations, the self-reported home locations of Transit App users were chosen to represent app utilization for this analysis. The home locations of Transit App users were imported into GIS and joined to census tracts based on their coordinates. The number of home locations was counted for each tract and compared to the population density in each tract from the census data. The number of home locations for each census tract was then compared with mean income, dominant race, and dominant age from the census data. The results are discussed in the following sections.

Transit App Users' Home Locations and Population Density

Transit App users' self-reported home locations and population density in census tracts across the five boroughs of New York and areas of New Jersey are shown in Figure 5. Transit App users' home locations appear to be distributed relatively equally among the Bronx, Manhattan, and Staten Island. In Manhattan, home locations have a slightly higher frequency on the west side of Manhattan. Also, the census tract including Central Park has the highest observed value of Transit App users' home locations (29 in total); this is likely due to the shift applied to the latitude and longitude by Transit App developers to respect user privacy since there is very high residential density on either side of Central Park. Staten Island has a relatively low number of Transit App users' home locations (fewer than 5 homes in most census tracts). Many of the census tracts in Queens with higher frequency of Transit App home locations are located near subway lines. In Brooklyn, the number of home locations in each census tract is higher in the areas closer to Manhattan and Queens (mainly 6–20 home locations per tract) and lower in the southern parts of Brooklyn (fewer than 5 home locations in each census tract). In New Jersey, Transit App users' home locations are mostly concentrated on the eastern part of the state close to Manhattan; many of the census tracts with higher numbers of Transit App users' homes are located near the Port Authority Trans-Hudson (PATH) lines and NJ TRANSIT's light rail lines.

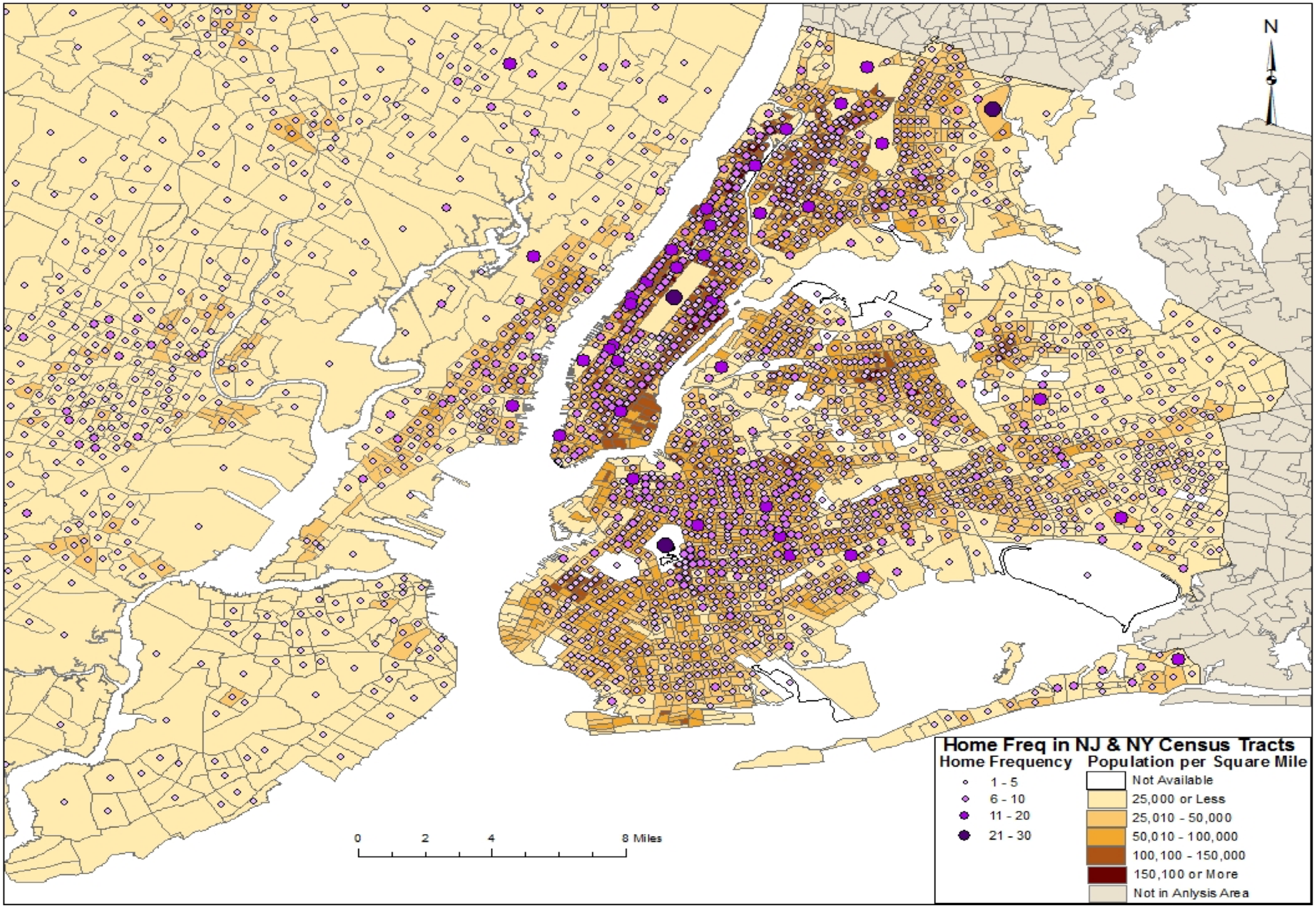


FIGURE 5. Population density and Transit App users' home locations in New York and New Jersey census tracts

Figure 5 also shows that population per square mile is relatively low (less than 25,000 people per square mile) and relatively homogeneous throughout the census tracts in New Jersey and Staten Island. Population density is higher and more diverse across census tracts in Brooklyn, Queens, and the Bronx. In these three boroughs, population density generally ranges from 25,000 to 100,000 people/square mile. The highest population density is observed in Manhattan's census tracts, which generally fall in the range of 50,000 to 150,000 people/square mile. Distribution of Transit App users' home locations and population density also shows that in the census tracts with higher population density, the number of Transit App users' home locations is also higher, which is an expected observation.

Income Visualization

Figure 6 shows Transit App users' home locations in relation to mean annual household income per census tract in the five boroughs of New York and areas of New Jersey. As can be seen in this figure, higher income levels are observed primarily in Manhattan (except the northern part). In the other boroughs, mean household income is lower in the majority of census tracts. Many census tracts have a mean annual household in the range of $40,000 to $80,000 in Brooklyn, the Bronx, and Queens. In Manhattan, the Bronx, and Staten Island, Transit App users' home locations are distributed relatively equally. In New Jersey, Queens, and Brooklyn, frequency of home locations is slightly higher in the areas with higher accessibility to other boroughs or higher concentrations of rail service. Therefore, based on graphical observations of mean household income, Transit App usage does not seem to be associated with household income levels in the New York City area, since Transit App users live in both high- and low-income areas.

Race Visualization

Figure 7 shows dominant race from the 2010 census data overlaid with the Transit App users' home locations. In Manhattan and Staten Island, the dominant race in most of the census tracts is white, except in the north of Manhattan. In these two boroughs, Transit App users' home locations are distributed relatively equally among the census tracts. In the Bronx, most census tracts have a dominant race of Hispanic/Latino or Black/African American. In Brooklyn, many census tracts in the northern part of the borough have a dominant race of Black/African American, and many census tracts in the south part have the dominant race of white. In Queens, the dominant race in the southern census tracts is Black/African American; in the other parts of Queens, most census tracts have a dominant race of white. The majority of census tracts in New Jersey have the dominant race of white except those close to Manhattan. In terms of Transit App users' home locations, there appears to be little, if any, relationship between dominant race and Transit App users' home locations in the New York City region based on this visualization.

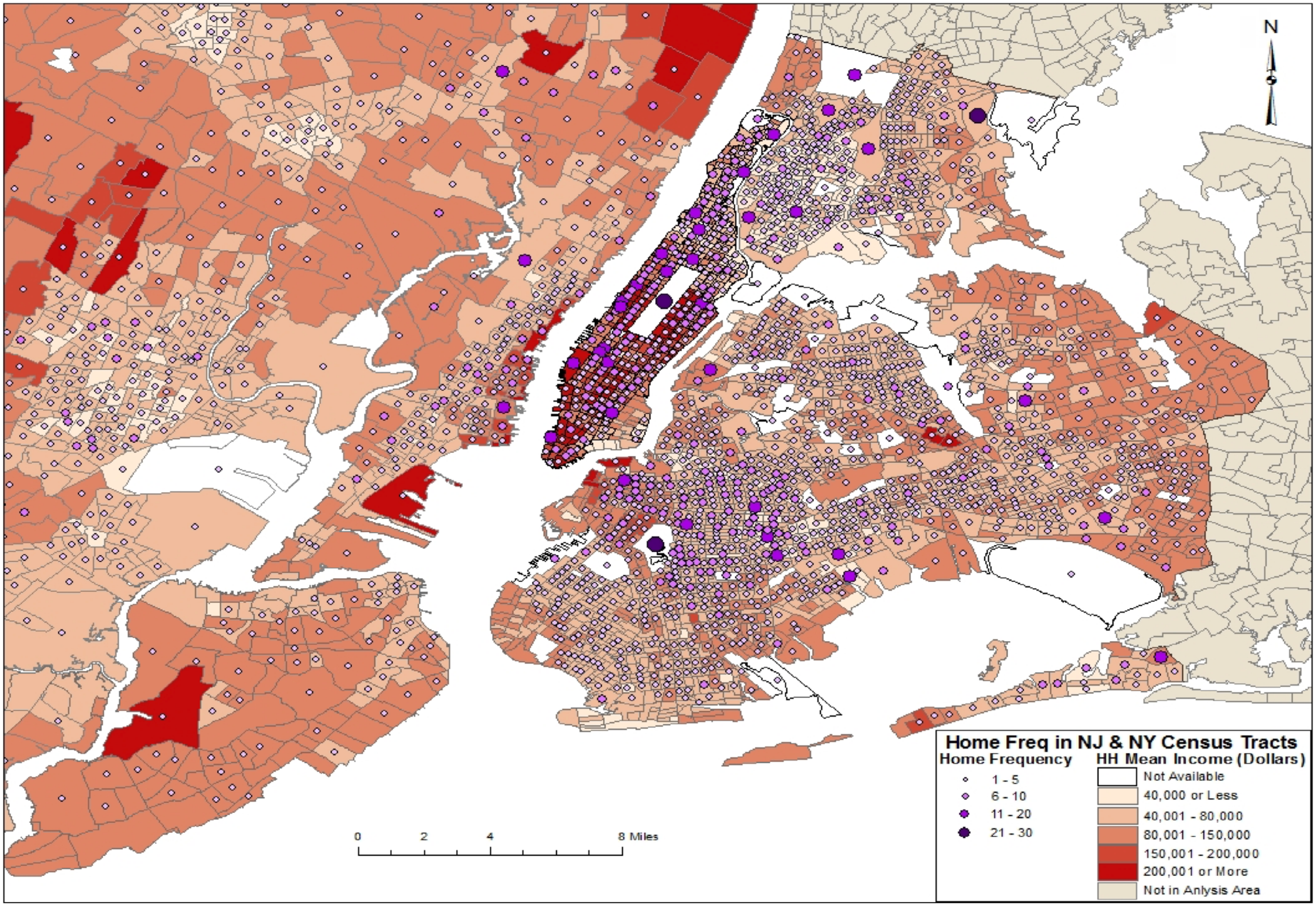


FIGURE 6. Mean annual household income and Transit App users' home locations in New York and New Jersey census tracts

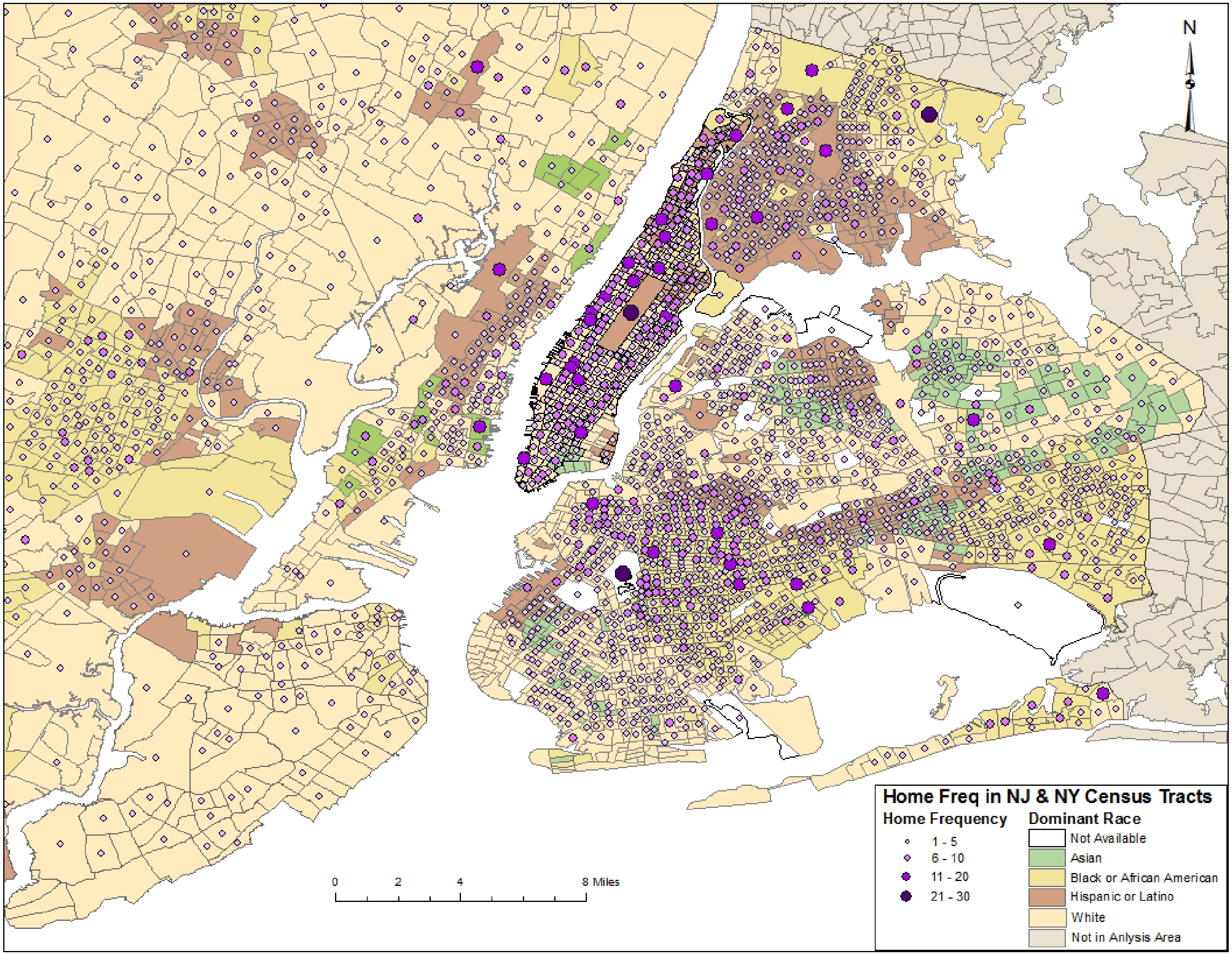


FIGURE 7. Dominant race and Transit App users' home locations in New York and New Jersey census tracts

Age Visualization

Figure 8 shows dominant age from the 2010 census data and the number of Transit App users' home locations per census tract. In Manhattan and Staten Island, the majority of the census tracts have relatively homogeneous dominant age group patterns; in Manhattan, the dominant age typically falls in the range of 25 to 34, and in Staten Island, it falls in the range of 45 to 54. Transit App users' home locations are distributed relatively equally in these two boroughs. Therefore, it is unclear if there is a relationship between age and frequency of using Transit App in these two boroughs. Distribution of dominant age is more diverse across the Bronx, Queens, and New Jersey census tracts. In these areas, the visualization does not show much, if any, relationship between age and Transit App users' home locations. However, in Brooklyn, many of the census tracts with more than six Transit App users' home locations fall in the dominant age range of 25 to 34, so age may play a role in influencing Transit App utilization in this borough.

Statistical Analysis

In addition to the visualizations presented in the previous section, a statistical analysis also was conducted to understand the relationship between household level socioeconomic characteristics from the census data and Transit App users' home locations. This analysis was performed at the census tract level in nine counties of New Jersey and five counties of New York. Table 1 shows the total number of census tracts, total number of the Transit App users' home locations, and the number of census tracts with at least one Transit App user's home location in each county considered for this analysis.

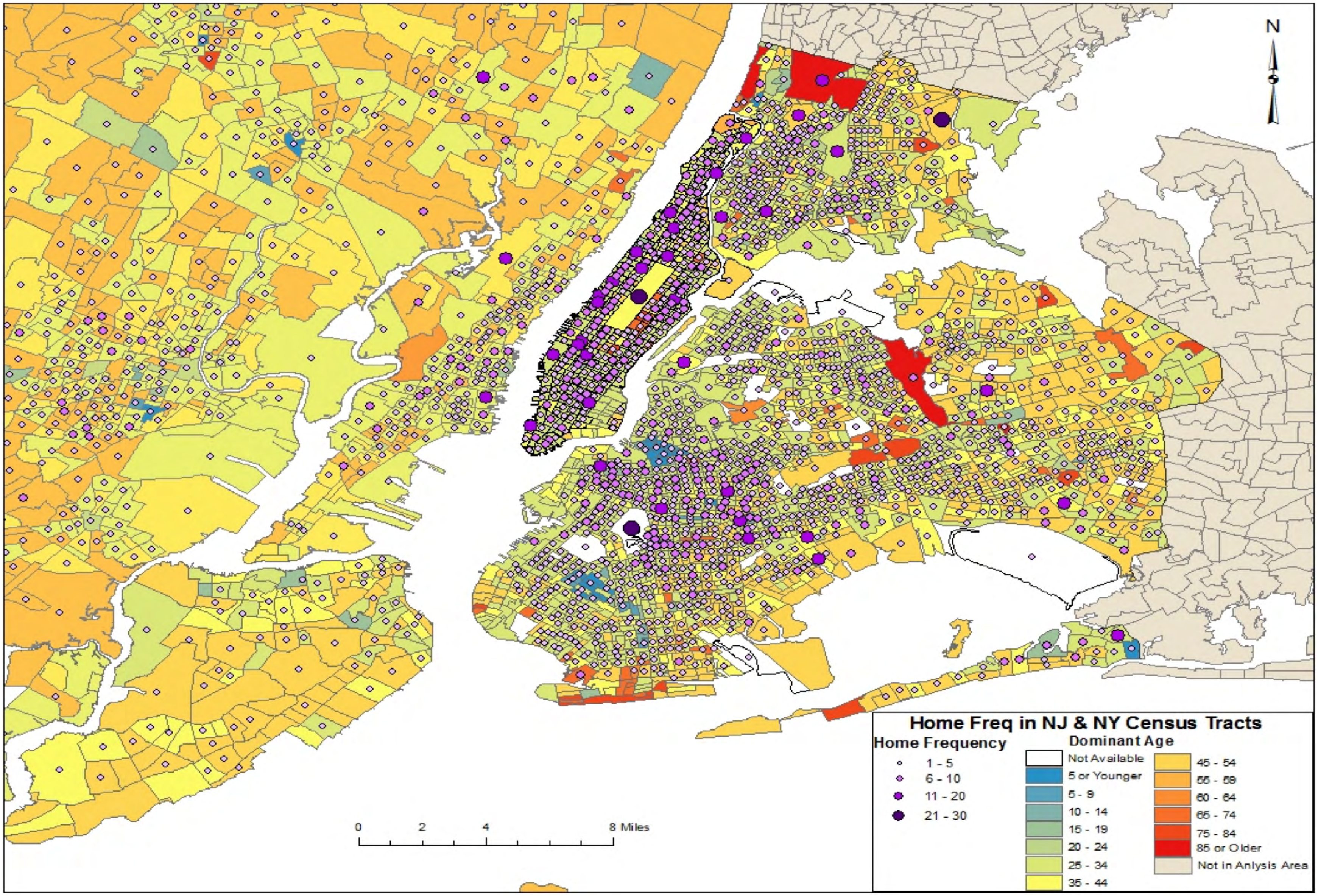


FIGURE 8. Dominant age and Transit App users' home locations in New York and New Jersey census tracts

TABLE 1.
Number of Census Tracts and Transit App Users' Home Locations

Geographic Area	Total Number of Transit App Users' Home Locations	Number of Census Tracts with at Least One Transit App Users' Home Location	Total Number of Census Tracts
Manhattan	1,258	253	288
Brooklyn	2,014	592	761
Bronx	906	280	339
Queens	1,462	542	669
Staten Island	126	65	110
New Jersey (9 counties)	1,675	684	1,250

To understand the relationship between household level socioeconomic characteristics obtained from census data and the number of Transit App users' home locations in each census tract, the Pearson correlation coefficient was calculated for each borough in New York City and for northern New Jersey. The Pearson correlation coefficient is a mathematical indicator of the relationship between two variables, and it ranges from -1 to +1, with -1 indicating total negative correlation, zero indicating no correlation, and +1 indicating total positive correlation. The Pearson correlation coefficient was calculated between the ratio of Transit App users' home locations to total population and mean household income, percentage of different age groups or percentage of different races in each census tract using RStudio.

The results of Pearson correlation analysis are shown in Table 2. Mean annual household income is negatively correlated with the number of Transit App users' home locations divided by the total population in three of the areas (Manhattan, the Bronx, and New Jersey). The correlation value is relatively small ($r \sim -0.2$ in New Jersey; $r \sim -0.01$ in Manhattan and the Bronx), implying that Transit App usage and mean household income are weakly dependent and that those in areas with higher income levels may use the Transit App less. In Staten Island, the observed correlation was positive ($r \sim 0.5$), which may be because of the low and equally-distributed Transit App usage across Staten Island's census tracts. There are fewer than five Transit App users' home locations in most of Staten Island's census tracts. The Pearson correlation coefficient showed little, if any, relationship for Brooklyn and Queens ($r < 0.01$).

Among different age groups, in Manhattan, Brooklyn, and New Jersey, the percentage of the population in the age range of 20 to 34 had slightly positive correlation with the number of Transit App users' home locations divided by the total population. Similarly, in the Bronx, Brooklyn, Queens, and Staten Island, the percentage of the population in the age range of 35 to 54 had slightly positive correlation with the number of Transit App users' home locations divided by total population. Many of the lowest correlation values were observed in the age groups of 55 to 64 and 65 or older. This suggests that areas with higher percentages of older residents may be less likely to use Transit App.

In the terms of ethnicity, correlation values between different race groups and the number of Transit App users' home locations divided by the total population were very small (close to zero) across all boroughs. The only exceptions were in New Jersey, where the percentage of Transit App users' home locations has a positive correlation with percentage of Black/African American population ($r \sim 0.358$), and in Staten Island, where percentage of Transit App users' home locations has a positive correlation with the percentage of Hispanic/Latino population (r ~ 0.334). Altogether, correlation values suggest that there is limited correlation between ethnicity and use of the Transit App as represented by user's home locations.

TABLE 2. Pearson Correlation Coefficient Results*

	Manhattan Census Tracts	Bronx Census Tracts	Brooklyn Census Tracts	Queens Census Tracts	Staten Island Census Tracts	New Jersey Census Tracts
Mean Household Income	-0.011	-0.017	0.005	0.009	0.497	-0.215
Percent Under Age 5	-0.098	-0.199	-0.092	-0.024	-0.208	0.196
Percent Ages 5–14	-0.232	-0.251	-0.092	-0.199	0.535	-0.142
Percent Ages 15–19	-0.033	-0.170	-0.020	-0.150	-0.221	-0.060
Percent Ages 20–34	0.010	-0.309	0.242	-0.223	-0.017	0.361
Percent Ages 35–54	-0.346	0.278	0.013	0.194	0.298	-0.107
Percent Ages 55–64	0.150	-0.200	-0.140	0.349	-0.286	-0.218
Percent Ages 65 and Over	0.338	0.384	-0.106	-0.009	-0.218	-0.212
Percent of White Population	0.093	-0.087	-0.142	0.062	0.041	-0.418
Percent of Asian Population	0.017	-0.053	-0.133	-0.071	-0.032	0.030
Percent of Hispanic/Latino Population	-0.124	-0.097	0.018	-0.074	0.334	0.145
Percent of Black/African American Population	-0.075	0.151	0.167	0.022	-0.018	0.358

**Pearson correlation coefficient results for socioeconomic characteristics and number of Transit App users' home locations divided by total population*

Conclusions and Future Research

Transit App is one of the most popular mobile applications in North America that provides real-time transit information and a-to-b directions based on transit schedules. This study used backend data from Transit App to examine when and where passengers use this information in the New York City metropolitan area in a two part analysis, and the key findings are summarized as follows.

General trends of Transit App usage were first assessed by time of day and day of week. The time of day analysis for overall utilization and the trip planning feature showed that there were two significant peaks—one in the morning and the second in the evening—for Monday through Thursday, which likely represents the typical pattern of transit ridership. On Fridays, the evening peak was slightly higher and wider than the evening peak on Mondays through Thursdays, which may be because people make more recreational or chained trips on Friday evenings for which they seek transit information. On the weekends, there were multiple small peaks in Transit App usage distributed relatively equally during the day. The day of the week analysis revealed that overall utilization of Transit App was highest on Mondays, whereas usage of the trip planning feature peaked on Fridays, which may be because of additional non-commute trips by app users. On Sundays, usage (both overall and trip planning specifically) was slightly lower, which likely reflects general trends in transit ridership.

Next, the frequency with which individual Transit App users typically check the app in a single day was assessed. The results show that approximately 60% of users utilize the trip planning feature of the app exactly once per day. This group of users might be infrequent users of the transit system or travelers making irregular trips who use the trip planning feature of the Transit App only occasionally. Examining overall utilization, the percentage of users who check the Transit App two times or more in one day is almost 80%, which could imply that the majority of real-time information users check this information for their commute and also for other trips, such as shopping and recreational trips. In other words, many transit riders may become accustomed to using the app and checking real-time information for most, if not all, of their transit trips.

The second part of the analysis assessed whether Transit App is used more frequently in areas with residents of certain socioeconomic characteristics based on 2010 census data. Visualizations of mean annual household income, dominant race, and dominant age per census tract showed limited, if any, relationship with the self-reported home locations of Transit App users. Transit App usage appeared to be higher in areas with a high concentration of transit service and high accessibility to businesses and recreational activities. Calculating the Pearson correlation coefficient between socioeconomic characteristics (household income, race, and age) and the number of Transit App users' self-reported home locations divided by the total population in each census tract also showed limited, if any, correlation. This finding implies that people throughout the New York City region use Transit App regardless of dominant age, race, or ethnicity in each area. Moreover, it suggests that mobile apps are becoming increasingly common and accessible to transit passengers in all areas.

In summary, this study used a new data source to assess temporal and spatial patterns of using mobile transit information use in the New York metropolitan area. Results from the temporal analysis of Transit App usage were similar to typical temporal patterns of transit system utilization, but results from the socioeconomic analysis were somewhat surprising. Limited, if any, relationship was found between Transit App usage and the socioeconomic characteristics of the population in the study region. This may be specific to New York City, which has very high transit usage in general. However, more analysis of this dataset in other regions is recommended to assess if this trend holds elsewhere.

There are numerous areas for improvement and future research that emerged from this study. One area for improvement is to compare Transit App usage with public transit ridership data. This could be done for time of day and day of week analysis, as well as the analysis of socioeconomic characteristics, in which the number of Transit App users' home locations were normalized by population per census tract since it is difficult to determine the number of transit riders per census tract. Additionally, the area of analysis could be expanded beyond the New York region to include other metropolitan areas; this is an interesting area of study because other metropolitan areas will have different socioeconomic characteristics (e.g., income and race) and varying levels of transit service. Future research also is suggested to verify the accuracy of locations (latitude/longitude) of users recorded in the Transit App backend server. Assessing trends in usage of the non-transit features in Transit App, such as Uber, bike sharing, and car sharing, could be examined in the future studies. Last, future research could be conducted to determine how this dataset could be integrated into the short- and long-term transit planning process.

Acknowledgments

This research was supported in part by the City University of New York (CUNY) Collaborative Incentive Research Grant (CIRG) program. We would like to acknowledge Professor Jonathan Peters at the College of Staten Island and graduate student Adam Davidson at the CUNY Graduate Center for their feedback. We also thank Transit App for providing the data used in this study, and we are particularly grateful to Jake Sion for his comments on this paper.

References

Barbeau, S., A. Borning, and K. Watkins. 2014. "OneBusAway Multi-Region—Rapidly Expanding Mobile Transit Apps to New Cities." *Journal of Public Transportation*, 17(4).

Brakewood, C., S. Barbeau, and K. Watkins. 2014. "An Experiment Evaluating the Impacts of Real-time Transit Information on Bus Riders in Tampa, Florida." T*ransportation Research Part A: Policy and Practice*, 69: 409-422.

Brakewood, C., G. Macfarlane, and K. Watkins. 2015. "The Impact of Real-time Information on Bus Ridership in New York City." *Transportation Research Part C: Emerging Technologies*, 53: 59-75.

Brakewood, C., F. Rojas, P. C. Zegras, K. Watkins, and J. Robin. 2015. "An Analysis of Commuter Rail Real-time Information in Boston." *Journal of Public Transportation*, 18(1): 1-20.

Carrel, A., A. Halvorsen, and J. L. Walker. 2013. "Passengers' Perception of and Behavioral Adaptation to Unreliability in Public Transportation." *Transportation Research Record*, 2351: 153-162.

Davidson, A. 2016. "Big Data Exhaust for Origin-Destination Surveys: Using Mobile Trip-Planning Data for Simple Surveying." *Proceedings of the 95th Annual Meeting of the Transportation Research Board*.

Dziekan, K., and A. Vermeulen. 2016. "Psychological Effects of and Design Preferences for Real-time Information Displays." *Journal of Public Transportation*, 9(1).

Dziekan, K., and K. Kottenhoff. 2007. "Dynamic At-stop Real-time Information Displays for Public Transport: Effects on Customers." *Transportation Research Part A: Policy and Practice*, 41(6): 489-501.

Feakins, J. 2013. "Planning Like It Is 2099: The Use and Distribution of Smartphone Transit Applications in Chicago, Illinois." Master's thesis, Department of Geography, Urban and Environmental Studies, Concordia University, Montreal, Quebec, Canada.

Ferris, B., K. Watkins, and A. Borning. 2010. "OneBusAway: Results from Providing Real-Time Arrival Information for Public Transit." *Proceedings: CHI*: 1807-1816.

Gooze, A., K. E. Watkins, and A. Borning. 2013. "Benefits of Real-Time Transit Information and Impacts of Data Accuracy on Rider Experience." *Transportation Research Record*, 2351: 95-103.

Hickman, D., and N. Wilson. 1995. "Passenger Travel Time and Path Choice Implications of Real-time Transit Information." *Transportation Research Part C: Emerging Technologies*, 3(4): 211-226.

McKenzie, B. and M. Rapino. 2011. "Commuting the United States: 2009." American Community Survey Reports, United States Census Bureau, http://www.census.gov/prod/2011pubs/acs-15.pdf.

Schweiger, C. 2011. "TCRP Synthesis 91: Use and Deployment of Mobile Device Technology for Real-Time Transit Information." Transit Cooperative Research Program Synthesis Project SA-25, Transportation Research Board, Washington, DC.

Tang, L., and P. Thakuriah. 2012. "Ridership Effects of Real-time Bus Information System: A Case Study in the City of Chicago." *Transportation Research Part C: Emerging Technologies*, 22: 146-161.

Tang, L., and P. Thakuriah. 2011. "Will Psychological Effects of Real-Time Transit Information Systems Lead to Ridership Gain?" *Transportation Research Record*, 2216: 67-74.

Tang, L., H. Ross, and X. Han. 2012. "Substitution or Complementarity: An Examination of the Ridership Effects of Real-time Bus Information on Transit Rail in the City of Chicago." *Proceedings of the 91st Annual Meeting of the Transportation Research Board*.

Transit App, http://transitapp.com/. Accessed August 1, 2015.

RStudio Team. RStudio: Integrated Development for RStudio, Inc. Boston, MA, http://www.rstudio.com/. Accessed August 1, 2015.

United States Census Bureau. New York Partnership Shapefile Batch Download. http://www.census.gov/geo/partnerships/pvs/partnership14v3/st36_ny.html. Accessed August 1, 2015.

United States Census Bureau. American Fact Finder. http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml. Accessed August 1, 2015.

Watkins, K., B. Ferris, A. Borning, G. S. Rutherford, and D. Layton. 2011. "Where Is My Bus? Impact of Mobile Real-time Information on the Perceived and Actual Wait Time of Transit Riders." *Transportation Research Part A: Policy and Practice*, 45(8): 839-848.

Zhang, F., Q. Shen, and K. J. Clifton. 2008. "Examination of Traveler Responses to Real-Time Information about Bus Arrivals Using Panel Data." *Transportation Research Record*, 2082: 107-115.

About the Authors

Niloofar Ghahramani (*nghahra000@citymail.cuny.edu*) is a doctoral student in Transportation Engineering at the City College of New York. She holds a bachelor's degree in Civil Engineering from Iran University of Science and Technology and a master's degree in Transportation Engineering from the City College of New York.

Dr. Candace Brakewood (*cbrakewood@ccny.cuny.edu*) is an Assistant Professor of Civil Engineering at the City College of New York. Her research focuses on public transportation, transportation planning, and intelligent transportation systems. She has a Ph.D. in Civil Engineering from Georgia Institute of Technology, dual Master of Science degrees in Transportation and Technology Policy from Massachusetts Institute of Technology, and a Bachelor of Science in Mechanical Engineering from Johns Hopkins University.

Evaluation of Horizontal Equity under a Distance-Based Transit Fare Structure

Milad Bandegani and Meisam Akbarzadeh
Isfahan University of Technology, Iran

Abstract

Horizontal equity requires equal distribution of investment/benefit/costs among equal members of society. In other words, a transit passenger should pay as much as he/she uses. This study evaluated the measure of fulfillment of this rule in a case study, developed a distance-based fare structure, and shows that justice is better served by switching to the proposed structure. Fare elasticity of demand and probability distribution of transit passenger trip lengths were investigated through a field survey. Although mainly used in the measurement of inequality in income or wealth, the Gini index and the recovery ratio (revenue to cost for each transit passenger) in evaluating equity were used in this study. Results show that the Gini index would decrease from 0.38 to 0.17 after switching from a flat to a distance-based structure. Assessment of the ratio of revenue per mile over cost per mile (RPM/CPM) shows that switching to a distance-based fare structure makes the RPM/CPM curve significantly flatter, which indicates more similarity among passengers. As a byproduct, the amount of change in demand and revenue of the transit system also were formulated.

Keywords: *Equity, elasticity, fare structure, Gini index.*

Introduction

This study aimed to quantify the effect of distance-based fare structure on horizontal equity in public transportation systems. Equity may be defined with respect to the distribution of the system's costs, benefits, or both among users (Pucher 1981). Access/egress time, waiting time, and monetary cost are the main impediments to public transportation ridership. Benefits of a public transportation system include accessibility and subsidy in payments. An extensive study of equity in public transportation systems should include all these elements. This study, however, focused on the monetary cost, since other factors are not expected to be sensitive to fare structure.

From economic and social points of view, equity is divided in two categories—horizontal and vertical. Horizontal equity requires equal treatment of equals, i.e., one pays as much as one uses/takes. Vertical equity, on the other hand, requires distribution of costs and/or benefits according to the users' need for the service or their capability for payment.

Two general structures of fare calculation are flat and graduated. In a flat structure, the fare of a line is predetermined and, therefore, is not sensitive to passenger trip characteristics (length, time, etc.). In a graduated fare structure, the fare rate may be dependent on a trip characteristic (length, time, zone, etc.) (Grey 1975; Nash 1982; Lovelock 1987).

From an organizational perspective, fare influences ridership and ridership determines revenue. To quantify the process, an acceptable estimate of price elasticity of demand is needed. Price elasticity of demand is the percentage of change in demand for a good or service as a result of a 1% change in its price. Therefore, elasticity establishes the relationship between fare and demand. Revenue, on the other hand, is the sum of all fares paid by passengers. In other words, price elasticity measures the rate of response of quantity demanded due to a price change and shows that percentage change in quantity demanded versus a 1% change in price.

Technological advances such as automatic fare collection (AFC) and automatic vehicle location (AVL) systems have paved the way for implementing distance-based fare structures. By using a ticket card upon boarding and alighting, the location and distance of a passenger's trip can be calculated, and the amount of fare can be determined accordingly. This process adds a few seconds to the station operation for each passenger but brings great benefits in terms of equity and cost incurred by passengers.

Literature Review

Fare Elasticity

Fare elasticity has a rich literature in which relationships between fare and transit operational factors are investigated. Fare elasticity is a fundamental parameter to estimate demand and income before any change actually occurs in the amount of fare. Some previous studies have investigated the effect of fare change on demand in the long and short terms (Dargay and Hanly 1999; Goodwin 1992). Litman (2015) concluded that the fare elasticity of transit ridership in the short term varies between -0.2 and -0.5 and in the long term varies between -0.6 and -0.9. Nowak and Savage (2013) assessed the cross elasticity between the price of gasoline and transit ridership in Chicago and found that it was small (about 0.05) when gas prices are under $3/gallon. When gas prices exceed $3/gallon, elasticity for rail-based transit modes is in the range of 0.12–0.14, and when gas prices exceed $4/gallon, elasticity is in the range of 0.28–0.38. Sirikijpanichkul and Winyoopadit (2013) investigated the price elasticity of demand for travelers of different ages and travel distances in Bangkok and found that passengers older than age 45 traveling long-distance trips have a higher price elasticity of demand than young and short-distance passengers. Wardman and Grant-Muller (2011) reported the price elasticity of the demand for excursion trips to be greater than business trips.

Wang et al. (2015) used metro smart card data of Beijing to evaluate the fare elasticity of demand and revenue and found that the elasticity of demand for short-range trips (< 5 kilometers) was more than longer trips.

Smith (2009) presented nine leading factors affecting the price elasticity of transit demand as user type, trip type, geography, type and direction of price change, time frame, distance, transit type and time of a day. Clements (1997) evaluated the response of dependent and discretionary transit riders and found that elasticity values of dependent riders tend to be significantly lower than discretionary riders. Linsalata and Pham (1991) conducted a study of 52 transit systems within the United States and determined the price elasticity in large and small cities for peak and off-peak hours. Their results showed that demand was less price-elastic during peak hours and in large cities. Horn af Rantzien and Rude (2014) assessed the price effects on the demand for public transport in peak- and off-peak periods in Stockholm; their results showed higher elasticities during off-peak periods compared to peak periods.

Fare Structures

Fare structures in public transportation include flat and graduated fare structures. Flat fares can be converted into variable fares based on factors such as distance, time, quality, cost, region (zone), and customer. A distance-based structure is based on the length of the trip. In a time-based fare structure, the amount of fare is determined based on trip duration or its occurrence during peak or off-peak hours. In cost-based pricing, the amount of fare is determined according to the cost incurred by the system to supply the service. In a zonal-based fare structure, the fare amount is determined based on the distance across zonal boundaries. In a customer-based fare structure, the fare rate is calculated according to the characteristics of the user, such as age and economic status.

Social Equity in Public Transportation

The importance of social equity together with a transportation system's profound impact on the fulfillment of equity has led to a significant amount of research in this regard. Related research focuses either on geographical distribution of transit benefits or on demographic distribution of transit costs. As an example of the first group, Welch and Mishra (2013) combined parameters including frequency, speed, and capacity of passing lines to introduce the power of each station and analyzed the distribution of transit power throughout an urban area using Gini index. Ricciardi et al. (2015) explored public transport equity for older residents, low-income households, and no-car households and compared the status of two major Australian cities.

As a seminal study in the second group, Cervero (1981, 1990) and Cervero et al. (1980) evaluated the efficiency and equity implications of alternative transit fare structures. They define pricing structures as being efficient when users contributed to the costs of their services in line with the benefits they receive, as reflected by the marginal costs of their trips. On the other hand, fares are considered equitable when they take into account the income capacities of riders. To inspect the effect of fare structures on groups of transit passengers, farebox recovery ratio was used as the ratio of fare price over the cost per passenger-mile. An example of a recent study within the second group is Farber et al. (2014), who incorporated a joint ordinal/continuous model of trip generation and distance traveled into a GIS Decision Support System. Applying this method to Wasatch Front, Utah, revealed that, overall, distance-based fares benefit low-income, older adult, and non-white populations. However, the effect was geographically uneven and even might be negative for members of these groups living on the urban fringe.

Methodology

This paper makes its contribution to the current body of literature by developing a mathematical foundation for a distance-based fare structure and systematically investigating its effect on horizontal equity.

To evaluate the effect of fare structure on equity, three steps should be taken: 1) price elasticity of transit demand should be estimated; 2) a formulation for fare structure should be developed; and 3) a reasonable framework for evaluating the equity should be developed.

As shown in Equation 1, price elasticity of demand (ε_p^D) is measured by the percentage of change in demand (*D*) as a result of 1% change in fare (*p*).

$$\varepsilon_p^D = \frac{\partial D}{\partial p} \times \frac{p}{D} \tag{1}$$

To fulfill the first requirement, a survey was conducted among transit passengers in Isfahan, a city of 1.7 million located in central Iran.The sample size included 300 passengers of 6 major lines of the bus transit system. Respondents were asked how much they were paying for fare and how much more they were willing to pay before switching to alternative modes, if any (consumer surplus). Data were collected during both peak and off-peak time periods. It is noteworthy that the Isfahan bus transit network is composed of 97 lines with an approximate length of 2K kilometers serving 900K passengers daily, which makes its share in the city's transportation equal to 20%. The transit lines all over the city are mostly radial and circumferential. Currently, the fare of each line is determined based on length. All the buses serving the Isfahan transit network are equipped with an AFC system; hence, a distance-based fare structure is implementable.

Comparison of the consequences of fixed and distance-based fare structures requries establishment of the mathematical relationship between the two structures. In a distance-based structure, the fare for traveling through i stations (F_i) consists of a fixed "flag-fall" charge (F_0) and a unit line haul charge per segment (F_1), where a segment is defined as the distance between two consecutive stations. Therefore, the fare would be calculated from Equation 2.

$$F_i = F_0 + (i - 1)\, F_1 \tag{2}$$

Without loss of generality, it could be assumed that in a fixed fare structure, the fare (F_{Flat}) is equal to the amount of fare for traveling through the whole line divided by a factor $K \in \mathbb{R}$. Hence, if *n* denotes the number of all stations in a line, the flat fare (F_{Flat}) can be formulated as Equation 3.

$$F_{Flat} = \frac{F_0 + (n-1)\, F_1}{K} \tag{3}$$

Therefore, by switching from a fixed to a distance-based fare structure, a passenger traveling *i* stations would experience a change in fare equal to ΔF:

$$\Delta F = F_i - F_{Flat} = \frac{(k-1)F_0 + [k(i-1)-(n-1)]F_1}{K} \tag{4}$$

From the definition of elasticity, it is evident that the percentage of change in demand ($\Delta D\%$) is equal to the percentage of change in fare ($\Delta F\%$) multiplied by the fare elasticity of demand (ε). On the other hand, the percentage of change in the fare amount is the sum of the fare change for trips with length of *i* stations. Hence:

$$\Delta D\% = \Delta F\% \cdot \varepsilon = \sum_{i=1}^{n} \frac{F_i - F_{Flat}}{F_{Flat}} \cdot \varepsilon_i \tag{5}$$

Therefore, demand under distance-based fare structure ($D_{D\text{-}B}$) can be calculated from Equation 6.

$$D_{D-B} = D_{Flat} \cdot (1 + \Delta D\%) \tag{6}$$

To assess the financial consequences caused by the change in fare structure, the amount of revenue must be analyzed. Equation 7 shows the change caused by switching from a flat-fare to a distance-based fare structure (ΔR).

$$\Delta R = \sum_{i=1}^{n} [D_{D-B}(i) \cdot F_i - D_{Flat} \cdot F_{Flat}] \tag{7}$$

Assessment of the Fairness of Fare Structures

Disparity between a passenger's benefit (trip length) and cost (fare) implies inequality. Revenue per Mile (RPM) is the revenue from fares, and Cost per Mile (CPM) is the cost incurred by the system. RPM/CPM would show if passengers are paying more than they benefit from the transit service or vice versa. This factor also measures the share of each user's trip cost covered by a rider's fare. Under the condition of perfect equity, the value of RPM/CPM would be equal to 1 for all trip lengths.

Based on value of RPM/CPM, two distinct types of evaluations were carried out. First, the distribution of RPM/CPM among the passengers with different trip lengths was analyzed. At perfect equity, the ratio of RPM/CPM is equal to 1 for all passengers regardless of trip length. Second, the distribution of RPM/CPM among the population of passengers could be analyzed and its fairness can be assessed via the use of Gini index. A Lorenz curve was used for assessing the uniformity of the distribution of benefits among the passengers. A Lorenz curve plots the cumulative percentages of total received benefit versus the cumulative number of recipients. The area between the Lorenz curve and a hypothetical line of absolute equality is the Gini index value. The Gini index (G_a)

measures the extent to which the distribution of an entity among units of concern deviates from a perfectly equal distribution. This number ranges between 0 (perfect equity) and 1 (perfect unequity) and is calculated using the following formula where X_k is the cumulative proportion of the population and and Y_k is the cumulative proportion of attribute k.

$$G_\alpha = 1 - \sum_{k=1}^{m}(X_k - X_{k-1})\times(Y_k + Y_{k-1}) \tag{8}$$

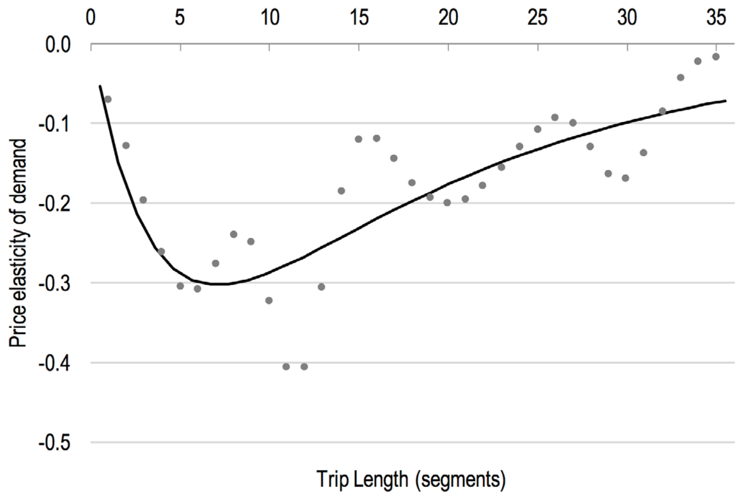
Case Study

Price elasticity of transit demand was calculated for different categories of passengers based on survey data. Passengers were categorized based on gender, income, trip distance, age, usage frequency, and available alternative mode. Results show that price elasticity was -0.33 and -0.3 for male and female passengers, respectively. The average fare elasticity for passengers younger than age 18 was -0.17 compared to -0.28 for respondents ages 18–40 and -0.4 for respondents ages 40+. Analysis showed that price elasticity falls as income increases. The average elasticity for passengers from households with a monthly income below \$330 is -0.36 compared to -0.32 for \$330–\$660 and -0.24 for whose household income was above \$660. Results of the survey also indicated a difference pertaining to an available alternative mode. The elasticity value for passengers who had a private vehicle at their disposal was -0.3. The values for passengers indicating bicycle as their alternative was -0.27, for taxi -0.3, for motorcycle -0.42, and for walking -0.48. The price elasticity value for passengers who use a bus every day was -0.33, for "often" users it was -0.25, and for "seldom" users it was -0.36. Results also show that elasticity is higher during off-peak hours compared to peak hours.

Since this study was based on trip distances, more elaboration was made on the demand elasticity of passengers with different trip lengths. Using collected data, price elasticity of demand for trips of length *i* ($\mathcal{E}_i$) was estimated. Figure 1 shows the data and Equation 9 shows the calibrated formula with coefficient of determination (R^2) equal to 0.67.

$$\mathcal{E}_i = -0.6e^{-0.06i} + 0.7e^{-0.3i} \tag{9}$$

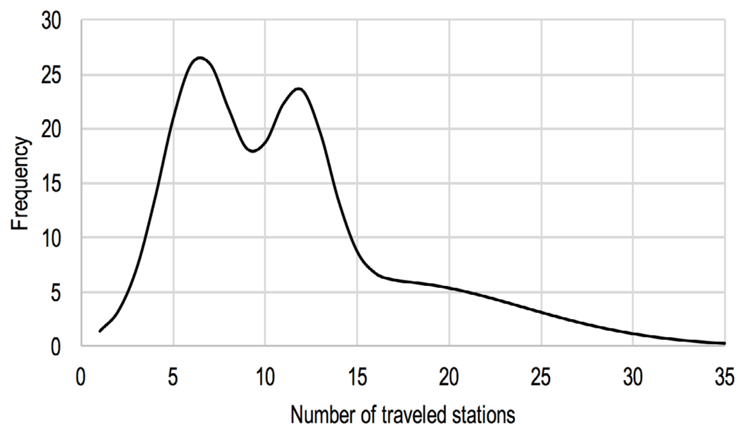
FIGURE 1.
Price elasticity of demand based on trip length



The trip distribution was derived from the survey data and is presented in Equation 10 and Figure 2.

$$D = \sum_{i=1}^{n}\left(24.1e^{-\left(\frac{i-6.4}{2.9}\right)^2} + 18.1e^{-\left(\frac{i-11.8}{2.3}\right)^2} + 6e^{-\left(\frac{i-16.5}{10.6}\right)^2}\right) \qquad (10)$$

FIGURE 2.
Frequency of trip lengths

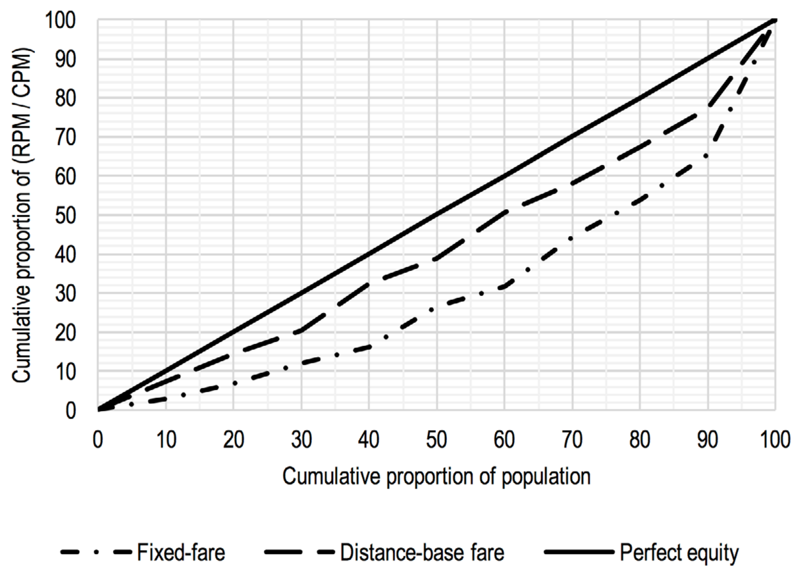


Equity and Fairness of Distance-Based Fare Structure

Total revenue was calculated by summing the product of demand and fare for each class of trip length. A unique value was assumed for the cost of traveling each segment. Figure 3 shows the Lorenz curve for fixed and distance-based fare. It is evident that by switching from a fixed to a distance-based fare structure, the Lorenz curve moves toward the bisector (complete equity). This merge could be quantified by the value of the Gini Index. The Gini index in fixed and distance-based fare structures was calculated to be 0.38 and 0.17, respectively. Hence, the Gini-index value declined after switching to a distance-based structure and, therefore, justice is better served. It should be noted that this figure is drawn F_{int} = \$0.13, F_0 = \$0.033, and F_1 =\$0.007. Values were calculated in local currency and transformed to US dollars. According to the Isfahan Bus Transit Organization, the cost of each passenger is about $0.13. Since this value is the same for all lines and passengers, it does not affect the methodology. However, it affects the prescribed values for parameters of the formulation, e.g., F_0 and F_1.

Figure 3 shows the difference between each fare structure and the full equity condition. In this figure, abscissa and ordinate represent the percentile of the population and the portion of the total value of the RPM/CPM respectively (Welch and Mishra, 2013).

FIGURE 3. Lorenz curves for fixed-fare and distance-based fare structure



The value of the ratio of RPM/CPM on all segments is depicted in Figure 4. The horizontal dashed line shows the perfect status for equity, the "subsidy threshold" (Cervero 1981). This threshold shows the situation in which every group of passenges compensates for the charges they incur to the system.

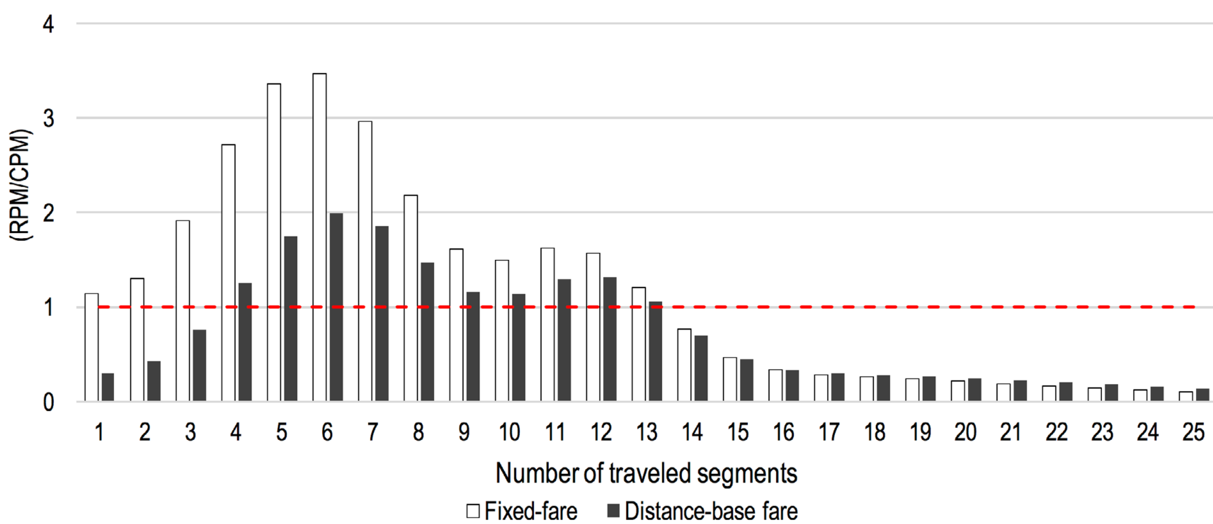


FIGURE 4. RPM/CPM for different trip lengths

Figure 4 demonsrates that under the current fare structure, passengers with short and medium trip lengths (trip lengths between 2 and 12 segments) are paying more than what they gain (white bars). On the other hand, passengers with longer trip lengths (trip lengths above 14 segments) are paying much less than what they gain. Actually, one group of passnegers is paying the cost of the other. In a distance-based fare structure, this unevenness is modified to a great extent (gray bars). It is evident that the deviation from the dashed line (perfect equity) has diminished considerably.

To quantify the effect of the change, absolute errors were calculated according to Equation 10. It was shown that the absolute error (absolute value of RPM/CPM minus 1) has decreased from 22 (under the current fare structure) to 14 (under the proposed distance-based fare structure), a more than 50% improvement.

Figure 5 shows how the unevenness of RPM/CPM is distributed among passengers based on their trip length. Comparing the bars shows that by switching to a distance-based structure, unevenness diminishes, especially for trip lengths between 5 and 15 stations which, according to Figure 2, constitutes the majority of passengers.

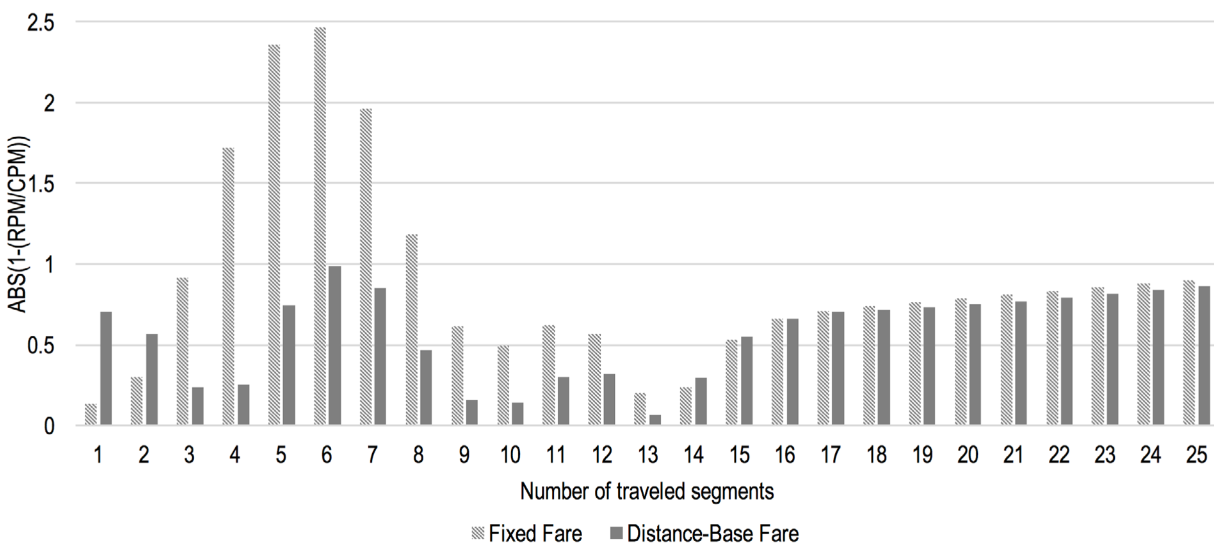


FIGURE 5. Deviation from equity for different trip lengths

Conclusion

The effect of a distance-based fare structure adoption on horizontal equity was quantified in this study. Adopting an appropriate fare structure influences transit ridership and revenue and has a profound effect on social equity. This paper investigated the distance-based fare structure from the social equity point of view. Results indicate that the status of social equity under a distance-based fare structure conforms to the social equity much more than a flat-fare regime. Both the Gini index and the revenue-to-cost ratio explicitly show that disparity in the distribution of transit benefits decreases under a distance-based structure. For Isfahan, the value of the Gini index would reduce from 0.38 to 0.17 by switching to a distance-based fare structure. Moreover, the sum of the absolute deviation from 1 (perfect inequity) diminished from 22 (under a flat-fare structure) to 14 (under a proposed distance-based fare structure) shows more than a 50% improvement.

Results of this study could be used by bus transit organizations to set fares equitably and profitably. For Isfahan, setting the F_0 = \$0.033 and F_1 =\$0.007 would halve the Gini index and increase the revenue. It should be noted that any change in the operational cost of a bus system or the demand pattern may change these values. New values may be calculated using the formulations presented in the paper.

Acknowledgment

The authors would like to thank the reviewers for their meticulous review and helpful comments.

References

Cervero, R. 1981. “Flat versus Differentiated Transit Pricing: What’s a Fair Fare?” *Transportation*, 10: 211-232.

Cervero, R. 1990. “Transit Pricing Research: A Review and Synthesis.” *Transportation*, 17: 117-139.

Cervero, R. B., M. Wachs, R. Berlin, and R. J. Gephart. 1980. “Efficiency and Equity Implications of Alternative Transit Fare Policies.” No. UMTA-CA-11-0019-80-1, Final Report.

Clements, H. 1997. “A New Way to Predict Transit Demand.” *Transportation Research Record*, 23: 49-52.

Dargay, J., and M. Hanly. 1999. “Bus Fare Elasticities.” Report to the UK Department of the Environment, Transport and the Regions. London, ESRC Transport Studies Unit, University College London, 132.

Farber, S., K. Bartholomew, X. Li, A. Páez, and K. M. N. Habib. 2014. “Assessing Social Equity in Distance Based Transit Fares Using a Model of Travel Behavior.” *Transportation Research Part A: Policy and Practice*, 67, 291-303.

Goodwin, P. B. 1992. “A Review of New Demand Elasticities with Special Reference to Short and Long Run Effects of Price Changes.” *Journal of Transport Economics and Policy*, 155-169.

Grey, A. 1975. *Urban Fare Policy*. Farnborough: Saxon House.

Horn af Rantzien, V., and A. Rude. 2014. “Peak-Load Pricing in Public Transport: A Case Study of Stockholm”. Journal of Transport Literature, 8(1): 52-94.

Kain, J. F., and Z. Liu. 1999. “Secrets of Success: Assessing The Large Increases in Transit Ridership Achieved by Houston and San Diego Transit Providers.” *Transportation Research Part A: Policy and Practice*, 33: 601-624.

Linsalata, J., and L. H. Pham. 1991. "Fare Elasticity and Its Application to Forecasting Transit Demand." American Public Transit Association, Washington, DC.

Litman, T., 2002. "Evaluating Transportation Equity." *World Transport Policy & Practice*, 8(2): 50-65.

Litman, T. 2015. "Evaluating Public Transit Benefits and Costs." Victoria Transport Policy Institute.

Lovelock, C. H., G. Lewin, G. S. Day, and J. E. G. Bateson. 1987. *Marketing Public Transit*. New York: Praeger Publishers.

Marshall, A. 1920. *Principles of Economics*. London: London: Macmillan, reprinted by Prometheus Books.

Matthew, J. S. 2009. "Public Transit and the Time-Based Fare Structure." Urban Transportation Center, University of Illinois at Chicago.

Nash, C. A. 1982. *Economics of Public Transport*. New York: Longman.

Nowak, W. P., and Savage I. 2013. "The Cross Elasticity between Gasoline Prices and Transit Use: Evidence from Chicago." *Transit Policy*, 29: 38-45.

Pucher, J. 1981. "Equity in Transit Finance: Distribution of Transit Subsidy Benefits and Costs among Income Classes." *Journal of the American Planning Association*, 47: 387-407.

Ricciardi, A. M., J. Xia, and G. Currie. 2015. "Exploring Public Transport Equity between Separate Disadvantaged Cohorts: A Case Study in Perth, Australia." *Journal of Transport Geography*, 43: 111-122.

Sirikijpanichkul, A., and S. Winyoopadit. 2013. "Price Elasticity of Demand and Transit Fare Strategy: A Case Study of Bangkok Mass Transit System." *Proceedings of the 4th International Conference on Engineering, Project, and Production Management (EPPM 2013)*, 346-360

Smith A. 2009. "Does the Quality of Public Transit Affect Commuters' Response to Gasoline Price Changes?" M.Sc. thesis, Duke University.

Taylor, B. D., and Camille N. Y. Fink. 2003. "The Factors Influencing Transit Ridership: A Review and Analysis of the Ridership Literature." University of California Transportation Center.

Taylor, B. D., and C. Fink. 2012. "Factors Influencing Transit Ridership: A Review and Analysis of the Ridership Literature." UCLA Department of Planning Working Paper.

Taylor, B. D., D. Miller, H. Iseki, and C. Fink. 2009. "Nature and/or Nurture? Analyzing the Determinants of Transit Ridership across US Urbanized Areas." *Transportation Research Part A: Policy and Practice*, 43: 60-77.

Wardman, M., and S. Grant-Muller. 2011. "Price Elasticities of Travel Demand in Great Britain: A Meta-Analysis." In *Transportation Research Board 90th Annual Meeting* (No. 11-3544).

Webster, F. V., and P. H. Bly. 1980. "The Demand for Public Transport. Report of an International Collaborative Study." Transport and Road Research Laboratory, Crowthorne, Berkshire.

Welch, T. F. and S. Mishra. 2013. "A Measure of Equity for Public Transit Connectivity." *Journal of Transport Geography*, 33: 29-41.

About the Authors

Meisam Akbarzadeh (*makbarzadeh@cc.iut.ac.ir*) is an Assistant Professor at the Isfahan University of Technology, Department of Transportation Engineering. His research areas of interest include public transportation and complex transportation networks.

Milad Bandegani (*miladbandegani@yahoo.com*) is an MSc candidate at the Isfahan University of Technology, Department of Transportation Engineering.

SUBSCRIPTIONS and PREVIOUS ISSUES

To subscribe or update your subscription to the *Journal of Public Transportation*, please visit *www.nctr.usf.edu/journal/subscriptions*.

Full-text issues of previous *Journal of Public Transportation* articles are available on the National Center for Transit Research website at *www.nctr.usf.edu/journal/full-text-issues*.

SUBMISSION OF MANUSCRIPTS

The *Journal of Public Transportation* is a quarterly, international journal containing original research and case studies associated with various forms of public transportation and related transportation and policy issues. Topics are approached from a variety of academic disciplines, including economics, engineering, planning, and others, and include policy, methodological, technological, and financial aspects. Emphasis is placed on the identification of innovative solutions to transportation problems.

All articles should be approximately 4,000 words in length (18–20 double-spaced pages). Manuscripts not submitted according to the journal's style will be returned. Submission of the manuscript implies commitment to publish in the journal. Papers previously published or under review by other journals are unacceptable. All articles are subject to peer review. Factors considered in review include validity and significance of information, substantive contribution to the field of public transportation, and clarity and quality of presentation. Copyright is retained by the publisher, and, upon acceptance, contributions will be subject to editorial amendment. Authors will be provided with proofs for approval prior to publication.

Formatting Requirements

All manuscripts must be submitted electronically in MS Word format, with *no linked images*. Tables in the manuscript must be created in Word or Excel format and must not be inserted as images. Figures should be inserted as images and, to meet Section 508 compliance requirements, must have alternative text (a thorough description of the image to assist persons with visual impairments in understanding the image). All tables and figures must be numbered consecutively and have a title. All non-original figures and graphics must indicate the source; the author should retain written permission for use of any non-original images.

All manuscripts should include sections in the following order, as specified:

- *Cover Page* – title (12 words or less), author(s) affiliation(s) and email address(es), and address/telephone for corresponding author
- *Main Body* – title, paper abstract (up to 150 words), text organized under section headings (do not use section or subsection numbering)
- *References* – author-date format (*Chicago Manual of Style*)
- *Biographical Sketch* – brief information for each author; include email address

Be sure to include the author's complete contact information, including email address, mailing address, telephone, and fax number.

Submit manuscripts via email to:
Lisa Ravenscroft, Assistant to the Editor
Journal of Public Transportation
National Center for Transit Research @ CUTR
Email: *jpt@cutr.usf.edu*
Phone: (813) 974-3120

Center for Urban Transportation Research

College of Engineering
University of South Florida
4202 E. Fowler Avenue, CUT100
Tampa, FL 33620-5375
(813) 974-3120, fax (813) 974-5168