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Planning for Bike Share Connectivity to Rail Transit

Greg Phillip Griffin and Ipek Nese Sener
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Abstract

Bike sharing can play a role in providing access to transit stations and then to final destinations, but early implementation of these systems in North America has been opportunistic rather than strategic. This study evaluates local intermodal plan goals using trip data and associated infrastructure such as transit stops and bike share station locations in Austin, Texas, and Chicago, Illinois. Bike sharing use data from both cities suggest a weak relationship with existing rail stations that could be strengthened through collaborative, intermodal planning. The study suggests a planning framework and example language that could be tailored to help address the linkage between bike sharing and transit. Rather than an exhaustive study of the practice, this study provides evidence from these two cities that identify opportunities to improve intermodal planning. Cities that are planning or expanding a bike sharing system should consider carefully how to leverage this mode with existing modes of transport. Regardless of a city’s status in implementing a bike sharing system, planners can leverage information on existing transport systems for planning at regional and local levels.

Keywords: Bike share; GIS; transit; plan evaluation; mixed methods

Introduction

Public transit is a critical component of sustainable transportation systems (Richter, Friman, and Gärling 2011), yet convenient last-mile access to and from transit stations is a persistent challenge for many communities (Cervero, Caldwell, and Cuellar 2013; Taylor and Hahmassani 1996). This restriction limits the utility of the mode for many urban dwellers, as well as access to jobs, goods, and services for those who do not have available other options such as personal automobiles. However, planning for transit station access can improve ridership and other performance measures over time (Boarnet and Compin 1999; Cervero and Gorham 2009).

Urban transit traditionally is accessed by any of the three other primary surface transportation modes. The most common is walking, but this mode is limited by distance, which affects the duration people are usually expected to walk to transit,
often ranging between 500 meters and a kilometer, or approximately ¼ to ½ mile (Crowley, Shalaby, and Zarei 2009). Most trips by public transit require either a mode switch or a route transfer to reach a desired destination. Through the siting of multiple routes at a single station, users can readily access a broader range of destinations. However, transfer times between routes depend on service headways, and this time adds to the barriers of transit use (Fan and Machemehl 2011). Personal vehicle access is another option, particularly at stations with areas for parking or kiss-and-ride service. Space needed for auto parking and access adds significantly to the cost of urban stations (Steiner et al. 2006; Pucher and Buehler 2009) and mitigates environmental and traffic benefits of transit service (Bartholomew and Ewing 2008). Finally, research on access to transit via bicycling indicates that it promises the sustainability benefits of walking while extending the effective access shed to a distance of 2 to 5 kilometers (1.2 to 3.1 miles), depending on the speed of the transit accessed (Krizek and Stonebraker 2010). In addition to distance, other barriers to bicycle transportation include perceived safety, exposure to weather, ownership of bicycles, and available secure parking (Hamre and Buehler 2014; Handy, Xing, and Buehler 2010; Mullan 2013; Orrick, Frick, and Ragland 2011; Twaddle, Hall, and Bracic 2010). Bike sharing provides at least a partial solution to the last two barriers.

Bike sharing is a relatively new mode that is increasing as a resource for urban trips and particularly as a connection to transit stations. The growth of bike sharing in areas served by transit offers the prospect to reduce the challenges some people may have in terms of time, comfort, and energy expenditure when trying to access a transit station (Ma, Liu, and Erdoğan 2015; Martin and Shaheen 2014). Bike sharing has the opportunity to serve as a feeder mode for the first and last mile of transit trips, potentially making transit and biking easier options to take more often, with mobility and health benefits for individuals and society (DeMaio and Gifford 2004; DeMaio 2009; Duvall and Main 2012; Winters et al. 2010).

Despite its promising role in providing alternative solutions to access to transit stations and then to final destinations, there have been relatively few studies quantifying bike sharing’s potential impact in facilitating transit trips. Recognizing this gap, this study aims at exploring the relationship between transportation planning goals related to bike sharing and transit, as well as variables of the local built environments affecting bike sharing ridership near transit. These topics are first explored through a review of previous studies on the combination of transit and bicycling. Then, bike share data from two central cities of United States are examined—Austin, Texas, and Chicago, Illinois. Both cities have growing bike share systems supported by significant planning efforts leading to recently improved bicycle networks, but not yet examined by earlier studies. Rather than direct comparison of Austin and Chicago, this study examined these two cities as a case study exploring key differences and similarities between them—particularly in key areas known to be related to bike sharing and transit. The next section focuses on the empirical and qualitative methods used in this study, before reporting the results and discussing implications to planning and transport geography. This paper concludes with a summary of contributions to planning for bike sharing and transit, in addition to needs for future study.
Potentials and Challenges of Bicycle Access to Transit

Two recent studies explored the relationship between bike sharing and transit, each using different data and methods. Both pointed out the need to extend similar research, noting two distinct paths. Martin and Shaheen (2014) raised the need to explore built-environment variables in examining bike share behavior, and Ma et al. (2015) identified a need to consider the proximity of bike sharing to transit stations.

In particular, Martin and Shaheen’s study (2014) focused on travel behavior change of bike share system members in Washington, DC, and Minneapolis, Minnesota. By mapping the location of survey responses, they found that users in less densely-developed areas often used bike share to access transit, as opposed to users in the dense urban core, who used bike share to get to transit faster and replaced some transit trips with bike share. A recent system-level analysis of Capital Bikeshare stations indicated that increasing bike-share trips by 10% would contribute to a 2.8% increase in Metrorail ridership (2015), suggesting bike share has a strong potential role as an access mode to and from transit trip ends. Both papers suggested that bike share can serve as a significant and complementary mode to extend the reach and effective speed of transit, but neither study considered the role of active planning of the system or the role of bicycle-specific infrastructure such as bike lanes.

Though bike sharing is a relatively new mode to be considered in the literature, several previous studies pointed out the importance of the bicycling environment on use of the mode. A recent study of bicycle-on-bus boardings from Cleveland, Ohio, suggested bike sharing at transit locations could help alleviate the crowding of transit systems related to on-board bicycles and conveyed the need for additional research on bicycling and transit (Flamm 2013). An analysis of Bay Area Rapid Transit stations supported this relationship as well, indicating that “cities with high transit usage and levels of cycling face on-board capacity constraints,” which can be mitigated with bicycle parking and “bike sharing at destination stations” (Cervero et al. 2013, 102).

Facilities at destinations are only as accessible as the infrastructure that connects to them, however. Iseki and Tingstrom (2014) pointed out the importance of street connectivity to offer bicyclists a range of route choices, particularly to avoid steep hills, and noted that bicycle-specific infrastructure can play an especially significant role where vehicle traffic volumes or speeds are high. Similarly, transit ridership has been associated with street connectivity, but not necessarily tied to traditional, gridded street networks (Thompson et al. 2006). Using National Household Travel Survey (NHTS) data from 2001 and 2009, Wang and Liu (2013) showed that rail transit attracts similar rates of intermodal bicyclists to bus transit and emphasized the need to improve integration of the two modes to leverage the advantages of each. The literature points to a complementary relationship between bicycling and transit, with several recent contributions on planning supportive infrastructure.

Infrastructure plays a key role in both the perception and reality of safety for bicyclists. Sidewalks, bike lanes, and off-street paths facilitate more comfortable, safe travel for cyclists to destinations such as transit stops (Akar and Clifton 2009; Duthie et al. 2010; Iseki and Tingstrom 2014; Krizek, Handy, and Forsyth 2009). Surveys of bicyclists...
indicate that higher levels of on-street bicycle accommodations, such as protected bike lanes rather than wide curb lanes, are preferred for general transportation by both men and women (Dill et al. 2015), and specifically for accessing transit stations (Taylor and Hahmassani 1996). Ehrenfeucht and Loukaitou-Sideris (2010) place a normative responsibility for the provision of adequate infrastructure on planners, noting the need to create “complete streets” for multi-modal transportation including sidewalks, crosswalks and bike lanes, as well as overhangs for weather protection, benches for sitting and trees for shade and comfort.” Bike sharing is inherently intermodal, assuming at least a short walk to and from bike share stations and transit stops. Therefore, all three modes (walk, bike, and transit) require adequate provision for intermodal transitions to work well.

Bicycling and walking are critical parts of intermodal transit trips. Previous studies confirm the importance of the planning community to remain engaged in these issues from a holistic perspective, but also one that considers the needs of each local community to facilitate bike sharing as a supportive link to transit systems and destinations.

Overview of Bike Sharing and Rail Transit in Austin and Chicago

Many large North American cities have implemented bike sharing systems on an opportunistic basis—developed with available public and private funding without a strategic connection to existing transportation plans. The problem with this approach is that it may not leverage advantages particular to the bike sharing mode, particularly as a connection to high-capacity transit stations. This article explores this challenge through the cases of recent bike share program development in Austin, Texas, and Chicago, Illinois, and offers suggestions on how to better integrate urban transportation planning for existing and emergent modes.

Both Chicago and Austin have developed multimodal transportation systems and participated in transportation planning at the regional and local levels. Planning for bike sharing systems is a relatively nascent field, and these two cities are working toward rapidly growing their systems concurrent with integrated, multimodal transportation planning. Based on the most current and applicable plans at the regional and local levels, neither bike share systems share long range plans, but Chicago’s Divvy system offers a map of expansion within the current year (2015). Since each bike share system is so new (both launched in 2013), only Austin’s bicycle plan developed in 2014 refers to the bike share system explicitly. A cursory review of other city plans indicates similar findings: bike sharing systems emerged as a solution to broadly define bicycle transportation opportunities rather than prescriptive solutions, and bike sharing is more common in plans since their popularization after 2010.

Neither system’s state-level plans address bike sharing explicitly. The Illinois Department of Transportation’s 2014 statewide Bike Transportation Plan mentions bike sharing as “great way to encourage bicycle transportation,” but it does not include bike sharing in any of its action items or objectives (Illinois Department of Transportation 2014). Currently, the Texas Department of Transportation’s plans do not include bike sharing.
News reports from El Paso, Texas, indicate the agency had denied support of that city’s bike sharing system that had been approved by the metropolitan planning organization using federal congestion mitigation air quality (CMAQ) funding, but later supported a scaled-back bike share program (Lopez 2015). In Texas and Illinois, leadership in bike sharing planning has come from local and regional transportation partnerships.

Table 1 provides illustrative examples of goals and benchmarks related to bicycle infrastructure in general and bike sharing specifically for both Austin and Chicago.

<table>
<thead>
<tr>
<th>Plan</th>
<th>Bicycle Network</th>
<th>Bike Share System</th>
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<tr>
<td><strong>Austin, TX</strong></td>
<td></td>
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<tr>
<td>2014 Bicycle Master Plan (City of Austin, 2014)</td>
<td>“Complete 20% of the short-term all ages and abilities network by 2017, 50% by 2020, and 80% by 2025.”</td>
<td>“Expand Austin’s bike share system from 40 stations to 100 stations by 2016 and to 300 stations by 2017.”</td>
</tr>
<tr>
<td><strong>Chicago, IL</strong></td>
<td></td>
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<tr>
<td>Bike 2015 Plan (Mayor’s Bicycle Advisory Council, 2006)</td>
<td>“Goal: Provide convenient connections between bicycling and transit.” “Performance Measure: Increase the number of bike-transit trips by 10% per year.”</td>
<td></td>
</tr>
<tr>
<td>Chicago Streets for Cycling Plan 2020 (Chicago Department of Transportation, 2013)</td>
<td>“Provide a bicycle accommodation within ½ mile of every Chicagoan.” “Provide a greater number of bikeways where more people live.” “Increase the amount of infrastructure where ridership is high, while establishing a strong backbone of infrastructure where ridership is currently lower.”</td>
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As indicated in the table, the cities’ goals and benchmarks are more specific in local plans, aligning with the strong responsibilities of cities versus regional planning bodies in the United States context. Though written before bike sharing implementation, Chicago’s regional and local plans directly address the potential for bicycle and transit to facilitate travel options. Detailed valuation of planning outcomes will have to be done in the years ahead as performance measures are tracked and travel choices change over time. The present study is prospective in this regard, seeking to anticipate potential planning outcomes and relationships to improve planning for this relatively new mode of transport.

Density differences between the two cities play an important role in the effect of transportation options. In 2013, Chicago’s population (2,718,782) was just over three times that of Austin’s (885,400) (U.S. Census Bureau 2013b). The municipal boundary of Chicago is slightly smaller than Austin’s, resulting in a city population density over 3.5 times greater. These differences in density also are reflected in the cities’ transportation system planning over time.
Both cities had streetcar systems by the end of the 19th century, which were abandoned as the automobile and bus systems were expanded—a typical pattern in American cities of the time (Brown, Morris, and Taylor 2009). Chicago’s first elevated rail transit line opened in October 1897, followed by opening of subways in 1943 and 1951, the addition of rail service in the median of three expressways from 1958 to 1970, and rail service expansion to its airports in 1984 and 1993 (Chicago Transit Authority 2015). In contrast, Austin’s single commuter rail line opened in 2010, and an urban rail funding plan was voted down in November 2014 (Tolbert 2014). Instead, Austin has several tolled expressways under development and could have as many as a dozen operational in the next decade (Wear 2014). Both cities have extensive suburbs with significant population, but bike sharing does not extend into them at present. Chicago and Austin’s differences in density and transit options provide an extreme selection of cases that may “reveal more information” than cases that typify urban planning conditions (Flyvbjerg 2006, 229). Flyvbjerg suggests that the best cases for comparison include some variables that are similar; Chicago and Austin currently have identical bicycle commuting mode shares, as shown in Table 2.

Table 2 also shows that Chicago’s bike share system is much larger, with more than six times the number of stations and bicycles in Austin. Analysis of both cities affords a view of the relationship between bike sharing and transit at very different scales: Chicago’s very large and mature transit system is quickly interfacing with a new bike share system, and Austin is adding bike sharing simultaneously with the development of a small but growing rapid transit system. In this study, each city varies widely in its historical urban transportation approaches, but the extent of intermodal planning regarding bike sharing are relatively similar.

Chicago’s extensive transit system plays a major role in a significant reduction of automobile trips, yet the two cities share the same bicycle commute rate of 1.4% of
persons reporting that they usually get to work in the previous week by biking, as reported in American Community Survey (ACS) statistics (U.S. Census Bureau 2013a). It should be noted that bicycling trips reported via this commute statistic are a small portion of all bicycle trips, since trips to school, shopping, or all other purposes are omitted.

Literature on the role of intermodal support or competition between bike sharing and transit is inconclusive. Initial studies suggest substitution of some shorter bus trips with bike sharing and a more symbiotic relationship with rail transit (Ma et al. 2015; Martin and Shaheen 2014). In addition to the general positive association between Metrorail ridership and Capital Bikeshare use (Ma et al. 2015), survey results from Minneapolis and Washington, DC suggest these relationships vary by city and neighborhood. Bike sharing may foster new connections to transit in less dense areas than in very dense locations that more often are served by passenger rail (Martin and Shaheen 2014). Rather than focusing on causal relationships of mode substitution, the data and methods in this study support analysis of planning that could foster intermodal support in the future.

Fully intermodal transportation planning considers the mobility needs of all users for all purposes, but this study focuses on bike sharing and rail transit. Our preliminary analysis of bus stop locations in proximity of bike share stations revealed a nearly ubiquitous relationship, one that will offer no useful differentiation in spatial analysis for the present case studies. Rail transit offers a special relationship with bike sharing, where the shortcoming of rail’s high speed and distance between stations can be served well with bike sharing to solve the well-researched last-mile problem. In addition, rail station locations are relatively permanent, implying impacts on long-range planning of both land use and transportation. Bus stops and routes are relatively transient in comparison, which can confound extension of analysis over the longer term.

**Data and Methods**

This study takes a mixed methods approach to evaluating the opportunity for bike share systems to improve first and last mile rail transit access, using descriptive statistics, plan evaluation techniques, and semi-structured interviews of bike share system planners. First, bike share use data from the two relatively young systems with proximity to rail transit are analyzed, and then each city’s planning performance measures related to the two modes is evaluated.

Bike share trips are recorded and disseminated by operators on a per-trip basis, often with unique bicycle numbers, and to and from station locations for each trip, excluding personally-identifiable information of the users. These tables were summarized by counts in a given time period, then joined to a spatial database of bike share station locations for further analysis. This allowed spatial analysis of bike share data with proximity to each city’s rail transit stations and density measures from the Environmental Protection Agency’s Smart Location Database (Ramsey and Bell 2014).

In addition to the basic system statistics in Table 2, spatial statistics were calculated to provide additional insights on the systems characteristics. Average nearest-neighbor statistics reveal Austin B-cycle’s smaller system is also closer together, at an average of 1,035 feet between stations versus 1,615 feet for Chicago’s Divvy system. Both were
calculated using a Manhattan distance (along x and y axes) to approximate urban navigation, recognizing that bicycle travel allows crossing parking lots and plazas rather than being fully bound to city streets or paths. These existing spatial datasets were then reviewed alongside planning documents from each city.

Plan evaluation focused on evaluation of goals to each city’s published documents related to bicycle planning. Plan evaluation is typically conducted as an entire document using content analysis methods (Stevens, Lyles, and Berke 2014; Stevens 2013), but the focus of this study is on the planning goals and benchmarks (also sometimes called performance measures) related to bicycle infrastructure and, in particular, bike sharing systems. The content of plans often omits experiences and perspectives of the planners themselves, however, and interviews can help reveal otherwise unrecorded details.

Semi-structured interviews were arranged with a primary bike share planner for each system. Local planners recommended key informants, and their anonymity was maintained to promote individual perspectives. Interviews were conducted using computer-based internet messaging software, offering a standardized interview environment appropriate for professionals experienced with online tools but lacking non-verbal information present in face-to-face interviews (Brabham 2010). The interview plan for each informant included six questions designed to be answerable in a half-hour session, including time for additional discussion. This mixed-method case-study approach provided a basis for context-dependent knowledge that is more valuable for analysis of human affairs than the search for “general, theoretical knowledge” that might support “predictive theories and universals” (Flyvbjerg 2006, 224).

To analyze each case of bike sharing and transit, bike station use volumes and urban densities at a station level were reviewed, and then considered proximity of bike stations to transit. These quantitative results suggested the current relationships between the modes, using measures supported by the review of literature. Survey results from each station offered additional quantitative results from users. Planning documents at multiple levels of government were reviewed to identify the extent to which the two modes have been planned in any integrated fashion. Finally, the semi-structured interviews filled gaps in understanding the planning process and suggested directions for improving intermodal planning.

Results

Bike Station Use and Density of Population and Employment

Figure 1 maps bike share trip counts for each city in the second quarter of 2014, with each city’s respective activity density displayed as jobs and housing units per acre. Both bike share systems do not yet serve either city’s extent of dense areas. In addition, Figure 1 shows that the bike share activity does not significantly decline towards the outer edges of either system, suggesting that neither system has spatially expanded as far as its density may support. The highest volume bike share stations are not necessarily located near the rail transit stations shown on the map, suggesting that either there is little natural relationship between the two or, perhaps, the relationship has yet to have been realized—which may be addressed through planning and implementation of targeted solutions.
Relationship of Proximity of Bike Share Volumes to Transit

Analysis of trips over the duration of the brief bike share systems’ lives reveals little apparent interaction with transit ridership at the system-level. Figure 2 shows the first 18 months of bike share system operation in Chicago. Divvy operates year-round, and use fluctuates strongly with the seasons. Colder climates have been shown to have a strong relationship with bicycling in previous studies (Heinen, Maat, and van Wee 2011; Mahmoud, El-Assi, and Habib 2015). Chicago’s bus and rail modes roughly parallel each other, with monthly volumes ranging between 17 million and 27 million, respectively. Overall transit mode use in 2013 and 2014 was relatively stable or slightly declining. However, bike share system use nearly doubled from October 2013 to the same time a year later, despite a lack of growth in the number of stations over this time.
Figure 2 suggests very little substitution effect at the system level, a finding consistent with a recent study of Divvy trips that showed a positive correlation of annual bike share trips from stations within 300 meters from a rail station, but the opposite relationship with day-use customers (Faghih-Imani and Eluru 2015b). This is an intuitive relationship—Divvy system users who chain intermodal trips with rail for regular trips would be expected to more likely choose an annual membership. The converse of this is that occasional or tourist uses of Divvy may be more likely to use the system for direct access to destinations. Since Divvy launched in June 2013, the first full year of operation was 2014, providing users with the opportunity to use the system as soon in the year as they desired. As Divvy continues to expand, growth in its use could be expected to level off, at which time additional empirical analysis of trip volumes with transit may be more appropriate.

Austin has a very different transit context, with a single commuter rail line serving nine stations and a bike share system composed of 50 stations tightly dispersed in a loose cross formation centered on downtown (as of 2015). Figure 3 shows the limited data available from Austin’s B-cycle system since its launch in December 2013. The relatively small size of Austin’s system is strained during large special events, such as the South by Southwest (SXSW) Festival held every March in Austin. The operator reports “On Friday, March 14, it set a U.S. system record of 2,774 checkouts for an average of 10.1 checkouts per bike/day, besting the previous record in September 2013 of 7.2 checkouts per bike/day set by the successful New York City Citi Bike program” (Austin B-cycle 2014). Austin transit and bike sharing systems also are likely affected by the seasonality of local colleges and universities, anchored by The University of Texas at Austin with more than 51,000 students enrolled.
FIGURE 3.
Austin transit and bike share ridership, 2013–2014

More than three-quarters of Austin’s bike share trips were taken with 24-hour passes, whereas a little more than half of Chicago’s bike share trips used daily passes. Many factors, such as membership policies, costs, and local economics, likely play a role, but Austin’s younger system age might play a role as well—people may be more likely to try the system in the first year with daily passes and consider membership at a later date. The SXSW Festival is a major factor in Austin, with 38.3% of survey respondents reporting that they used B-cycle at SXSW, 96.7% of whom used 24-hour B-cycle passes (Opinion Analysts Inc. 2014). Regardless, this factor should be considered in bike share system planning, with recent research supporting analysis for reallocation of stations during high tourism months (Faghih-Imani and Eluru 2015a).

Analysis of both cities’ bike share embarks shows that just under half are within 400 meters from a rail station, a maximum distance suggested by operators for spacing between bike share stations (Shaheen, Cohen, and Martin 2013). Chicago’s extensive rail station coverage, shown in Figure 1, covers about half of the Divvy stations across the city. As shown in Table 3, 47% of Austin’s bike share embarks are within 400 meters from a passenger station, but the city has only two rail stations near the B-cycle service area. The small size of the system, however, limits statistical evaluation of local conditions that may be fostering this relationship. Indeed, the currently small system does not serve areas far from the central business district.

### Table 3.
Mean Bike Share Embarks Near and Far from Passenger Rail Stations

<table>
<thead>
<tr>
<th></th>
<th>&lt;400 Meters from Passenger Rail Station (% of total embarks)</th>
<th>&gt;400 Meters from Passenger Rail Station (% of total embarks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austin, TX</td>
<td>957 (46.9%)</td>
<td>1,083 (53.0%)</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>360,165 (44.6 %)</td>
<td>447,256 (55.4%)</td>
</tr>
</tbody>
</table>

**Bike Share System Surveys**

Both systems also have surveyed users about their use of bike share, but differences between the questions asked limit comparison of the systems using this source. As shown in Table 2, 76% of Divvy members surveyed in January 2014 reported using bike share to travel to or from transit “sometimes” or “often” (City of Chicago 2014). Austin B-cycle asked a sample of members and non-member users two questions related to transit. A total of 48% reported that the B-cycle system makes them more likely to
use transit than if it were not available (Opinion Analysts Inc. 2014), and 9% said they replaced a bus or rail transit trip with B-cycle the last time they used the system. These results indicate that bike share users report a two-sided relationship with transit—it may help provide access to transit stops, and it also can replace some transit trips. Insights from the survey of each bike share system are only partially supported by the cities’ planning goals at present and may be helpful in guiding further advancements.

**Evaluating System Planning Goals**

The Austin region’s current draft transportation plan aims to improve active transportation with a strategy to add “more sidewalks and designated bicycle lanes” and to add or expand bike sharing programs. The plan uses soft language to target only 15% of available CAMPO discretionary federal funding under the Surface Transportation Program-Metropolitan Mobility (STP-MM) program to bicycle and pedestrian projects (Capital Area Metropolitan Planning Organization 2015, 220), whereas the previous regional plan set this value as the minimum. Since STP-MM was used for the initial development of Austin B-cycle, this policy change could counter its own stated strategies to improve healthy mobility with active transportation improvements. The local plan from the City of Austin maybe one of the first to explicitly incorporate specific bike sharing expansion goals in its planning, stating its desire to “Expand Austin’s bike share system from 40 stations to 100 stations by 2016 and to 300 stations by 2017.” To be most effective, plans should offer both a specific objective to achieve a goal and a likely funding mechanism to reach it.

Chicago’s municipal and regional plans had not been updated recently enough to consider bike share as part of the transportation plan explicitly, but the documents had highlighted the importance of the bicycle mode to connect and extend transit service. Though written nearly a decade before launching the city’s bike share system, Chicago’s bike plan goal to “Provide convenient connections between bicycling and transit” (Mayor’s Bicycle Advisory Council 2006, 20) is served by the current bike share system, as are additional improvements to the bicycle network such as adding protected bike lanes on existing roadways and adding safe and comfortable bicycle access to transit stations. The Chicago bike plan lays out five objectives to achieve this goal, with specific strategies and performance measures to achieve them. Possible funding sources are listed for each objective, strengthening likely implementation of this plan. Chicago’s Bike 2015 Plan was developed to be comprehensive, clear, and achievable, but the current Streets for Cycling 2020 plan (Chicago Department of Transportation 2013) is focused on improving the network without its predecessor’s broad perspective.

Each city’s strong goals and planning shortcomings reflect a desire to increase use of the bicycling mode—bike share systems and transit service are seen as positive complements to each city’s cycling goals, leading to implications for improving next-generation planning. Both cities leave visible gaps in their approaches to integrating bike share and transit planning reflected in the planning documents, but the actual bike share station planners have additional knowledge about the processes.
Semi-structured Interviews

Interview questions with each system planner spanned across how the public was involved in the process; how locations were actually decided, including addressing conflicts; and considerations of rail transit and collaborative planning. Planning of both systems included analysis of objective data on bike facilities, parks, entertainment, employment density, future development, and physical barriers to cycling. Each of them also included an online public participation geographic information system (PPGIS) to gather citizen ideas on where stations should be located. The Austin planner reported that every suggested location within the area covered by its grant (through the United States’ Surface Transportation Program-Metropolitan Mobility) was taken into account and that most of them were clustered in the same areas, similar to restrictions noted by the planner for Divvy. The planner that worked on the Chicago system reported combining in-person public engagement with the online platform by “ask[ing] people to access the online platform at the in-person meetings.” The PPGIS method for bike share planning was described as being different from other experiences:

There is a very concrete task that the public can help with, specifically, where is best to site bike share stations? With other planning or infrastructure projects, you need feedback on “issues,” and then the planners interpret it.

The public suggestions for bike share locations were analyzed by the planners in terms of roadway compatibility between stations and construction feasibility that considered issues such as public right-of-way, sidewalk accessibility requirements, and utilities. Though Austin’s planner did not respond directly to the question about planning with rail transit, Chicago’s planner reported considering proximity and frequency of transit as a factor in the initial suitability analysis and that their planning effort included “a bike share station at every fixed rail stop.” Both systems ended up placing large-capacity bike share locations near their busiest transit stations. Neither system planner reported any existing guidance that could help them develop the bike share plan in an integrated manner with rail transit.

Discussion

Implications for Bike Share System Planning

Bike share systems vary in their relationship to centralized transportation planning authorities. In most cases, however, cities and regional planning bodies work closely with bike share operators, and often subsidize capital and, less often, operating costs. This leads to some natural variation in how effective cities may be in fostering growth of bike share systems and their role in complementing transit. The evidence presented in this study suggests that bike share system planning for connectivity to transit should address system-level policies, a strong tie between strategic planning and measurable implementation and a nuanced, highly-local approach for station placement and network improvements.

The variance of planning policies in these two cities reflects both a rapid advancement in the role of bike sharing and suggests a lack of planning between modes, perhaps constrained by funding silos and bureaucracy. Indeed, the growth of urban bike
sharing systems is a global phenomenon, yet the system of laws and funding control in American cities is highly local (Rodriguez and Shoked 2014). Rodriguez and Shoked (2014) suggest that policy development through the bike share planning process tend to underplay the importance of specific funding mechanisms, and this oversight has led to several systems’ poor financial footing and subsequent restructuring. They indicate this could be mitigated through local separation of powers, where a strong mayor’s role in policymaking and funding allocation could be reconsidered to improve urban policymaking. Austin and Chicago share a rapid turnover in agency leadership at the city and county levels that tend to trickle over into the boards of metropolitan planning organizations and transit agencies, leading to a valuable staff role in the development, implementation, and monitoring of transportation plans.

Analysis of bike share use and built environment variables support the role of knowledgeable staff and robust public involvement in planning of bike share kiosk placement and the subsequent connections to transit service. In terms of bike share kiosk placement, planners need to consider many complex site-level needs including and beyond the variables in this study, including land ownership, neighborhood desires, and sight distance. This approach is a diversion from previous studies that looked primarily at system-level statistics (Fishman, Washington, and Haworth 2013). However, small-scale analysis is both an advantage and a limitation of this study.

**Toward a Framework for Integrated Bike Share and Transit Planning**

This study’s review of planning for bike sharing and transit in Austin and Chicago suggests that, to date, each city’s approach to the modes have been relatively fragmented. Only Austin’s most recent (2014) bike plan addresses bike sharing, and it does not strategically tie the importance of this mode to the region’s transit planning. Grounded in John Dewey’s pragmatism that influenced engineering sciences and the communicative action theory of Jürgen Habermas associated with social mobilization, this framework is positioned within the mainstream of theories for transportation planning (Friedmann 1987; R. Willson 2001). Figure 4 suggests an approach in which transit planning incorporates bike share and network planning by regional and local agencies in partnership with the bike share provider, recognizing that it can be public or private, within an umbrella agency, or on its own. Similar to current transportation planning concepts that rely heavily on public participation as well as expert-identified needs (Brooks 2002; Willson, Payne, and Smith 2003), the process starts with a simultaneous assessment of needs from both perspectives. The cross-disciplinary team then formulates goals to address the transit access issues found in the first step. Specific strategies then need to be developed, again leaning heavily on a partnership with the local bike sharing provider to work proactively towards the shared goals. Performance measurement and public participation extend the process throughout implementation of the bike sharing and transit development process, providing feedback to the original assessment of needs; an annual revisiting schedule is suggested.
The general framework presented in Figure 4 can help define partners and processes, but specific language sometimes is needed to help guide how different agencies can best work together. Table 4 suggests some examples of goals, strategies, and performance measures that could be tailored to local needs, demonstrating at least one potential method to work towards a plan that addresses the gap between bike share development and long-and-short-range transit planning.

### TABLE 4. Example Language for Integrated Bike Share and Transit Planning

<table>
<thead>
<tr>
<th>Plan Type</th>
<th>Bicycle Network</th>
<th>Bike Share System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Range Transportation Plan (LRTP)</td>
<td>[X %] of regionally-significant roads include a bicycle accommodation1 by [date].</td>
<td>Bike sharing is accessible at [X number] of regional transit stations by [date].</td>
</tr>
<tr>
<td>Goal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strategy</td>
<td>Include bicycle accommodations1 on new and reconstructed, regionally-significant roads within [X distance] of transit stations by [date].</td>
<td>Support implementation of bike sharing systems near transit stops through available surface transportation funding.</td>
</tr>
<tr>
<td>Performance Measure (data source)</td>
<td>% of new and reconstructed road centerline miles with bicycle accommodations within [X distance] of transit stations (Transportation Improvement Program).</td>
<td>% of available surface transportation funding (Transportation Improvement Program); [X number] of regional transit stations with bike share access (regional information system).</td>
</tr>
<tr>
<td>Transit service or city transportation plan</td>
<td>[X%] of collector streets include a bicycle accommodation1 by [date].</td>
<td>Bike sharing is accessible at [X number] of local transit stops by [date].</td>
</tr>
<tr>
<td>Goal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strategy</td>
<td>Street resurfacing and construction includes bicycle accommodations1 on collector streets within [X distance] of transit stations by [date].</td>
<td>Support implementation of bike sharing systems near transit stops through available local funding.</td>
</tr>
<tr>
<td>Performance Measure (data source)</td>
<td>% of new and resurfaced collector centerline miles with bicycle accommodations within [X distance] of transit stations (Capital Improvement Program).</td>
<td>[X number] of local transit stops with bike share access (local information system).</td>
</tr>
</tbody>
</table>

1 Reference locally-developed or adopted standards for bicycle accommodation, such as American Association of State Highway and Transportation Officials 2012; Institute of Transportation Engineers 2010; National Association of City Transportation Officials 2014.
Limitations of Data and Multi-City Comparisons

Since both cities’ systems are relatively new, this study incorporates a limited dataset. Public response to system changes can be expected to fluctuate, though not necessarily in predictable ways. Changes in payment or other operational characteristics, outreach to low-income communities, and other service improvements may change the relationships presented in this study.

Though Chicago and Austin are geographically located near the center of the U.S., the sheer size of their populations and transit systems limit their direct comparability in terms of transportation system performance. Rather than focusing on comparing these cities, this study provides these examples for future longitudinal studies, as well as potential benchmarks for comparing other bike share systems. Replication of methods in this study in other locations and over time could lead to further support or variances from our conclusions.

Conclusions

Among the primary surface transportation modes of walking, biking, automobile, and bus and rail transit, the latter is distinguished by its access only at designated stops and stations. This study analyzed the content of transportation plans in Austin and Chicago for goals related to bike share and transit modes and analyzed bike share use volumes in the two cities in 2014. Analysis of planning documents indicated opportunity to extend planning processes across the bicycling and transit modes at both the municipal and regional planning scales. Semi-structured interviews suggested a valuable role in public engagement, supported using an online location suggestion map, and pointed out a lack of guidance in integrated planning.

The rapid changeover in agency leadership and their roles in implementing bike share systems are implicated in system planning and implementation challenges, which planning staff may be able to partially mitigate through engaging with political leadership and by fostering effective public participation. Though many bike share systems are under development throughout the world, many opportunities exist to improve their planning and integration with transportation systems at the regional and neighborhood levels. This study introduced the need to address the issues from a broad perspective while developing partnerships for effective planning between bike share companies, transportation agencies, and the public.

This study used a mixed-methods dataset, combining empirical data from each bike share operator with review of planning documents and semi-structured interviews with system planners. The planning of bike sharing in conjunction with passenger rail stations may leverage each of their advantages, but the role of bus transit and bike sharing should be analyzed in future studies. Particularly as bus rapid transit (BRT) planning has grown in recent years, there are many opportunities to research how planning can be improved for these modes.
Acknowledgments

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Planning for Bike Share Connectivity to Rail Transit


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Factors Influencing Demand for Buses Powered by Alternative Energy Sources

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Abstract

Transit buses consume high amounts of fossil fuels, with the consequent release of greenhouse gases into the atmosphere. In recent decades, much effort has been concentrated on the development of cleaner fuels to mitigate this externality. However, market shares for cleaner-fueled buses are still modest, which is why it is relevant to evaluate the aspects influencing their acceptance. This article presents an econometric model to evaluate factors influencing demand for transit buses in Colombia powered by cleaner fuels. For this purpose, a stated preference survey was applied to public transportation entrepreneurs. Results suggest that the target population considers acquisition cost and operating cost as the most important variables when choosing fuel technology for their fleets. The power offered by the bus engine was relevant for some alternative fuel alternatives, but not the full range.

Keywords: Transit equipment, alternative-fueled buses, Colombian public transportation

Introduction

Diesel fuel and gasoline traditionally have been used as the main energy sources for buses. In particular, diesel fuel is massively used for transit buses in Colombia (UPME 2012), as well as worldwide. The burning of fossil fuels involves gas emissions resulting from the combustion process such as CO₂, CO, NOₓ and SOₓ. These gases are associated with global warming and the greenhouse effect (IPCC 2007). Environmental concern about air quality has motivated the development of cleaner energy technologies for public transportation systems.

Although development of vehicles powered by alternative energy sources is a dynamic research topic, their level of acceptance and market penetration is still too small when compared with traditional technologies. Consequently, proposing policies or strategies to increase demand for cleaner buses requires a better understanding of consumer behavior (i.e., transportation companies) and the variables influencing their buying decisions. This paper aims to identify the factors underlying the purchase decision for transit vehicles powered by clean energy sources. A demand model for buses powered
by alternative fuel technologies was calibrated using data gathered from Colombian transit entrepreneurs and following the discrete choice modeling approach.

Discrete choice models are widely used in demand studies and consumer behavior analysis because they allow the forecasting of market shares for real or hypothetical alternatives. Observed decisions and information about attributes describing technological alternatives (i.e., commonly collected through revealed or stated preference surveys) are used to calibrate the models and, consequently, to analyze the importance of attributes in the choice decision process.

This paper is structured as follows: in the next two sections previous studies related to the research topic are reviewed and the context of public transportation in Colombia is explained. Then, the methodological approach used is presented. After that, a complete description of the data and the main results are shown. Finally, the most relevant conclusions and guidelines for future research are listed.

Background
The transportation sector is responsible for 13.1% of global greenhouse gas (GHG) emissions and nearly 95% of the world’s energy used for moving people and goods proceeds from petroleum-based fuels (mostly gasoline and diesel) (EPA 2013). This fact demonstrates that road transportation, including public services, is one of the largest emitters of GHGs. Governments and international organizations around the world have proposed using alternative energy sources, seeking alternatives to mitigate this externality. They have proposed the use of electric power, hydrogen fuel cells, and hybrid technologies that could be a combination of conventional and non-conventional energy sources (Caultfield, Farrell, and McMahon 2010; Litman and Delucci 2006). Compressed natural gas (CNG) is another fuel suggested as an alternative to conventional fuels. Some authors claim that CNG produces a significant reduction in GHG emissions compared to conventional fossil fuels such as diesel and gasoline (Hekkert et al. 2005; Yeh 2007).

Several models and approaches have been used to study buying preferences, most of them focused on private cars. The most popular econometric approaches to study demand for alternative-fueled cars are linear regression, multinomial logit (MNL), ordered logit, ordered probit, and Poisson regression (Potoglou and Kanaroglou 2008). In Colombia, Soto, Cantillo, and Arellana (2014) estimated hybrid choice models to evaluate demand for alternatively-fueled cars incorporating explicitly-observed and latent factors that could affect the next vehicle purchase.

Although related literature on private alternative-fuel vehicle choice can be used as a reference to approaching alternative-fuel bus acquisition, the decision choice processes that lead to the purchase of a personal car vs. a bus are different. A car for an individual represents a personal use good, whereas a bus for a transit company represents working equipment that has to be profitable.

There are few demand studies on alternative-fuel buses around the world, with the exception of CNG buses. The reason is that the market success of other alternative
technologies is marginal, and urban buses running on non-CNG alternative fuels are not available in many countries worldwide.

The first research studies related to alternative-fuel commercial vehicles are those conducted by manufacturers and transportation companies in the early 1990s, with studies mainly focused on trucks. Their main objective was to find the importance of some attributes in the choice of fuel technology for that kind of vehicle. Golob et al. (1997) estimated logit models using stated preference (SP) data collected in 1995: a total of 2,000 truck fleet operators were asked to choose among vehicles running on electricity, CNG, methanol, and gasoline based on operational characteristics and their acquisition costs. Parker, Fletchall, and Pettijohn (1997) presented a descriptive analysis of the perceptions of truck operators about the use of alternative fuels. They concluded that the most important decision variables when choosing truck fuel technology were capital costs, availability of charging stations, and operating costs.

Other authors have focused on determining the main barriers and factors that encourage market acceptance of alternative fuels for buses and trucks. SP surveys were applied in Hong Kong to evaluate the acceptance of public light buses (PLB) among operators for using alternative fuels (Loo, Wong, and Hau 2006). The SP experiment presented two alternatives: diesel and liquefied petroleum gas (LPG). Collected data were used to calibrate multinomial logit models (MNL). Results showed that PLB operators were not inclined to switch from conventional diesel buses to LPG. Vehicle price was not a significant attribute for PLB operators in Hong Kong, possibly because there is a subsidy from the government for the purchase of public transportation buses.

Mattson (2012) described motivating factors and deterrents for adoption of alternative fuels for buses, using the experience of different transit agencies. He examined factors such as costs, maintenance, reliability, and overall satisfaction between those agencies that have used alternative fuel vehicles and those that have not, as well as differences between rural and small urban areas. The author concluded that the size of a transit agency is important at the time of adopting new fuel technologies. Mattson (2012) also found that larger agencies were more suitable to using alternatively-fueled vehicles. In addition, agencies considered cost savings as one of the most important factors when deciding the type of vehicle to buy. They also were worried about fuel supply and costs associated with infrastructure.

Wang and Gonzalez (2013) evaluated the feasibility of electric buses for small and medium-size cities based on qualitative and quantitative data available from diverse sources such as literature reviews and manufacturers’ information. An electric alternative was compared with diesel, diesel-hybrid, and CNG. Results suggested that the operation of electric buses is ideal for small and medium-size communities because of their zero emissions and low noise. However, electric buses indirectly affect the environment due to the amount of energy consumption and present some acquisition barriers because their purchase cost is higher than that of CNG and hybrid alternatives.

Finally, some authors have focused their research on the attitudes of bus and truck operators toward alternative fuels and their environmental impact. Saxe, Folkesson, and Alyfors (2007) found that safety concerns related to new hydrogen fuel cell buses is not
an issue among drivers and that operators were pleased with the reliability of the buses. Schweitzer, Brodrick, and Spivey (2007) evaluated attitudes of truck drivers towards technologies for idling reduction as a way to decrease emissions and fuel consumption and concluded that costs of technology and fuel are the key factors affecting the adoption of idle-reduction technologies. Meanwhile, Gota, Gosu, and Anthapur (2014) studied three leading bus companies in India to assess their attitudes and strategies on fuel economy and emission reduction, concluding that the assessed companies do not have a commitment to ensuring improvement in fuel efficiency nor have they implemented strategies to reduce emissions.

The Colombian Public Transportation Context

Public transportation services in Colombia are regulated by the national government through the Ministry of Transportation, which issues general guidelines for transit operations. However, city governments are responsible for issuing local regulations, assigning bus routes, and defining schedules, frequencies, and fleet sizes of bus companies (Ardila 2005). City governments also oversee the implementation of the general guidelines issued by the national government.

Transit services are provided by private bus companies. It is quite common that private bus companies do not own enough vehicles to meet demand. Therefore, most transit company business is to affiliate buses from owners, who must pay a fee for the right to operate the bus on the companies’ assigned routes. The owners of the buses are responsible for their own equipment and bear the whole cost of acquisition and maintenance during the useful life of the buses. Almost 96% of public transportation companies own less than 10% of fleets (Ardila 2005).

Unlike other countries, urban public transportation in Colombia is not subsidized by the national government. To subsidize transportation with national funds is against the law. However, local authorities can subsidize public transportation with their own resources but, in practice, budget constraints do not allow it. Bus transit services are run by private companies that must finance their operations via the collection of fares.

In the last 15 years, Colombia has been working on its policies to update its public transportation systems. Six cities in Colombia (Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, and Pereira) have bus rapid transit (BRT) systems, and a seventh city (Cartagena) is now implementing this service. However, the BRT systems have had many difficulties and challenges from their start (Kash and Hidalgo 2014). One of the main causes of those difficulties is related to the competition from informal services as well as the traditional and outdated transit systems that still operate in those cities.

City governments are now developing integrated transportation systems and promoting intermodality for passengers, including other services such as tram, metro, and cable cars. Currently, Medellin is the only Colombian city with integrated fares for multimodal services (i.e., cable cars, metro services and Metroplus, the BRT system in that city). Recently, Bogotá and Cali have begun implementing integrated fares for the different bus services in the whole city.
Methodological Approach

Discrete choice models are based on random utility theory, which states that consumers seek to maximize their utility (McFadden 2001). Therefore, it is considered that individuals or companies make rational choices. Discrete choice modeling could be used to model a bus transit owner’s decision to adopt alternative fuel technologies. It is assumed that bus transit companies make the decision to adopt an alternative fuel technology based on its impact on their operations and, in particular, on their expected profit. This assumption is supported by the fact that in Colombia there are no clear policies encouraging the adoption of clean technologies for buses. Although Law 223/95 provides financial support for environmental conversion projects and Law 1715-2014 regulates the integration of non-conventional renewable energy, it is still expensive to implement clean technologies projects in public transportation, and policies are not focused on prioritizing their use. Indeed, companies have to totally assume the cost of transforming their current equipment or buying new alternatively-fueled vehicles.

In the long term, using cleaner alternatively-fueled vehicles impact costs associated with fuel consumption and vehicle maintenance. They also impact the social cost of operating transit vehicles by reducing negative environmental externalities. However, the social impact is frequently not considered by private companies.

In the proposed approach, each individual (bus owner or bus company) in the choice process faces a set of eligible alternatives (type of propulsion technology), which are described by a number of measurable and comparable attributes (e.g., acquisition costs, operation costs, range, engine power, and maintenance costs). Alternative \( A_j \) has an associated utility \( U_{jq} \) for individual \( q \in Q \), described by the following:

\[
U_{jq} = V_{jq} + \varepsilon_{jq}
\]  

(1)

The term \( V_{jq} \) is a systematic component of the utility that can be measured. This component is based on a number of measurable attributes, \( X_{jq} \), specific to each alternative. Frequently, when the systematic utility is expressed as linear in the parameters, then \( V_{jq} = \theta X_{jq} \), where \( \theta \) is a set of parameters to be estimated.

The observed choice of the individual \( q \) is the one that maximizes utility (profit). On the other hand, \( \varepsilon_{jq} \) is a random component that reflects the uncertainty about attributes considered by consumers that cannot be observed by the modeler (McFadden 2001). This uncertainty can explain two situations that can be considered irrational, such as 1) two individuals with identical attributes and equal alternatives making a different choice, or 2) one individual who does not select the best apparent alternative (Ortuzar and Willumsen 2011).

Depending on the assumption about the random term in Eq. (1), different choice models will result. In particular, when an independent and identical Gumbel distribution is assumed for random terms, the classical multinomial logit model (MNL) is obtained (Ortuzar and Willumsen 2011). For this model, the probability that the individual \( q \) chooses the alternative \( A_i \) is given by Eq. (2), where \( \lambda = 1 \) is normalized by the inability to be estimated independently from the set of parameters \( \theta \).

\[
P_{iq} = \frac{\exp\left(\lambda V_{iq}\right)}{\sum_{A_i \in A_q} \exp\left(\lambda V_{iq}\right)}
\]  

(2)
Factors Influencing Demand for Buses Powered by Alternative Energy Sources

Data
For this study, stated preference data were collected from bus owners and urban bus company CEOs. Trained interviewers scheduled appointments with the respondents to conduct the survey face-to-face using an online form to store the data. (Readers interested in the survey may contact the authors.)

Surveys were applied in the six largest Colombian cities. Due to the difficulty in obtaining responses from bus owners in Colombia and an expected high non-response rate, 12 scenarios were presented to each respondent to get a significant number of observations for modeling and to evaluate respondent perceptions on diverse situations. In each hypothetical choice scenario, respondents had to choose the best alternative among three or four alternatives presented. A fractional factorial design of 48 rows was obtained using the software NGENE* (Choicemetrics 2012). Four blocks were generated to get the 12 choice situations faced by each respondent.

The survey was structured in two sections. The first collected general characteristics and fleet information about bus owners and urban transportation companies; in the second, a stated preference experiment was presented.

The attributes considered to describe each alternative in the stated choice experiment were cost of purchasing a new vehicle chassis (cost), range reached with a full fuel load (range), the cost of a full fuel load (refueling cost), engine power offered as a percentage of the diesel bus engine power (power ratio), and the cost associated with fuel consumption for running 1 kilometer (cost per kilometer). Attributes are shown in Table 1 with the units and levels considered.

### TABLE 1. Attributes and Levels Involved in Stated Preference Design

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Midibus (~30 passengers)</th>
<th>Standard Bus (~40 passengers)</th>
<th>Large (~80 passengers)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel Type</strong></td>
<td>Diesel</td>
<td>Hybrid</td>
<td>CNG</td>
</tr>
<tr>
<td><strong>Cost (USD)</strong></td>
<td>$58,997</td>
<td>$88,496</td>
<td>$78,663</td>
</tr>
<tr>
<td><strong>Range (km)</strong></td>
<td>580</td>
<td>760</td>
<td>420</td>
</tr>
<tr>
<td><strong>Refueling cost (USD)</strong></td>
<td>$187</td>
<td>$187</td>
<td>$93</td>
</tr>
<tr>
<td><strong>AFB/diesel power ratio (%)</strong></td>
<td>100</td>
<td>100</td>
<td>80</td>
</tr>
<tr>
<td><strong>Fuel Consumption (USD/km)</strong></td>
<td>$0.32</td>
<td>$0.25</td>
<td>$0.22</td>
</tr>
</tbody>
</table>

* Cost includes only vehicle chassis, not body.
AFB = alternative-fueled bus
Source: Manufacturers and UPME 2012
Choice alternatives and attribute levels, which refer to values of the variables of each alternative and choice scenario, were customized for different bus classes. Customization was performed to guarantee that every respondent would face attribute levels according to the class of bus they owned. Three different bus categories were considered based on the bus fleets in Colombian cities—midibus with an average capacity of 30 passengers, standard bus with an average capacity of 40 passengers, and large bus with an average of 80 passengers. For the first two categories, four types of alternative-fuel buses were presented: diesel, hybrid, CNG, and electric bus. For the third category (large), the electric bus alternative was excluded because there was no information about the use of this fuel technology in this kind of bus. The attribute level values presented in the survey were collected from literature related to bus technologies, manufacturers, and fuel markets.

A total of 114 SP surveys were completed, which resulted in 1,368 choices. The diesel alternative was chosen in 45.1% of the choice situations, followed by the hybrid alternative, which was chosen in 21.5% of the choice situations (Table 2). These results suggest the presence of the “inertia phenomenon” (Cantillo, Ortúzar, and Williams 2007), the tendency to choose the known and mature technology while avoiding the new one. It could be inferred that respondents may consider the hybrid-electric bus as a second-best option because of the similarities with the diesel-fueled bus.

The fact that the CNG alternative had the lowest number of stated choices in Table 2 could be explained by the fact that in the late 1980s in Colombia, there were many conversions from diesel and gasoline technology to CNG in urban buses. During that time, there were technological problems causing unexpected bus performance and economic losses for bus owners, generating aversion to the use of the CNG technology in buses, and respondents mentioned that in several occasions in the survey.

From a total of 114 respondents, 71 were owners or managers of buses linked to urban transit, representing more than 62% of respondents. The other 43 offered other transit services, as shown in Table 3. The midibus was the most common type of vehicle. The 114 surveyed entrepreneurs owned a total of 1,671 buses, most of which were powered by diesel fuel, evidencing its market strength and the popularity of this technology. Gasoline buses are still in operation, but they run in the oldest models. The average age of the fleet was close to seven years, an age at which vehicles require constant maintenance. For a summary of the main characteristics of the respondents that participated in the survey, see Table 3.
TABLE 3.
Respondent Characteristics

<table>
<thead>
<tr>
<th>Operating Mode</th>
<th>Total Respondents</th>
<th>114</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban transit</td>
<td></td>
<td>71</td>
</tr>
<tr>
<td>Shuttle service</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>Regional transit</td>
<td></td>
<td>23</td>
</tr>
<tr>
<td>Mixed services</td>
<td></td>
<td>13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Buses per Fuel Technology</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel</td>
<td>1,621 (97.9%)</td>
<td></td>
</tr>
<tr>
<td>CNG</td>
<td>40 (1.2%)</td>
<td></td>
</tr>
<tr>
<td>Gasoline</td>
<td>10 (0.9%)</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,671</td>
<td></td>
</tr>
</tbody>
</table>

Average age of buses (yrs) 7.3

The research had two main limitations: 1) limitations associated with the use of stated preference data (Ortúzar and Willumsen 2011), and 2) lack of data for additional variables that could have an important role in explaining the reported preferences of respondents (e.g., maintenance-related and reliability variables).

Results
Different models were explored. A nested logit model was structured grouping alternative fuel buses in one nest and leaving the conventional diesel alternative in another. A mixed logit model also was structured. Also, due to multiple responses per respondent, a panel effect term was considered in the modeling. None of these approaches showed an improvement when compared to the traditional MNL, which was the most robust and simple model (see Table 4).

TABLE 4.
Results of MNL Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>t-test</th>
<th>Robust t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel ASC</td>
<td>Fixed</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CNG ASC</td>
<td>-3.63</td>
<td>-2.77</td>
<td>-2.77</td>
</tr>
<tr>
<td>Electric ASC</td>
<td>-1.76</td>
<td>-1.52</td>
<td>-1.52</td>
</tr>
<tr>
<td>Hybrid ASC</td>
<td>-0.210</td>
<td>-1.25</td>
<td>-1.25</td>
</tr>
<tr>
<td>Cost (10^3 US$)</td>
<td>-0.02451</td>
<td>-6.60</td>
<td>-6.62</td>
</tr>
<tr>
<td>Fuel consumption (US$/km)</td>
<td>-3.287</td>
<td>-2.45</td>
<td>-2.58</td>
</tr>
<tr>
<td>Power ratio electric</td>
<td>0.0187</td>
<td>1.30</td>
<td>1.29</td>
</tr>
<tr>
<td>Power ratio CNG</td>
<td>0.0322</td>
<td>2.11</td>
<td>2.11</td>
</tr>
<tr>
<td>Range - regional transit</td>
<td>0.000279</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>Observations</td>
<td>1368</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Final log-likelihood</td>
<td>-1728.647</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Final log-likelihood for EL model</td>
<td>-1754.997</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LR test</td>
<td>52.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\chi^2) (8, 95%)</td>
<td>15.51</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Results are in line with microeconomic *a priori* expectations. Parameters related to monetary cost variables (*cost* and *cost per kilometer*) show a negative sign, evidencing the expected marginal effect. Moreover, it is expected that the sign of the *power ratio* parameter be positive, as it increases the expected utility.

Attribute range was included in a preliminary version of the model but its parameter was not significant (*p*-value = 0.35), suggesting that it was not relevant to respondents. The attribute was included in the model interacting with a dummy variable that was 1 if the bus operated in regional transit services, considering that urban buses in Colombia travel relatively short distances per cycle. For instance, in Bogotá (the capital and most sprawled city of the country), an average bus travels less than 180 km per day in about 5 cycles (Ardila 2005). Due to the fact that the shortest value for the range attribute in each choice situation and every alternative was enough to accomplish a regular urban route in a typical cycle with no need of refueling on the way, this is possibly not an issue for the respondents. However, the parameter estimated for the attribute *range* was not significant at 0.05 level.

The level of significance of the parameters in the model suggests that respondents are quite sensitive to cost variables. One interesting result is related to the *power ratio* parameter, which is expected to be important for bus owners in Colombia at the moment of buying a new vehicle because of the diverse topography in several Colombian cities that urban public buses must face daily.

There is a solid disincentive for bus owners to shift to CNG buses. The CNG alternative specific constant (ASC) is significant and has a negative sign, confirming the aversion to the CNG alternative discussed previously. On the other hand, ASC for electric and hybrid alternatives was not significant at the 0.05 level. Those results suggest that, *ceteris paribus*, there is not a clear preference for these kinds of fuel technologies when compared with the diesel alternative.

The marginal substitution rate between *fuel consumption* and *capital cost* states that entrepreneurs are willing to pay about $1,401 US extra for a bus that allows saving 1¢ in terms of fuel consumption per kilometer. Considering, again, an average covered distance of 180 kilometers per day per vehicle, the additional capital cost could be recovered in about two and a half years of operation. On the other hand, they are willing to pay about $700 US extra for increasing the engine power of the bus by 1% in relation to the diesel engine power.

It is important to take into account that the former relationship between fuel consumption and capital cost will depend on the average revenue-km of each bus agency. Agencies that use buses more intensively, with higher vehicle-km traveled, are expected to be more sensitive to fuel consumption. Other agencies maybe could be more sensitive to capital costs.

Utilities and market shares were simulated considering different scenarios for the cost of a typical diesel bus and keeping constant the remaining attributes with the average values shown in Table 5.
Figure 1 shows that the price of a new diesel bus has to be more than $110,000 US to let the other alternatives take a significant market share.

Figures 2, 3, and 4 show the simulated market shares considering the different ratios of an alternatively-fueled bus cost to a diesel bus cost, using the parameters shown in Tables 6, 7, and 8. From Figure 2, it can be concluded that the cost of a CNG bus must be less than 70% of the cost of a diesel bus to have the highest market share among the reviewed technologies. Even if the cost of diesel and CNG are the same, the latter would have the lowest market share.

**TABLE 5.**

<table>
<thead>
<tr>
<th>Parameters Used to Simulate Market Share Varying Diesel Bus Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (10^3 US$)</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>$105</td>
</tr>
<tr>
<td>Fuel consumption (US$/km)</td>
</tr>
<tr>
<td>Power ratio</td>
</tr>
</tbody>
</table>

**FIGURE 1.**

Variation of demand to cost of diesel bus

![Figure 1](image)

**FIGURE 2.**

Variation of demand to cost of CNG bus

![Figure 2](image)
Factors Influencing Demand for Buses Powered by Alternative Energy Sources

**FIGURE 3.**
Variation of demand to cost of electric bus

**FIGURE 4.**
Variation of demand to cost of hybrid bus

**TABLE 6.**
Parameters Used to Simulate Market Share Varying CNG Bus Cost

<table>
<thead>
<tr>
<th></th>
<th>Diesel</th>
<th>Gas</th>
<th>Electric</th>
<th>Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (10^3 US$)</td>
<td>80</td>
<td>-</td>
<td>133</td>
<td>114</td>
</tr>
<tr>
<td>Fuel consumption (US$/km)</td>
<td>0.382</td>
<td>0.279</td>
<td>0.138</td>
<td>0.299</td>
</tr>
<tr>
<td>Power ratio</td>
<td>100</td>
<td>85</td>
<td>75</td>
<td>104</td>
</tr>
</tbody>
</table>

**TABLE 7.**
Parameters Used to Simulate Market Share Varying Electric Bus Cost

<table>
<thead>
<tr>
<th></th>
<th>Diesel</th>
<th>Gas</th>
<th>Electric</th>
<th>Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (10^3 US$)</td>
<td>80</td>
<td>105</td>
<td>-</td>
<td>114</td>
</tr>
<tr>
<td>Fuel consumption (US$/km)</td>
<td>0.382</td>
<td>0.279</td>
<td>0.138</td>
<td>0.299</td>
</tr>
<tr>
<td>Power ratio</td>
<td>100</td>
<td>85</td>
<td>75</td>
<td>104</td>
</tr>
</tbody>
</table>
In the case of the electric bus (Figure 3), it was found that if the cost of this technology is less than 120% of the cost of the diesel bus, it would be the alternative with the highest market share. Figure 4 infers that the highest choice probability for hybrid buses could be achieved if the hybrid bus cost is competitive when compared with the cost of the diesel alternative. For this purpose, the price of a hybrid vehicle could be similar or less than the cost of the diesel alternative.

Direct and cross elasticities were evaluated for every attribute in the model; results are shown in Table 9. The attribute whose variation causes the greatest impact on the choice probability for every alternative is the acquisition cost. In particular, an increase of 1% in the cost of a hybrid bus will cause a decrease of 2.17% in its market share. On the other hand, if the cost of a diesel bus rises by 1%, it will lead to a decrease of 1.10% in its market share. Even though direct elasticities with respect to cost are greater than 1 and could be viewed as very large, it should be noted that market shares for buses powered by alternative fuel technologies are currently very modest. These kinds of technologies are, right now, in the very elastic part of the demand curve. In contrast, the direct elasticity of demand respect to cost for diesel buses, which is the most mature technology, is shorter than the direct elasticity of any other technology.

The demand for each alternative is less impacted by the variations in the cost per kilometer. Policies should be meant to encourage the choice for alternative fuel buses and must be oriented primarily on affecting the cost and then the cost per kilometer. Bus manufacturers could improve alternative fuel bus technology to offer higher power ratios and higher efficiencies in terms of the energy source consumption.

From the cross elasticities, it can be also inferred that the variations in the diesel bus attributes cause the highest impact on alternative fuel bus demand. An increase in the

---

**TABLE 8.**
Parameters Used to Simulate Market Share Varying Hybrid Bus Cost

<table>
<thead>
<tr>
<th></th>
<th>Diesel</th>
<th>Gas</th>
<th>Electric</th>
<th>Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (10^3 US$)</td>
<td>80</td>
<td>105</td>
<td>133</td>
<td>-</td>
</tr>
<tr>
<td>Fuel consumption (US$/km)</td>
<td>0.382</td>
<td>0.279</td>
<td>0.138</td>
<td>0.299</td>
</tr>
<tr>
<td>Power ratio</td>
<td>100</td>
<td>85</td>
<td>75</td>
<td>104</td>
</tr>
</tbody>
</table>

---

**TABLE 9.**
Direct and Cross Elasticities with Respect to Different Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Diesel</th>
<th>CNG</th>
<th>Electric</th>
<th>Hybrid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diesel</td>
<td>-1.097</td>
<td>0.879</td>
<td>0.879</td>
<td>0.879</td>
</tr>
<tr>
<td>CNG</td>
<td>0.384</td>
<td>-2.190</td>
<td>0.384</td>
<td>0.384</td>
</tr>
<tr>
<td>Electric</td>
<td>0.576</td>
<td>0.576</td>
<td>-2.695</td>
<td>0.576</td>
</tr>
<tr>
<td>Hybrid</td>
<td>0.625</td>
<td>0.625</td>
<td>0.625</td>
<td>-2.170</td>
</tr>
<tr>
<td>Cost/km</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diesel</td>
<td>-0.694</td>
<td>0.563</td>
<td>0.563</td>
<td>0.563</td>
</tr>
<tr>
<td>CNG</td>
<td>0.137</td>
<td>-0.781</td>
<td>0.137</td>
<td>0.137</td>
</tr>
<tr>
<td>Electric</td>
<td>0.080</td>
<td>0.080</td>
<td>-0.372</td>
<td>0.080</td>
</tr>
<tr>
<td>Hybrid</td>
<td>0.222</td>
<td>0.222</td>
<td>0.222</td>
<td>-0.761</td>
</tr>
<tr>
<td>Power ratio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNG</td>
<td>-0.418</td>
<td>2.318</td>
<td>-0.418</td>
<td>-0.418</td>
</tr>
<tr>
<td>Electric</td>
<td>-0.249</td>
<td>-0.249</td>
<td>1.141</td>
<td>-0.249</td>
</tr>
</tbody>
</table>

---

*Factors Influencing Demand for Buses Powered by Alternative Energy Sources*

Factors Influencing Demand for Buses Powered by Alternative Energy Sources

diesel cost of 1% will lead to an increase of 0.88% in the demand for the alternatively-fueled buses. On the other hand, an increase in the diesel cost per kilometer will lead to an increase of 0.56% in the demand for the alternatively-fueled buses. The former results suggest that if proper incentives and policies are offered by policymakers and manufacturers, these alternatives could be substitutes for the diesel bus.

To encourage the shift from conventional fuel bus technologies towards cleaner ones, Colombian policymakers should formulate appropriate policies and stimuli. As variables related to cost were the most important, reducing or subsidizing the cost of alternative fuels (CNG, electricity), increasing taxes to conventional diesel fuel, and subsidizing purchasing costs or reducing taxes of alternative-fueled buses could be policy options to consider.

Conclusions
The model for estimating demand for alternatively-fueled buses in Colombia suggested that the most relevant attributes considered by private public transportation companies at the time of buying a new vehicle are those related to money. The most significant are purchase price and the cost per kilometer. According to results, range was not considered as an important attribute of the buses.

The results indicate that, ceteris paribus, diesel bus was the most attractive alternative. On the other hand, CNG technology was the least preferred by respondents, and it consistently got the lowest choice probability in the scenarios evaluated. CNG buses must be much cheaper than the diesel alternative to get an important market share. The second best competitor was hybrid bus.

To encourage the shift to cleaner technologies, policies aimed at reducing purchasing and operating costs for bus companies should be established. This could be achieved through subsidies or tax benefits.

In addition, to incentivize choosing alternatively-fueled buses, bus manufacturers and sellers could bring new fuel technologies closer to bus owners through information campaigns, advertisements, forums, demonstrations, and field or test drives. These strategies can counteract the effects of the bad experiences that bus owners and drivers previously had with the conversion to CNG.

Future research could focus on the effect of perceptions on the choice for alternatively-fueled buses. Safety and security perceptions, environmental concerns, and attitudes toward government policies related to clean technologies in buses, among others, could be considered. This could be done by using hybrid choice modeling including latent variables. Also, the possibility of combining different data sources such as stated and revealed preferences surveys to enrich the data could be considered.

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Influence of Socio-Demography and Operating Streetscape on Last-Mile Mode Choice

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TUM CREATE and Nanyang Technological University

P. P. Koh and Y. D. Wong
Nanyang Technological University

Abstract

This study investigated how personal and operational factors (travel distance and streetscape) influence traveler mode choice decisions for the last-mile home-bound trip stage from rail transit stations. Personal factors include the socio-demography of travelers, and attributes of the streetscape include the built environment (degree of areal development), prevalence of cycling, availability of short-range transport modes, and walking/cycling infrastructure. Interviewers randomly intercepted pedestrians to administer a mode choice survey at five rail transit station exits and engaged all available cyclists at bicycle parking areas in the vicinity of stations in Singapore. A multimodal logit regression model revealed a significant relationship between the last-mile home-bound trip maker’s mode choice with factors of age, gender, travel distance between transit station and destination, number of cyclists along adjacent links surrounding transit stations, number of feeder bus services to destination, availability of private vehicle, and household income. The calibrated model was applied to compute the probability of walking, cycling, and taking a feeder bus for the last-mile home-bound trip maker from a transit station. This study provides useful information for improving the efficiency and connectivity of first/last-mile mobility in a multimodal transport network.

Key words: Last-mile home-bound trip; operating streetscape; mode choice; transit stations; multimodal logit regression model.

Introduction

With burgeoning population growth and constraints in new road space in metropolises, rail transit has become a major transport mode in everyday mobility. Promoting greater rail transit usage results in commensurate reductions in personal vehicle trips and lower traffic congestion and emissions. In this regard, much research has been devoted to the
methodological development and practical applications of efficient rail transit systems from the planning and operational perspectives for several decades. Rail transit stations usually are located amidst residential precincts or office clusters, and accessibility of a station is a factor in determining if rail transit is selected as a travel mode (Krygsman et al. 2004). Therefore, the accessibility of rail transit has become a research focus in recent years.

For a seamless journey via public transit, especially mainstay rail-centric trips, it is imperative to critically examine the bearing of the operating streetscape on first/last-mile movements between transit stations and origins/destinations. Of particular interest are the predominant first-mile trip stages (also known as access stages) linking homes to transit stations (especially for a work-bound commute) and the last-mile home-bound trip stages (also known as egress stages) from transit stations to homes (or to neighborhood amenities en route to homes). Well-provisioned first/last movement facilities directly influence the level of service and connectivity of a transportation network serving residential areas and transit stations. The commonly-available modes for first/last-mile trip stages are walking, cycling, feeder bus, and car commuting (e.g., park-and-ride, kiss-and-ride). Walking is the most universal form of transport for first/last-mile trip stages, and cycling is emerging strongly as an attractive alternative for first/last-mile trip stages with the rising concerns related to health and sustainable development. Commensurate developments of non-motorized transport (NMT) infrastructure have been provided, such as dedicated cycling tracks and sheltered walkways in the periphery of rail transit stations. Feeder bus is designed to integrate with rail transit to provide wider service. The mode share of car commuting for first/last-mile trip stages varies by city depending on the provision of parking facilities and regulation policies. In some developed countries, such as the U.S. and Canada, the car commuting mode is expanding, especially for the first-mile trip stage. Most parking facilities for car commuting are sited either in the suburbs of metropolitan areas or on the outer edges of large cities. Therefore, in focusing on the urban transport system within a large metropolis, the car commuting mode is not considered in this study, as the influence factors for this kind of trip are substantially different.

This study focuses on identifying the manner in which travel distance, personal factors, and local physical environmental factors influence a person’s mode choice for the last-mile trip stage. In addition to the usual influence factors such as cost, distance, and personal factors, the operating streetscape has been found to exert influence on travel mode choice (Boarnet and Crane 2001; Ewing and Cervero 2001; Schwanen and Mokhtarian 2005). Three modes are considered for predominant modes for last-mile trip stages, namely walking, cycling, and feeder bus. Thus far, most research is focused on motorized trips, and the influence of streetscape on NMT trips is seldom discussed (Rodríguez and Joo 2004; McDonald 2007). Moreover, NMT trips often are not accurately represented in nationwide household interview travel surveys due to the relatively short-range NMT trips when compared to motorized modes. Thus, it is difficult to examine the travel characteristics of last-mile NMT trips from household interview travel surveys, in particular for rail-centric journeys, which often involve other modes in the main haul of the journey.
Literature Review
Multimodal mode choice modeling has been well-studied by using discrete choice theory. It is, in general, based on the utility maximization hypothesis that assumes that an individual’s mode choice is a reflection of underlying preferences for each of the available alternatives and that the individual selects the mode with the highest utility among several alternative modes (Badoe and Miller 1995; Rajamani et al., 2003; Bhatta and Larsen 2011). Among various types of discrete choice models, the multinomial logit model (MNL) is a typical formulation, as it has the advantage of a closed form mathematical structure, which simplifies computation in both estimation and prediction (Koppelman and Wen 2000; Ben-Akiva and Lerman 1985; Schwanen and Mokhtarian 2005; Dissanayake and Morikawa 2010). The random item in the utility function in an MNL model is assumed to be independently Gumbel-distributed. Since the influence factors in mode choice decisions are mutually interdependent, integrating them into the same modeling framework is important. Therefore, this study proposes an MNL modeling approach as a suitable means to analyze mode choice decisions.

Existing studies show that socio-demographic factors and operating streetscapes are important factors that influence a travelers’ mode choice (Sanchez et al. 2004; Grengs 2010; Tilahun and Fan 2014). In recent years, attention has been placed on the influence factors affecting mode choice for first/last-mile trip stages as an increased requirement for the accessibility of public transit, especially rail transit including light rail transit. Meanwhile, it has been accepted that better understanding the first/last-mile home-bound trip stages is useful for transport modeling, infrastructure planning, urban design, and health research communities (Clifton and Muhs 2012). The common sense that distance has a steeper negative effect on the choice of walking and cycling as compared to motorized modes has been demonstrated in many studies (Debrezion et al. 2009; Sohn and Shim 2010; Wardman and Tyler 2010). In addition to distance, research has been carried out on the characteristics of the first/last-mile trip stages with respect to time and facility attributes (Hine and Scott 2000; Kuby et al. 2004; Guo and Wilson 2011). Kim et al. (2007) found that full-time student status, high-income transit riders, trips made during the evening, and good security (low crime) at stations are significant factors associated with an increased share of walking for trips between home and light rail stations.

Givoni and Rietveld’s (2007) research findings in the Netherlands showed that most passengers choose walking, bicycle, and public transport to get to or from a rail transit station and that the availability of a car does not have a strong effect on the choice of access mode to a station. Similar results were found by Martens (2004) based on analysis of three countries with widely differing bicycle cultures and infrastructure: the Netherlands, Germany, and the UK. Pucher and Buehler (2009) suggested provisions of secure, sheltered bike parking at rail transit stations to enhance cycling access to public transit. Koh and Wong (2013a) used data collected at nine rail transit stations to estimate the propensity for walking and other modes of transport; after controlling for various demographic and infrastructural factors, their logit choice models showed that travel distance, number of parked bicycles at transit stations, percentage of land under commercial use, and distance between origin/destination and nearest bus stop
with services serving the rail transit station were influential variables on the propensity to walk. Wang (2012) studied the supply side of the last-mile transport problem and proposed a model for determining approximate resource requirements. Lesh (2013) espoused that operational strategies and technologies can improve the convenient mobility choices in the last-mile home-bound trip stage, such as electric bikes, dynamic ride-sharing, and automated transit networks. A more recent study by Tilahun et al. (2014) took a close look at the Chicago Metropolitan area; their study showed that security issues such as violent crimes around transit stations can discourage walking to transit stops and using transit.

This study focused on last-mile mode choice for home-bound trip stages through conducting a field survey to investigate influence factors including travel distance, personal information, and local streetscape attributes.

**Methodology**

The foundation of this study was gathering information on last-mile home-bound trip makers for each mode using quota sampling instead of stratified random sampling. The quota sampling method often is used to interview disembarking passengers from transport modes (Richardson et al. 1995), in this case from rail transit stations. It was targeted to randomly obtain at least 50 respondents for each of these groups (cyclists, pedestrians, and others) in each station. Five rail transit stations—the major stations in the north, south, west, east, and middle parts of Singapore—were selected, as shown in Figure 1. The street patterns of each study area are shown in Figure 2. All are surface stations with evidenced amounts of cycling activities (via counts of parked bicycles and bicycle volumes).
Table 1 shows some broad characteristics contained within a 2.6-km radius of the selected transit stations for the study. The presence of an integrated hub means that the transit station is integrated with a bus interchange and residential and large-scale commercial activities, whereas a town center typically comprises clusters of shop-houses with variant activities (including residential functions).

**TABLE 1. Descriptions of Sampled Transit Stations**

<table>
<thead>
<tr>
<th>Station</th>
<th>% Residential</th>
<th>Integrated Hub</th>
<th>Town Center</th>
<th>Number of Parked Bicycles</th>
<th>Average Bicycle Flow(^2) along Links</th>
<th>Average Bicycle Flow along Nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admiralty</td>
<td>33</td>
<td>No</td>
<td>Yes</td>
<td>478</td>
<td>6.8</td>
<td>5.3</td>
</tr>
<tr>
<td>Aljunied</td>
<td>70</td>
<td>No</td>
<td>No</td>
<td>185</td>
<td>3.8</td>
<td>5.9</td>
</tr>
<tr>
<td>Ang Mo Kio</td>
<td>66</td>
<td>Yes</td>
<td>Yes</td>
<td>139</td>
<td>2.5</td>
<td>3.6</td>
</tr>
<tr>
<td>Bedok</td>
<td>60</td>
<td>No(^1)</td>
<td>Yes</td>
<td>196</td>
<td>2.8</td>
<td>7.6</td>
</tr>
<tr>
<td>Boon Lay</td>
<td>38</td>
<td>Yes</td>
<td>Yes</td>
<td>483</td>
<td>3.2</td>
<td>3.7</td>
</tr>
</tbody>
</table>

\(^1\) Integrated hub being planned
\(^2\) Number/10min/segment
Interviewers were deployed during evening peak hours (during non-rainy and non-school holidays) to randomly intercept passengers at rail transit station exits and to engage all available cyclists at the bicycle parking areas. Respondents were asked to report their onward destinations and their intended modes of transport. A number of trip-related attributes were extracted from the records of the collected survey sample, as elaborated in the following.

Table 2 summarizes the list of independent variables affecting mode choice of last-mile home-bound trip makers. Travel distance was considered as a variable separate from other factors because it is the most significant factor that affects mode choice. In addition to personal factors, local physical environment factors were categorized into built-environment (degrees of areal development), prevalence of cycling, availability of short-range transport modes, and walking/cycling infrastructure.

<table>
<thead>
<tr>
<th>No.</th>
<th>Variable</th>
<th>Abbrev.</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
<td>Actual distance traveled</td>
<td>ADistance</td>
<td>Continuous</td>
</tr>
<tr>
<td>P2</td>
<td>Age</td>
<td>Age</td>
<td>Continuous</td>
</tr>
<tr>
<td>P3</td>
<td>Gender</td>
<td>Gender</td>
<td>Discrete: Male*, Female</td>
</tr>
<tr>
<td>P4</td>
<td>Trip purpose</td>
<td>TPurp</td>
<td>Discrete: GoHome, GoSchool, GoWork, PartOWork, PersonalB, Social</td>
</tr>
<tr>
<td>P5</td>
<td>Household income</td>
<td>HInc</td>
<td>Discrete: &lt;2K, 2-3K, 3-4K, 4-6K, 6-8K, &gt;8K</td>
</tr>
<tr>
<td>P6</td>
<td>Occupation</td>
<td>Occup</td>
<td>Discrete: Employed, Student, Housewife, Retired</td>
</tr>
<tr>
<td>B7</td>
<td>Percentage of residential</td>
<td>Pres</td>
<td>Continuous</td>
</tr>
<tr>
<td>B8</td>
<td>Percentage of commercial</td>
<td>PCom</td>
<td>Continuous</td>
</tr>
<tr>
<td>B9</td>
<td>Percentage of industrial</td>
<td>PInd</td>
<td>Continuous</td>
</tr>
<tr>
<td>B10</td>
<td>Presence of integrated transport hub</td>
<td>PIntTH</td>
<td>Discrete: Yes, No</td>
</tr>
<tr>
<td>B11</td>
<td>Presence of town centre</td>
<td>PTown</td>
<td>Discrete: Yes, No</td>
</tr>
<tr>
<td>S12</td>
<td>No. of parked bicycles at transit stations</td>
<td>NPBic</td>
<td>Continuous</td>
</tr>
<tr>
<td>S13</td>
<td>No. of bicycles along intermediate links</td>
<td>NLBic</td>
<td>Continuous</td>
</tr>
<tr>
<td>S14</td>
<td>Number of cyclists along intermediate nodes</td>
<td>NNBic</td>
<td>Continuous</td>
</tr>
<tr>
<td>A15</td>
<td>No. of bus services to destination</td>
<td>NBus</td>
<td>Continuous</td>
</tr>
<tr>
<td>A16</td>
<td>Distance from bus stop to destination</td>
<td>DBus</td>
<td>Continuous</td>
</tr>
<tr>
<td>A17</td>
<td>Availability of personal household vehicle</td>
<td>AVeh</td>
<td>Discrete: Yes, No</td>
</tr>
<tr>
<td>C18</td>
<td>SAI for walking</td>
<td>SAIw</td>
<td>Continuous</td>
</tr>
<tr>
<td>C19</td>
<td>SAI for cycling</td>
<td>SAIc</td>
<td>Continuous</td>
</tr>
<tr>
<td>C20</td>
<td>Location (dummy variable)</td>
<td>Location</td>
<td>Discrete: Bedok, Ang Mo Kio, Boon Lay, Aljunied, Admiralty</td>
</tr>
</tbody>
</table>

* Reference group for a discrete variable is highlighted in bold italic letters.
The most obvious Influencing (I) factor was distance or time taken to travel from transit station to destination as measured from frequently-used routes (from transit stations to destinations) traced by respondents on a provided map.

Personal (P) factors were obtained from the demographic details of respondents and included age, gender, trip purpose, household income, and occupation.

Built-environment (B) factors were area-based factors and included percentage of residential, commercial, and industrial areas, as based on the land use depicted on Urban Redevelopment Authority’s Masterplan 2008 map (Urban Redevelopment Authority 2008). The percentages were calculated within a 2.6-km radius surrounding the MRT station and the boundary lines that are of equal distance from the adjacent station(s). The 2.6-km radius is the 85th percentile distance traveled by feeder bus from the transit station.

The prevalence of cycling (S) factors was meant to get a general idea of cycling popularity in the study area, as estimated by the number of parked bicycles and bicycle traffic along links and nodes near the transit station. The number of parked bicycles, whether parked legally or not, was counted during mid-day, which typically has the highest occupancy. The cyclist volume also was counted along links during evening peak hours (footpaths or cycle tracks) surrounding the transit stations and at the nodes (signalized pedestrian crossings) next to the transit stations.

The Availability (A) of short-range transport modes included the number of feeder bus services and the walking distance from the nearest bus stop to the destination. Feeder bus services found near a transit station is a competing mode against NMT and, hence, is an important factor to consider when estimating NMT demand. As such, for each respondent, the number of feeder bus services that served the transit station was counted at the nearest bus stop (to the destination end). This represents the amount of direct public bus service emanating from the transit station to the destination. Walking distance from the nearest bus stop to the final destination also was measured based on the stated feeder bus service provided by each respondent.

Walking/cycling infrastructure (C) refers to the existing NMT infrastructure provision and performance, estimated from auditing commonly-used routes (Koh and Wong 2013b). In essence, for each precinct, a set of alternative routes was audited and assigned the Safety and Accessibility Index (SAI) values. The SAI, for a route \( r \) was calculated by a weighted summation of the SAI, values of respective segments constituting that route. The SAI, of a given segment \( s \) is formed from 11 infrastructure compatibility attributes, including intersection safety, street design, land use, perceived safety, traffic (volume and speed), sidewalk completeness, security, greenery, shops, building height, and number of people, by summing all the points, \( P_i \), collected as follows:

\[
\text{SAI}_s = \sum_{i=1}^{11} P_i \text{[Maximum : 100 points]}
\]

where \( P_i \) is the converted percentage points awarded to that audited segment for attribute \( i \).
Results and Findings

General Statistics

In total, 851 respondents were interviewed. Table 3 shows the breakdown of the respondents by the mode of transport used. Only a few respondents used other modes such as taxi and private vehicle; hence, the group “Others” was ignored, resulting in a three-mode choice model. It should be noted that since cyclists were intentionally “captured” and not a random sample, the actual proportion of cyclists among the modes could not be determined in a representative manner.

<table>
<thead>
<tr>
<th>Location</th>
<th>Count</th>
<th>Mode Choice</th>
<th>Cycle</th>
<th>Walk</th>
<th>Feeder Bus</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admiralty</td>
<td>218</td>
<td></td>
<td>69</td>
<td>137</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>Aljunied</td>
<td>185</td>
<td></td>
<td>50</td>
<td>122</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>Ang Mo Kio</td>
<td>143</td>
<td></td>
<td>47</td>
<td>67</td>
<td>24</td>
<td>5</td>
</tr>
<tr>
<td>Bedok</td>
<td>148</td>
<td></td>
<td>50</td>
<td>54</td>
<td>42</td>
<td>2</td>
</tr>
<tr>
<td>Boon Lay</td>
<td>157</td>
<td></td>
<td>55</td>
<td>76</td>
<td>24</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td>851</td>
<td></td>
<td>271</td>
<td>456</td>
<td>107</td>
<td>13</td>
</tr>
</tbody>
</table>

The gender split was about 50–50, which follows the national proportion. Figure 3 depicts the breakdown by age group of the respondents. Surprisingly, the proportion of respondents who refused to indicate their age was relatively small (at 2%). Children were under-represented, which is not unexpected, as responses were targeted at the caregivers.

Two in three respondents were employed, 25% were students, and the rest were homemakers, unemployed, or retired. This is not surprising, as the study period was during evening peaks from the transit stations. About one in three respondents had a vehicle in the household. The principal trip purpose was to go home (at 84%), with the remainder heading for amenities in the home area.
Mode Choice Modeling

Since the dependent variable, mode choice, is a multinomial response, a generalized logits approach was used to model the mode choice behavior using SAS® (a statistical software package). Three dependent variables were defined: \( P(\text{walking}) \), the probability that a last-mile home-bound trip maker chooses to walk from an MRT station to the destination; \( P(\text{cycling}) \), the probability that a last-mile home-bound trip maker chooses to cycle; and \( P(\text{taking bus}) \), the probability that a last-mile home-bound trip maker chooses to take a public feeder bus. By definition, these three probabilities add up to 1.

\[
P(\text{walking}) = \frac{e^{a_1 + b_1 x_i}}{1 + e^{a_1 + b_1 x_i} + e^{a_2 + b_2 x_i}}
\]

(2)

\[
P(\text{cycling}) = \frac{e^{a_2 + b_2 x_i}}{1 + e^{a_1 + b_1 x_i} + e^{a_2 + b_2 x_i}}
\]

(3)

\[
P(\text{taking bus}) = 1 - \frac{e^{a_1 + b_1 x_i}}{1 + e^{a_1 + b_1 x_i} + e^{a_2 + b_2 x_i}} - \frac{e^{a_2 + b_2 x_i}}{1 + e^{a_1 + b_1 x_i} + e^{a_2 + b_2 x_i}}
\]

(4)

In Eqs (2), (3), and (4), \( x_i \) (\( i = 1, 2, 3 \ldots n \)) denotes the attributes of alternative that were relevant to the choice being considered; \( a_1, a_2 \) are the intercepts, \( b_1, b_2 \) ... are the coefficients of independent variables. The dependent variable is the last-mile home-bound trip maker’s mode choice (the list of independent variables is summarized in Table 2).

The influencing variables listed in Table 2 were included in the first step of model-building by way of univariate analysis. Moreover, the age-squared variable also was included since the distribution of age may be in a quadratic form for cycling. The variable Location was included as a dummy variable to account for any effects pertaining to site characteristics that were not addressed by other variables. The respective Chi-squared and p values for the likelihood ratio test are summarized in Table 4. Variables with small Chi-squared values and large p-values (more than 0.05) were dropped from the model in subsequent multivariate analysis. These included NNBic, NBus, and DBus.
TABLE 4.
Univariate Analysis Results

<table>
<thead>
<tr>
<th>No.</th>
<th>Variable</th>
<th>N*</th>
<th>$\chi^2$</th>
<th>Pr &gt; $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
<td>ADistance</td>
<td>692</td>
<td>356.16</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P2</td>
<td>Age</td>
<td>823</td>
<td>36.35</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P3</td>
<td>Agesq</td>
<td>823</td>
<td>34.33</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P4</td>
<td>Gender</td>
<td>823</td>
<td>27.65</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P5</td>
<td>TPurp</td>
<td>790</td>
<td>43.29</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P6</td>
<td>HInc</td>
<td>698</td>
<td>87.30</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>P7</td>
<td>Occup</td>
<td>823</td>
<td>52.20</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>B8</td>
<td>PRVin</td>
<td>833</td>
<td>6.99</td>
<td>0.0304</td>
</tr>
<tr>
<td>B9</td>
<td>PCom</td>
<td>833</td>
<td>53.94</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>B10</td>
<td>PInd</td>
<td>833</td>
<td>13.31</td>
<td>0.0013</td>
</tr>
<tr>
<td>B11</td>
<td>PIntTH</td>
<td>833</td>
<td>7.82</td>
<td>0.0201</td>
</tr>
<tr>
<td>B12</td>
<td>PTown</td>
<td>833</td>
<td>18.07</td>
<td>0.0001</td>
</tr>
<tr>
<td>S13</td>
<td>NPBic</td>
<td>833</td>
<td>11.95</td>
<td>0.0025</td>
</tr>
<tr>
<td>S14</td>
<td>NLBic</td>
<td>833</td>
<td>51.95</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>S15</td>
<td>NNBic</td>
<td>833</td>
<td>4.47</td>
<td>0.1072</td>
</tr>
<tr>
<td>A16</td>
<td>NBus</td>
<td>761</td>
<td>1.71</td>
<td>0.4247</td>
</tr>
<tr>
<td>A17</td>
<td>DBus</td>
<td>761</td>
<td>2.33</td>
<td>0.3118</td>
</tr>
<tr>
<td>A18</td>
<td>AVeh</td>
<td>812</td>
<td>42.94</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>C19</td>
<td>SAIw</td>
<td>367</td>
<td>7.45</td>
<td>0.0241</td>
</tr>
<tr>
<td>C20</td>
<td>SAIc</td>
<td>334</td>
<td>25.34</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>C21</td>
<td>Location</td>
<td>833</td>
<td>78.03</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

*Number of observations used

For multivariate analysis, an improved stepwise method was used. This involved examining the number of usable data (N) when each variable entered the model. The variables ADistance, HInc, SAIw, and SAIc had less than 85% of the total readable data that were usable; the inclusion of these variables might affect the overall stability of the model (due to smaller sample size). Herein, one has to gauge the tradeoff between the importance of such a variable with the degradation of the model. For example, as ADistance inevitably is an important factor in affecting mode choice (as evidenced by the highest $\chi^2$ value), it must be included in the model despite the smaller data count.

Using the automatic selection option in SAS, ADistance, PIntTH, Age, Agesq, AVeh, NLBic, and Gender were chosen for the final model. Apart from automatic variable selection, the variables were put into the model one by one together with the variable ADistance. The next variable (NLBic) that had the greatest $\chi^2$ and significant p-values was chosen to be the second variable to enter into the model. With this second variable in the model, the significance of the previous variable (ADistance) and this variable (NLBic) was checked. The steps were repeated until there were no other variables that could have significant influence on the model at about 90% confidence level. Interactions among variables (which refers to the non-constant effect of a variable over levels of other variables) also were checked. Possible interaction terms (based on statistical and practical considerations) such as ADistance*Age and ADistance*Gender...
were added to the model one at a time containing all main effects and their significance assessed using a likelihood ratio test. Two-variable interaction terms were found not to be significant and were not included in the model.

Table 5 shows the results of the final multinomial logit regression model (with 570 points) for last-mile home-bound trip maker mode choice. The parameter estimates are shown, and those parameters that were significant at a 95% confidence level are shown in bold. The final model showed that Actual distance between transit station and destination (ADistance), Number of bicycles along intermediate links surrounding transit stations (NLBic), Age, Agesq, Gender, Number of bus services to destination (Nbus), Availability of vehicle (AVeh), and Household income (HInc) have an effect on the mode choice of last-mile home-bound trip makers.

**TABLE 5.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Function Number*</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>$\chi^2$</th>
<th>Pr &gt; $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>2.31</td>
<td>1.81</td>
<td>1.63</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-5.64</td>
<td>1.90</td>
<td>8.81</td>
<td>0.00</td>
</tr>
<tr>
<td>ADistance (continuous)</td>
<td>1</td>
<td>-5.9×10^{-3}</td>
<td>0.00</td>
<td>104.22</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-2.1×10^{-3}</td>
<td>0.00</td>
<td>24.39</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>NLBic (continuous)</td>
<td>1</td>
<td>0.64</td>
<td>0.28</td>
<td>5.19</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.83</td>
<td>0.28</td>
<td>8.42</td>
<td>0.00</td>
</tr>
<tr>
<td>Age (continuous)</td>
<td>1</td>
<td>0.20</td>
<td>0.07</td>
<td>8.73</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.30</td>
<td>0.07</td>
<td>17.05</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Agesq (continuous)</td>
<td>1</td>
<td>-2.5×10^{-3}</td>
<td>0.00</td>
<td>9.14</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-3.1×10^{-3}</td>
<td>0.00</td>
<td>14.26</td>
<td>0.00</td>
</tr>
<tr>
<td>Gender (ref=female)</td>
<td>1</td>
<td>0.47</td>
<td>0.41</td>
<td>1.31</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2.26</td>
<td>0.40</td>
<td>8.56</td>
<td>0.00</td>
</tr>
<tr>
<td>NBus (continuous)</td>
<td>1</td>
<td>-0.18</td>
<td>0.07</td>
<td>6.16</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-0.12</td>
<td>0.07</td>
<td>2.69</td>
<td>0.10</td>
</tr>
<tr>
<td>AVeh (ref=y)</td>
<td>1</td>
<td>-0.02</td>
<td>0.46</td>
<td>0.00</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-0.51</td>
<td>0.46</td>
<td>1.22</td>
<td>0.14</td>
</tr>
<tr>
<td>HInc (ref=’&gt; 8k’)</td>
<td>1</td>
<td>-0.86</td>
<td>0.95</td>
<td>0.82</td>
<td>0.36</td>
</tr>
<tr>
<td>&lt;2k</td>
<td>2</td>
<td>-1.00</td>
<td>1.06</td>
<td>0.89</td>
<td>0.35</td>
</tr>
<tr>
<td>2–3k</td>
<td>1</td>
<td>-0.05</td>
<td>0.84</td>
<td>0.00</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.68</td>
<td>0.87</td>
<td>3.72</td>
<td>0.05</td>
</tr>
<tr>
<td>3–4k</td>
<td>1</td>
<td>0.33</td>
<td>0.82</td>
<td>0.17</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.16</td>
<td>0.86</td>
<td>1.81</td>
<td>0.18</td>
</tr>
<tr>
<td>4–6k</td>
<td>1</td>
<td>-1.12</td>
<td>0.81</td>
<td>1.88</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.11</td>
<td>0.85</td>
<td>0.02</td>
<td>0.90</td>
</tr>
<tr>
<td>6–8k</td>
<td>1</td>
<td>0.44</td>
<td>0.89</td>
<td>0.25</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.24</td>
<td>0.91</td>
<td>1.83</td>
<td>0.18</td>
</tr>
</tbody>
</table>

* 1 = walking; 2 = cycling; taking bus is the base
Goodness-of-Fit of Model
The Pearson test statistic was used to test the fit of the current model versus the saturated model, noting that the Hosmer-Lemeshow Goodness-of-Fit test is available only for binary response (SAS 2012b). The final model had a P value of 0.0808 and -2 Log 1053.851, which was not significant at a 95% confidence level; hence, there was insufficient evidence to reject the null hypothesis that the model fits the data well.

Interpreting the Results
The descriptive statistics for the explanatory variables in the model are given in Table 6. For the interpretation of the model results (see Table 5), a positive parameter estimate for a continuous variable (\( \chi \), say) means that as \( \chi \) increases by one unit, the probability of the event (either walking or cycling) is higher, in comparison with the reference category (Taking Bus), holding all other predictors constant. For example, every 200m increase in ADistance decreased the odds of walking (1 - e^{-0.00558*200}=1-0.33=0.67), in comparison with the option of taking a bus. When there was a higher number of cyclists (NLBic), the likelihood of cycling was higher. Surprisingly, as Age increased, this increased the likelihood of cycling. The non-availability of a private vehicle (AVeh) increased the likelihood of walking and cycling. Males were more likely to walk and cycle than females. The odds for a male last-mile home-bound trip maker to choose walking over taking a bus was 1.63 times the odds for a female last-mile home-bound trip maker. Those with household incomes (HInc) less than $2,000 were more likely to cycle than take a bus in the last-mile home-bound trip.

TABLE 6.
Descriptive Statistics for Explanatory Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>N*</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADistance</td>
<td>699</td>
<td>17.4</td>
<td>5368.2</td>
<td>845.3</td>
<td>592.4</td>
</tr>
<tr>
<td>NLBic</td>
<td>757</td>
<td>1</td>
<td>11</td>
<td>3.8</td>
<td>1.7</td>
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Applications of Mode Choice Model
Consider the following scenario: an older adult male (age 65) and a middle-age man (age 30) are exiting a transit station, with the number of bicycles along nearby links (NLBic) at 5 bicycles/10min/m and 20 feeder bus services (Nbus). The trip makers have no access to private vehicles, and their household income is $2,000 to $3,000. For the conditions of this scenario, Figure 4 depicts the probability plots of walking, cycling, and taking a feeder bus for the last-mile home-bound trip makers at the transit station. It shows the declining effect of the probability of walking with distance, with almost none walking beyond a distance of 2,000 m or further. The probability of cycling is a bell-shape curve that peaks at about 1,000 m away from a transit station and declines after that. The probability of taking a feeder bus increases as the distance from a transit station increases. An age-65 older adult has a greater propensity to cycle and a lower propensity
to walk than a middle-age adult when the distance is less than 1,000 m. The intersection points reflects the mode choice threshold; for example, an age-65 older adult prefers to cycle if the distance for the last-mile trip stage is 250–2,000 m, whereas this threshold for an age-30 male is 500–2,000 m. Travelers would prefer to walk if the actual travel distance is below the threshold and to take the bus if the actual distance is above the threshold. It should be noted that the quota sampling would not allow the degree of representativeness to be quantified. Nevertheless, the model serves to illustrate the manner in which mode choice can be calibrated and then applied to estimate mode distribution in relation to the modeled variables.

FIGURE 4.
Mode choice model of last-mile home-bound trip makers

Conclusions
Operating streetscape attributes, including built-environmental factors (degrees of areal development), prevalence of cycling, availability of alternative short-range transport modes, and walking/cycling infrastructure, were considered in this study together with influencing factors (travel distance/time) and personal factors to investigate their impact on the mode choice decisions of last-mile home-bound trip makers. These data were collected in field surveys of travelers at five rail transit stations in Singapore. An improved stepwise method was used to determine the significant variables. The factors of age, gender, actual distance between transit station and destination, number of bicycles along links surrounding transit stations, number of feeder bus services to destination, availability of vehicle, and household income were rated to be significantly important on the mode choice of last-mile home-bound trip makers. The results serve to indicate the important attributes associated with the last-mile transport facility/service. Developing a convenient cycling system from a transit station to a residential
area will promote cycling usage in the last-mile home-bound trip stage, which is in conformity with the requirements of sustainable development.

A multimodal logit regression model was established, offering new insights on the understanding of the last-mile home-bound mode choice decision. Among those influencing factors, actual distance between transit station and destination and number of bicycles along intermediate links surrounding a transit station are the most significant as related to the mode choice for last-mile trip stages, which corroborated with other study results. Second-tier influence factors are socio-demography variables including age, gender, and household income; third-tier influence factors are the number of feeder bus services to destination and availability of vehicle. In general, for shorter distances from a rail transit station to a destination, travelers prefer to walk. With an increase in the distance, travelers tend to choose cycling. For even further distances, travelers choose public bus. The number of cyclists along immediate links is positively associated with the mode choices of walking and cycling. The results also showed, in particular, that as age increases, the likelihood of cycling increases. Males are more likely to walk and cycle than females. Travelers with household incomes less than $2,000 tend to cycle rather than take a bus in the last-mile home-bound trip. Similarly, the non-availability of a private vehicle raises the likelihood of walking and cycling. This study's findings provide valuable inputs for planning non-motorized facilities and rail-bus service planning around transit stations.

Acknowledgments

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References


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Commuting by Customized Bus: A Comparative Analysis with Private Car and Conventional Public Transport in Two Cities

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Abstract

Commuting is a major component in the creation of traffic and travel problems. Thus, more attention should be given to its practice. Private car (PC) transport, the dominant mode of commuting in most of the world’s major cities, creates traffic-related social problems such as traffic congestion, traffic fatalities and injuries, and adverse environmental impacts. This study proposes a novel commuting travel mode—a customized bus (CB) transit system that provides advanced, personalized, and flexible demand-interactive minibus service using Internet, telephone, and smartphone apps. The aim was to assess and compare the performance of CB with PC and with conventional public transport (PT) systems. A methodological analysis framework was constructed to quantify operational performance measures that enable the comparison of the different travel modes. This analysis framework was then applied to two cities—Auckland, New Zealand, and Paris, France—to assess the overall performance metrics of PC, PT, and CB, such as travel costs, travel time, and fuel consumption. This comparison sheds light on the differences between the travel modes, their viability, and their competitiveness. The results of the case study show that PC is the fastest commuting mode, but the travel costs incurred by it are twice as much as for PT and CB and involve higher fuel consumption. CB also can provide a useful alternative for commuter trips in Auckland and Paris. For increased commuter trips, CB proved to be more efficient than the PC and PT modes. Finally, the CB system tends to be more profitable in Auckland than in Paris.

Keywords: Commuting, customized bus, private car, public transport, travel mode.
Introduction
Commuting is a widespread social activity that plays an important role in daily life and constitutes a considerable share of total household trip-making. Private car (PC) transport is still the dominant mode of commuting in most major cities around the world (AASHTO 2015; Statistics NZ 2009; Statistics NZ 2014), and rapid economic growth and employment have led to increased numbers of commuters. Combined with rapid urban sprawl, this results in an increased use of PC, which has led to various traffic-related social problems, including traffic congestion, traffic fatalities and injuries, and adverse environmental effects. However, it seems that continual expansion of road networks and traditional demand-management measures have not been effective historically in mitigating such adverse effects (Liu and Ceder 2015; Xu et al. 2015). As a result, the need for an efficient, reliable, and reasonably-priced public transport (PT) system has become increasingly pressing (Ceder 2007, 2016).

Conventional PT systems, especially those involving buses, use an old concept involving fixed routes, fixed stops, fixed terminals, fixed timetables, and fixed vehicle and driver scheduling. This traditional PT concept produces services that are not always appealing and do not necessarily attract commuters (Ceder 2007, 2016). In fact, commuting as a daily activity generates the lowest level of positive affect as well as a relatively high level of negative affect (Stutzer and Frey 2008). For most people, long-distance commuting is often the cause of many physical, financial, and mental problems, such as stress and out-of-pocket costs. Likewise, it has an effect on the work-family balance and increases the risk of divorce (Koslowsky et al. 1995; Stutzer and Frey 2008; Sandow 2011). To make commuting using PT a pleasant experience, an advanced, attractive PT system needs to be developed. As pointed out by Ceder (2007, 2016), an advanced and attractive PT system should operate reliably and relatively rapidly, with smooth, synchronized transfers, as part of the door-to-door passenger chain.

Accordingly, customized bus (CB) offers such an attractive PT commuting system that provides advanced, personalized, and flexible demand-interactive PT service to commuters (Liu and Ceder 2015). It has been launched and implemented successfully in many cities around the world, such as Beijing, Lisbon, and San Francisco (Shaheen 2001; Eiró et al. 2011; Martínez et al. 2014; Liu and Ceder 2015), and has great potential for meeting the ever-increasing, diversified commuting mobility needs of large populations and helping to improve the commuting experience.

Background on Customized Bus
CB is a new and innovative mode of cyber-enabled, demand-interactive transit systems that provides advanced, attractive, and user-oriented minibus service to commuters by aggregating their similar travel-demand patterns using online information platforms such as Internet, telephone, and smartphone apps. Unlike conventional PT service, CB users are actively involved in various interactive operational planning activities, including online demand collection, network route design, timetable development, and vehicle and crew scheduling. CB service is more comfortable, convenient, and reliable than conventional PT service and more efficient, cost-effective, and environmentally-friendly than PC. Therefore, CB serves as a good alternative for reducing urban traffic congestion,
improving traffic safety, and alleviating energy consumption and greenhouse gas emission problems (Eiró et al. 2011; Martinez et al. 2014; Liu and Ceder 2015).

CB can be regarded as a new hybrid transit system that integrates conventional fixed-route, fixed-schedule PT systems and demand-interactive collective transit systems such as carpooling, carsharing, and subscription bus (Shaheen 1998; TCRP 1999; Shaheen 2001). CB service is designed and implemented by using a human–computer interactive, integrated ridematching platform with the participation of users and operators. By interacting with users in real time, it closely caters to their demands and better meets ever-increasing, diversified, commuting mobility needs. Therefore, it is considered a viable and competitive alternative to private car and conventional PT service. A systematic description of the detailed operation-planning process of CB can be found in Liu and Ceder (2015).

Objectives
This study proposes a new commuting travel mode, a customized bus transit system, for commuters in Auckland, New Zealand, and Paris, France. The aim was to assess and compare the performance of this new transit system with PC and conventional PT systems. This work had three objectives: 1) to construct an initial methodological framework for quantifying operational performance measures, such as travel time, travel cost, energy consumption, 2) to apply this framework to assessing the overall performance of PC, PT, and CB in case studies in Auckland and Paris, and 3) to conduct comparisons between the cities and provide recommendations for actual CB service improvement and implementation.

Related Literature Review

Commuting Mode Choice between Private Car and Public Transportation

The choice of mode between PC and PT is a complex decision process that is influenced by various factors. Trip characteristics such as trip purposes, time, regularity, and household characteristics have been shown to be significant factors in mode choice (Ye et al. 2007). PC usually is perceived to be more attractive than PT because of its convenience, flexibility, independence, comfort, speed, and reliability and because driving is perceived to be more pleasurable and bears a status symbol (Steg 2003). The use of PT has been shown to decline as age and income increase. Women have a slightly higher probability of using PT for trip purposes other than commuting (Kuhnimhof et al. 2006). Other factors that have been identified are quality of PT services, lack of connection, out-of-pocket travel cost, access distance to and from stations, and distance to/from home-work (Galdames et al. 2001; Kingham et al. 2001). Terloolen et al. (1998) showed that PC travelers display a psychological resistance towards switching to PT.

PC use has been preferred to PT not only for its instrumental functions (freedom, comfort, and convenience), but also for its symbolic (status in society) and affective (driving is perceived as being pleasurable) functions (Hiscock et al. 2002; Beirão and Cabral 2007). Other literature has shown that once private vehicles are acquired, their use becomes more of a necessity than a luxury to the owner. Private vehicle use can become a habit for a large group of travelers after acquisition (Anable 2005). Increased
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complexity of trip chains due to changes in traditional household travel patterns with more women entering the workforce also has been identified as a barrier to PT use (Hensher and Reyes 2000; Nobis and Lenz 2005). Therefore, methods to instigate mode switch from PC to PT, particularly for commuters, remain a hot topic of interest for many transportation specialists.

Commuter-based Carsharing

The concept of vehicle sharing is not new. The earliest car-sharing system was introduced in Zurich in 1948 (Shaheen et al. 1998). There have been five phases in the history of North American ridesharing, and it is estimated that there are now about 638 ridesharing services in the U.S. and Canada (Chan and Shaheen 2012). The share of driving alone continues to grow for total commuting, whereas the share for carpooling has declined continuously since 1980 in the U.S. (AASHTO 2015). In recent years, new ridesharing programs that incorporate Internet, smartphone apps, and social networking have been developed for better online matching between commuters and service providers by employing information and communication technologies (Eiró et al. 2011; Chan and Shaheen 2012; Martínez et al. 2014; Liu and Ceder 2015). This new kind of travel mode is viewed as a good alternative to PC and a complementary mobility option that supports traditional PT systems.

Methodological Framework

The methodological framework for the comparative analysis of commuting travel modes is shown in Figure 1. This methodological framework was constructed by an input-component output format, elaborating the systematic decision sequence and process of the analysis. The output of each component positioned higher in the sequence becomes an important input into lower-level decisions. This analysis framework was customized to achieve the three objectives of this study. Accordingly, to determine and compare the performance measures for the three different commuting modes in Auckland and Paris, this customized framework included four stages:

1. Preliminary study area map establishment
2. Data collection
3. Determination of performance metrics
4. Performance comparison of travel modes

The first stage identified the study areas and established a preliminary road network map and PT networks. Potential commuting trips in the selected study areas were identified in the second stage. Data on trip origins/destinations, expected arrival times at destinations, and vehicle type used were collected. The demand collection process was completed by using a human-computer interactive with an integrated information platform such as Internet, telephone, and smartphone app with the participation of both users and operators. In this stage, grouping and vehicle routing strategies was adopted for designing and routing CB vehicles to pick up commuters from their origins and drop them off at their destinations. After generating the routes, Google Maps and Via Michelin Itinéraire smartphone app were used to collect data on trip travel time, travel cost, and fuel consumptions based on some simplified assumptions. In the last
stage, performance comparisons of PC, PT, and CB, and performance comparisons between Auckland and Paris were conducted using the calculated performance metrics.

**FIGURE 1.**
Methodological framework

Overall, the performance metric comparisons of different commuting modes in different cities can help us to better understand the different travel modes and their viability and competitiveness in different conditions. This can help in planning for future CB improvements.

**Study Area**

**Auckland**
The Auckland metropolis is New Zealand’s largest and most cosmopolitan region, with a population of 1.5 million. The Auckland region is a major part of the New Zealand’s demography and economy, with a 35% share of the national GDP (Statistics NZ 2013). Such a significant place obviously plays a leading role in the country’s economy. It is a PC-dominated city and has serious traffic congestion during peak hours. It is estimated that more than 60 million trips are made annually within the Auckland metropolis by using PT systems, which consist of trains, buses, and ferries. For this study, only travel between Auckland suburbs and the central business district (CBD) that are daily work trips were considered.
Figure 2 shows the study area, which includes the Auckland city center and the regions of Newmarket, Grey Lynn, Epsom, Penrose, Remuera, Ellerslie and Mount Wellington. All possible buses and three train lines in this area, namely the Southern line, the Eastern line and the Western line, were taken into consideration.

**FIGURE 2.** Study area in Auckland, New Zealand

**Paris**

The Paris metropolis is France's largest and most cosmopolitan region, with a population of 11.9 million and a GDP of 572,398 million euros (Institute Development and Urban Planning in the Region of Île-de-France 2015). It is France's most productive (economically
and socially) region. This economic activity would not be possible without an efficient commuter transport system, especially efficient PT systems. The RATP Group is the PT operator and provides a complex PT network that consists of trains, buses, metros, and tramways. It is estimated that there are three billion PT trips annually.

For this study, the selected area, as shown in Figure 3, included La Défense and the western part of metropolitan Paris, which is composed of the cities of Vauréal, Ménucourt, Courdimanche, Croissy, Aigremont, Carrières sous Poissy, Chambourcy, Fourqueux, Mareil-Marly, Bezon, and Houilles. Most of the people living in these cities work in Paris and have to travel long distances to and from work, either by private car or PT.

Data Collection

To compare the performances of the three different commuting modes—PC, conventional PT, and CB—four performance metrics were determined: average
difference between expected and actual arrival times, average total travel time, average total travel cost, and average total fuel consumption. The selected study time periods for the two study areas were from 6:45 AM to 10:00 AM, spread over normal and rush hours to obtain a global view of different traffic conditions.

For the two study areas, trip origins in which commuters can use both PC and PT were regarded as potential service points. For the purposes of a representative sample, 100 trips in Paris and 100 trips in Auckland were examined. For Paris, five different RER A train stations and 20 addresses in the proximity of each station were selected in the attempt to cover as large an area as possible. Google Maps was used to do this work, as illustrated in Figure 4(a).

**FIGURE 4.**
Using Google Maps and Via Michelin Itinéraire to collect data

(a) Candidate trip origins selection  (b) Travel time estimation

(c) User interface of Via Michelin app
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The Via Michelin app was used to collect PC data. As shown in Figure 4(c), the app allows the user to choose between distance and money device, vehicle, and fuel type. Fuel cost can be adjusted by the user. Thereafter, the user needs only to enter the original and destination places. The app calculates the best way and gives the travel cost in euros, travel time, time to be spent in congestion, and distance to be traveled. To collect PT data, bus and RER timetables were used, and those that included the lowest transfer waiting time were selected.

In addition, the shortest travel paths were selected to collect CB data. First, a grouping strategy was used to group potential commuters into common trips by a minibus with 15 seats. The first selection feature was the RER timetable. People were grouped with similar origins/destinations into the same CB trip. To be profitable, minibuses should travel with at least six passengers. When this loading level is not met, CB service is not provided. In this case, groups were changed, forcing people to take a train; sometimes, individual trips were not grouped into common trips due to the long difference between expected arrival time and actual arrival time. In this case, travelers involved had to use PC or PT. After grouping, the nearest neighbor algorithm (Haksever et al. 2000) was used to determine the routing of minibuses. After determining the routes, Google Maps was used to estimate the entire travel time needed for each route. Figure 4(b) shows an example of estimating route travel time in Paris.

Data Processing

**Difference Arrival Time**

The expected arrival time (EAT) is the time at which a commuter hopes to arrive at his/her destination. The difference arrival time (DAT) is the difference between the EAT and the actual arrival time (AAT). For conventional PT, AAT depends on planned timetables and road traffic conditions. To determiate DAT, EAT was fixed for each passenger. Google Maps and Via Michelin Itinéraire (for Paris) were used to get the time and route of travel trips for PC commuters. In same way, by combining the timetables of buses and trains, the AAT of each commuter using conventional PT also could be obtained. DAT was calculated by

\[ DAT = |EAT - AAT| \]  

**Travel Time (TT)**

The total travel time (TTT) may contain several parts, such as in-vehicle travel time, out-of-vehicle waiting time, walking time, and transfer waiting time. For PC, the TTT is the sum of the time spent driving from home to the car parking place (TT) and the walking time from the parking place to the workplace (WkT). Both were estimated with Google Maps. The estimation was run from 7:00 AM to 10:00 AM based on the departure hour of each passenger. An estimation of the time lost in congestion also was included in the final results.

Using the same methods, the estimation for PT was repeated. Here, TT denotes the time spent on buses or trains. The WkT is composed of the walking time to the bus/train stations, the potential walking time for making transfers, and the walking time to the workplace. However, in the case of including transfers, some extra time may be
wasted because of transfer waiting; this transfer waiting time is denoted by $W_{tT}$. Using Google Maps to determine an itinerary, routes were specified in detail. The transfer waiting time was then calculated by simple subtraction.

The travel data with the CB were separated into two parts. First, commuters are picked up by minibuses, and then brought to the nearest train stations. The nearest neighbor algorithm was adopted to generate vehicle routes based on a predefined loading level. The estimation of $TTT$ for CB based on the summation of all individual origin to destination pairs was the same as that done for PT. It should be noted that for CB, the $TT$ is composed of the time spent in the minibus and the train, and the $W_{kT}$ corresponds to the travel time from the final train station to the workplace. Thus, the $TTT$ for CB was calculated by

$$TTT = TT + W_{kT} = W_{tT}$$

(2)

**Travel Cost**

For most people, travel cost (TC) is one of the dominant factors in their choice of commuting travel modes (Chowdhury et al. 2015). Travel costs were calculated for the whole day, taking both morning and evening trips into consideration.

Diesel is the fuel used most in New Zealand and France. Accordingly, our hypothesis relates to calculations for vehicles operating on diesel engines. In France, the diesel price is €1.354 /L (MoEID 2015). The Via Michelin app was used to get the fuel consumption (FC) in euros for one-way trips. Then, the car parking price (CPP) per day was calculated.

For Auckland, a price of $1.33/L was used (AA 2015), and distance traveled was estimated using Google Maps. The FC was determined by multiplying the distance and unit distance price. For this study, the daily car parking price had to be estimated due to a lack of accurate information regarding monthly subscription rates; the calculation was made by

$$TC = (2 \times FC) + CPP$$

(3)

In Paris, a subscription card called Navigo Card allows the use of buses tramways, metros, and the Paris RER for one year with the card. The subscription price (SP) depends on the areas in which the travel takes place. The Paris metropolis is divided into five tariff zones, as shown in Figure 5. This study related only to a subscription for areas 3-4 and 3-5, which have an SP of €2.06/day and €2.5/day, respectively.
FIGURE 5. Paris tariff zones

To estimate CB cost, the following distance tariff scheme was used, which includes two fare components: variable fare and constant fare. The variable fare was calculated by

\[ F_1 = \max \left\{ 0, F' \cdot \left\lfloor \frac{L - L_0}{L_1} \right\rfloor \right\} + F_0 \]  

where \( L \) is the length of a trip, \( F_0 \) is the basic fare that is compulsorily charged as long as one uses the CB service, \( F' \) is the fare factor employed for calculating fares for different trip lengths, \( L_0 \) and \( L_1 \) are the threshold length and length factor respectively, and function \( \left\lfloor x \right\rfloor \) is the ceiling function, which gives the smallest integer.
According to this definition, when the length of a trip is less than the threshold length, $L_0$, the charge will be only for the basic fare $F_0$.

Combining the variable fare with the constant fare, the total fare was calculated by

$$ F = a_1 \cdot F_1 + a_2 \cdot F_2 $$

(5)

where $F_2$ is the constant fare, $a_1$, ($0 \leq a_1 \leq 1$) and $a_2$, ($0 \leq a_2 \leq 1$) are the discount factors of the constant fare and the variable fare, respectively.

The cost per kilometer includes fuel cost, maintenance cost, driver payment, and insurance. A fuel consumption of 26 L/km at a price of €1.354/L was considered, which amounts to a fuel cost of €0.352/km. For the maintenance cost, an Iveco minibus was used as an example, which has a maintenance cost of €0.0229/km. In France, the average driver income is around €1550 per month (CIDJ 2015). As minibus maintenance is necessary either every six months or every 10,000 km, it was considered that a driver travels around 1667 km in one month. In keeping with these estimations, the driver wage was estimated to be €0.93/km. Insurance costs are around €4000 per year. Using the same hypothesis as above, the insurance cost was €0.2/km. Thus, the outcome is $F_0 = €1.29$. We set $L_0 = 5.16$km, $L_1 = 10$, and $F' = 2$, which are the common values used in practice. Repeating the same process, $F'_0 = $2.75 and $L_0 = 6.57$km for Auckland.

Subsequently, Eq. (5) was used to calculate the travel cost for CB users.

**Fuel Consumption**

Fuel consumption (FC) was calculated by liter per person. For cars in Paris, the Via Michelin app was used to obtain the FC in euro per person, which was divided by the diesel price of €1.354/L. For Auckland, an average fuel consumption of 8.61L/100km was used and was multiplied by the distance traveled (D). For PT, fuel consumption was estimated to be 0.45L/km, which was multiplied by the distance traveled (D) and then divided by the number of people on the bus, estimated at an average of 10 people. The FC for PT was calculated by

$$ FC_{pt} = \frac{0.45 \times D}{10} $$

(6)

The fuel consumption of CB was estimated to be 0.26L/km, which is the average consumption of a minibus. The calculation method was the same as for PT, but minibuses with 15 seats were considered, with an average of seven on-board users assumed. Thus, the FC for PT was calculated by

$$ FC_{cb} = \frac{0.26 \times D}{7} $$

(7)
Results

For each study area, 100 candidate commuting trips were randomly generated. Travel time, travel cost, and fuel consumption data were collected for all trips. Average values were calculated to make comparisons of the three different commuting travel modes.

Auckland

The group-specific results obtained for the Auckland case study are summarized in Table 1. This table includes the performance metrics of the difference arrival time (min), walking time from parking place to workplace (min), transfer waiting time (min), total travel time (min), travel cost (€/day), and fuel consumption (L/person).

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DAT = difference arrival time, WkT = walking time from parking place to workplace, WtT = transfer waiting time, TTT = total travel time, TC = travel cost, FC = fuel consumption, PC = private car, CB = customized bus, PT = public transportation

The average results for these eight groups are graphically shown in Figure 6. It can be seen that, generally, in Auckland, PT and CB perform somewhat similarly compared to PC. However, CB appears to be less expensive than both PT and PC. This may be because PT service in Auckland is very expensive. What’s more, PC has the shortest average travel time and lowest average difference time; however, it consumes much more fuel and costs much more than PT and CB. Although CB consumes a little more fuel than conventional PT, it provides much greater comfort, as it eliminates congestion and transfer waiting and guarantees seats. More importantly, this initial study was limited by the number of candidate trips. If more commuter trips are taken into account, the CB will be more efficient than PC and PT.
Table 2 shows group-specific results obtained from the Paris case study. It should be noted that the 12th group is composed of 25 commuting trips that could not be grouped due to low vehicle loading levels. The average metric values for all groups were calculated to compare the performance of the different three travel modes; the average results of these 12 groups are shown in Figure 7, which illustrates that PC has the lowest deviation from expected arrival time and CB has the largest deviation from expected arrival time. This may reflect the small and poor sample trips that were distributed over a relatively large area, which increases the time for picking up commuters from their homes. However, compared to PC, CB is much cheaper and consumes much less fuel. Moreover, a comparison between CB and PT shows that CB is 15% faster than PT, but is 33% more expensive than PT. This may be a result of the reduced transfer time. The average travel cost and fuel consumption could be further reduced for CB by involving more commuting trips.
TABLE 2. Performance Metrics Measured per Group in Paris

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DAT = difference arrival time, WkT = walking time from parking place to workplace, WtT = transfer waiting time, TTT = total travel time, TC = travel cost, FC = fuel consumption, PC = private car, CB = customized bus, PT = public transportation

FIGURE 7. Average performance metrics measured per mode in Paris
Comparisons of the Two Cities

From the case study results for Auckland and Paris, it has been shown that CB is a promising commuting mode compared to PC and conventional PT. In both cities, compared to PC, CB has a lower average travel cost and consumes much less fuel. However, it appears that it is more suitable and performs much better in Auckland than in Paris. Indeed, in terms of average travel cost, PT is more attractive than CB in Paris, whereas the opposite result was attained for Auckland. In addition, the PT network in Paris is better than that in Auckland because of better PT network connectivity (mainly because of its Metro service), transfer synchronization, and service frequencies. Moreover, in Paris, the DAT of CB is twice that of PT, which could be of significant concern to commuters. However, this is a direct result of the manner of creating the groups for CB and the limited size of the study sample. This is the main reason why CB performs much better in Auckland.

Currently, there is a lack of investment in increasing the efficiency of Auckland PT systems, which inevitably would lead to mass use of PC. The Auckland Regional Public Transport Plan was created recently for the purpose of shifting public transport routing towards a hierarchical structure of networks that interact with each other so as to improve accessibility to PT service (Auckland Transport 2013). This study revealed that CB can be a good alternative to PC and PT and can help to improve commuter travel in Auckland. CB may help to reduce not only traffic congestion but also commuting travel costs. Furthermore, in Auckland, using PT or CB is basically similar with respect to price, travel time, and DAT. The only advantage for PT is fuel consumption, which is 15% less than CB. However, CB brings comfort with the commuting experience, reducing walking, waiting, and transferring times.

If minibus consumption was lowered and an attractive price compared to PT was maintained, CB would appear to be a very attractive solution in Auckland. For Paris, both fuel consumption and travel costs of CB are a little higher than those of PT, thus complicating its competitiveness with PT. However, if there are participants, CB can beat PC and PT.

Conclusions

With traffic congestion as a global issue in urban cities due to massive use of private vehicles by commuters, government agencies have focused on creating an attractive alternative. However, the conventional PT system possesses a high level of negative affect and requires improvements. The aim of this study was to propose a new commuting travel mode: customized buses. This potential novel transportation mode was compared to PT and PC in the cities of Auckland and Paris. Accordingly, a methodological framework was constructed to quantify operational performance measures. Subsequently, this framework was applied to the two cities to assess overall performance of PC, PT, and CB. Performance metrics such as travel cost, travel time, and fuel consumption were evaluated. Ultimately, a comparison of results for each city was made reflecting improvements CB could provide, followed by recommendations for actual implementation.
The results show that the PC is the fastest and most reliable mode of commuting, as expected. However, travel cost by PC is twice as much as for PT or CB in both Paris and Auckland and also consumes considerably more fuel. The results also demonstrate that a CB system would be more profitable in Auckland than in Paris. The French capital’s first class commuter transport system is better than CB with respect to most performance measures selected. Indeed, commuters would reduce not only their travel costs but also the difference in arrival time by using PT instead of CB. On the contrary, in Auckland, PT and CB exhibit many similarities. Both average DAT and average travel time are almost the same. However, using CB in Auckland would be financially attractive due to a lower fare cost than PT. Regardless of the city, even though private car is still in the lead, by far, CB appears to consume more fuel than PT. This singular shortcoming is superseded by the comfort CB brings to commuters. Reducing walking time, less wasted time during transfers, and assuring uncrowded vehicles contribute to commuters feeling at ease.

In summary, this study revealed that CB can provide a useful alternative for commuting travel in Auckland and Paris. However, this initial study was limited by the number of candidate trips. If more commuter trips were considered, CB would prove to be more efficient than PC and PT. Generally speaking, a CB system can improve its performance in urban areas with long commuting distance, high population density, and inefficient existing PT systems. Further research can evaluate the impact using an electric minibus on the performance of CB systems as well as the impact of other factors such as accessibility, flexibility, and value of time on commuters' mode choice behavior.

References


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**Romain Bologna** was, in 2015, with The University of Auckland, New Zealand. Currently, he is with the Urban Engineering School of EIVP in Paris.

**Benjamin Cabantous** was, in 2015, with The University of Auckland, New Zealand. Currently, he is with the Urban Engineering School of EIVP in Paris.
Estimation of Modal Shift Potential for a New Form of Dial-A-Ride Service

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Akdeniz University, Turkey

Ingmar Andreasson
Royal Institute of Technology, Sweden

Serdal Terzi
Suleyman Demirel University, Turkey

Abstract

The concept of a dynamic and flexible Intelligent Subscription Bus Service (I-Service) was developed, and two integrated questionnaires were conducted among the commuters of a large university campus. To determine travel times to the campus by I-Service, a digital urban road network map with travel time databases was produced, and software was developed to calculate optimum routes using these databases. Travel times for each participant were determined by the shortest travel time principle. The proposed hypothetical service was introduced to participants, and anticipated advantages for each participant were reported back to them by means of a second questionnaire to determine if they would prefer using I-Service. As a result, a 49% modal shift potential from all other modes in general and a 52% modal shift potential from private car to I-Service were found.

Keywords: Flexible public transport, optimum route, modal shift, road network map, dial-a-ride

Introduction

Today, people favor private cars and regard conventional public transport as a last solution. The primary reason for this is the inconvenience of public transport, including inappropriate routes, lack of services, lack of stops within walking distance, waiting at stops (especially in poor weather), lack of information on arrival times, in-vehicle crowding, shortcomings of payment systems, and excessive stops, all of which vary from place to place. The inability of conventional public transport to deter people from using private cars and the increase in citizen demand for private cars cause traffic problems, and infrastructure investments to eliminate these traffic problems require significant
Estimation of Modal Shift Potential for a New Form of Dial-A-Ride Service

Expenditures. Traffic jams, which occur as cities become building sites and alternative roads are inadequate, show that it is necessary to find alternative solutions to traffic problems. Proposals and services that enable people to favor public transport over private cars are the strongest of these alternatives.

To solve the transport problems experienced in urban areas in the recent years, various studies have been conducted in travel demand management, which aims to supervise demand rather than create additional demand through the construction of new roads. Travel demand management can be defined as shaping the available transport infrastructure through small investments that will allow citizens to use it more efficiently and ensure that journeys will shift to fuller and higher-capacity vehicles (Ozsöy 2005). In parallel with these objectives, orientation toward flexible transport services instead of fixed-route transport is among the important issues that will make the use of public transport more efficient. Flexible transport services have no fixed routes and no specified boarding/alighting points and times and are carried out by vehicles with a capacity of 4–20 people (Josselin et al. 2009). They aim to implement service that provides the best balance between unit cost and service quality and that provide an opportunity of offering comfort similar to the comfort of a private car (Hatipoglu et al. 2007; Akgol et al. 2014).

A flexible urban mode of transport to compete with the use of private cars should not be considered a competitor of, but complementary to, conventional public transport and should enhance the attractiveness of public transport. This mode is more flexible in terms of route and time than conventional public transport (Finn 2012) and includes on-demand transport, shared taxi, service vehicles of establishments, vehicle sharing, and group transport for the mobility impaired. In such systems, routes are determined according to incoming demand and shortest route optimization. The type of vehicle may vary by density and demand, and the method of payment may differ depending on demand by passengers. Reservations to use the service are made via Internet or telephone (Brake et al. 2007). Flexible public transport also is a comfortable transport option for those who do not own a private car or who are unable to drive or own a private car and is a good travel alternative for those who have difficulty using available public transport. It is a strong alternative to the use of private cars and encourages public transport (Hatipoglu et al. 2007).

Mulley et al. (2012) emphasized the necessity of encouraging the application of flexible public transport services and proposed a number of solutions to overcome the difficulties faced by these services in Australia, Europe and the U.S. Early regular applications of on-demand services were launched in the U.S. in the early 1970s. Currently being implemented in many countries around the world, particularly England, these services are spreading rapidly. Today, in the U.S. alone, there are about 23,000 companies and more than 370,000 vehicles serving in this mode of transport (Hatipoglu et al. 2007). Many local governments and public transport operators in England and Ireland use flexible transport service for social improvement, especially in areas in which public transport is difficult (Kamruzzaman et al. 2011); the service generally has been implemented in rural areas in terms of design and operation. In Switzerland, demand-responsive PubliCar minibuses run in connection with conventional public transport in
Estimation of Modal Shift Potential for a New Form of Dial-A-Ride Service

For passengers, factors such as cost, capacity, time, flexibility, and reliability are important for comparing different services. Considering these factors, passenger demand could be shifted from conventional public transport to flexible transport services (Vedagiri and Arasan 2009). Recent developments in communication technology have helped to alleviate transportation problems by enhancing alternative transport modes (Chow 2014), such as through vehicle position and customer demand determinations in real time, thus making flexible public transport more attractive (Hosni et al. 2014; Jung and Jayakrishnan 2011; Agatz et al. 2011). Dial-a-ride is one of these flexible public transport types.

Psaraftis (1980), Horn (2002), and Sayarshad and Chow (2015) studied dynamism in dial-a-ride using the “traveling salesman” problem for route selection. In this paper, however, we used the Dijkstra algorithm, as is demonstrated later. Other researchers who used the Dijkstra algorithm for similar problems include Gebeyehu and Takano (2008), Moloo et al. (2013), and Nykl et al. (2014). In this paper, the Dijkstra algorithm was used due to its convenience and simplicity for various programming and computation requirements, such as the capability of evaluating rising demand and instant acceptance/rejection.

According to Ramazzotti and Lios (2009), public transport authorities can support decision-makers with specific data and surveys to determine if the service is sustainable from different points of view. Hauser and Wisinewski (1982) studied the future potential of dial-a-ride transportation through questionnaires with no particular reference to modal shift as a result of increased use of the system.

In this paper, we generated the concept of Intelligent Subscription Bus Service (I-Service) and estimated the impact of this service on the rate of preference; in other words, we investigated whether people would favor available modes of transport over a proposed service with an intelligent and flexible vehicle fleet. I-Service is a dynamic and flexible transport service that determines its route according to incoming instant demand. This service can receive reservations at the last moment via Internet or telephone and can offer alternative payment possibilities. This new concept includes an algorithm capable of accepting or rejecting real-time demand (with flexible routes) as opposed to existing systems (especially the subscription buses currently in use in Turkey). These (existing) services operate on a monthly or annual subscription basis; hence, they charge more compared to ordinary public transport services. In addition, they operate only on fixed routes, giving rise to considerably long journey times. I-Service, on the other hand, is conceptualized on a “pay-as-you-go” basis. By optimizing between demand and journey time, overall travel times are kept to a minimum. When I-Service is compared with reserved taxis, the biggest difference is fares, since the seating capacities of taxis are
much smaller than the I-Service vehicles proposed. Fare cost, therefore, is one of the most important factors affecting demand for such services.

**Material and Method**

**Questionnaire I**

A survey was conducted with 606 people on the main campus of Akdeniz University in Antalya, Turkey, to determine the current travel characteristics of passengers who regularly commuted to and from the campus. Using respondent address information, digital maps that showed the need for transport to the campus within different time periods were determined. The optimum number of vehicles required for users of this service, the travel kilometers of the vehicles, and the new transport characteristics of the passengers were determined by modeling the I-Service. Finally, the participants in the survey were individually notified of the information on the new transport characteristics via their email addresses and asked if they would prefer to use the service. In this way, the shift likely to occur in the mode of transport was estimated.

**The A-Service Model**

A university campus was selected as the pilot area, and possible users of the system were students, academic staff, and other staff. Participants were asked to provide personal information (e.g., occupation, age, gender, health status) and residence location; the importance they attached to comfort; whether they possessed their own car; their existing travel mode; travel times, days, and hours they commuted; total waiting and travel times of their use of available public transport; and their email addresses. Participant responses were grouped according to their times of commuting to and from the campus, and the groups were geocoded by means of Geographic Information Systems (GIS) according to the address information they provided.

This study aimed to determine the service duration of I-Service during the day and data about the travel times of potential passengers by modeling the concept of I-Service vehicles. For this purpose, information on the speeds that could be performed on the urban road network of Antalya in different time periods was collected. To do this, 10 global positioning system (GPS) devices were placed in approximately 100 vehicles for four months; the GPS devices were monitored online, and the data received were recorded via a central computer. In this way, information on the speeds that could be performed at different times regarding each road link was obtained, and 34 speed maps were created.

The model developed for I-Service aimed to carry as many subscribers as possible at minimum total journey time since time was chosen as the most important parameter. That is, travel time was prevented from exceeding a specific range by increasing the number of vehicles when necessary. Dijkstra’s algorithm, which calculates the shortest route from a source node to all other points on a network, was used in the model (Taha 2007). For the model, software was developed in Java to compute the shortest routes between given sets of origin and destination points (Figure 1).
For route calculations, the link travel times data gathered earlier were used, as shown in Table 1.

<table>
<thead>
<tr>
<th>Link</th>
<th>Travel Time</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$A_1$</td>
<td>$B_1$</td>
</tr>
<tr>
<td>2</td>
<td>$A_2$</td>
<td>$B_2$</td>
</tr>
</tbody>
</table>

$X = \text{Coefficient of resistance for demand (X=0.001)}$. In quickest route calculations, coefficient encourages I-Service vehicle to use this link where there is demand; achieved by intentionally reducing travel times on these links.

$A_i = \text{Travel time for link } i$

$B_i = \text{Number demanded for link } i$

In this case, the link travel times were calculated (based on the Dijkstra algorithm) by the following:

If a call (demand) exists; $(B_1 \neq 0)$. Travel time for this link (Link 1) =

$$\frac{A_1}{B_1 + X}$$  \tag{1}$$

If a call (demand) does not exist, $(B_2 = 0)$. Travel time for this link (Link 2) =

$$\frac{A_2}{X}$$  \tag{2}$$
After setting up the model, data on the number of people boarding and the identity of the links onto which they boarded were entered into the software database. When the shortest route was calculated according to the Dijkstra algorithm, the vehicle was assigned to the links with service demand. In this way, results were obtained for such questions as how many people were carried by how many vehicles, how many kilometers were traveled in total, and how the travel times turned out for each respondent for “a typical day.” Based on the results produced by the software, it was determined that 64 vehicles would be required if all respondents used this service for commuting to and from campus. In this case, a distance of 5,300 kilometres (3,293 miles), on average, was traveled per day.

**Cost**
To estimate the single fare for a one-way journey by I-Service, the monthly total cost was computed. As a result of a number of calculations, the details of which are outside the scope of this paper, this figure was determined to be a total of TL 135,500 ($52,613). The number of people using the service also was calculated to determine the travel fare per capita for this service. For this purpose, data from Questionnaire I on the number of possible users of the service vehicle were used. Responses to “If you had a chance to choose for commuting to and from the campus among the modes of transport classified as public transport, service vehicle, automobile, motorcycle, bicycle, and pedestrian, what would be your order of preference?” from Questionnaire I determined the rates of preference of academic staff, other staff, and students. In total, 100% of those who preferred service vehicles in the first place and 50% of those who preferred them in the second place were calculated, and the percentages of possible users were determined. Accordingly, 42.7% of academic staff, 66.4% of administrative staff, and 30% of students were possible users of the service. The number of commuters to and from the campus were 2,081 academic staff, 3,294 other staff, and 37,379 students (obtained from the university). Thus, it was determined that I-Service would have 888 + 2,188 + 11,196 = 14,272 potential users at Akdeniz University. As this figure is higher than the total passenger capacity, the travel cost would depend only on the rate of occupancy of the vehicles. The correlation between the travel costs per capita for I-Service vehicles and the total rates of occupancy of the vehicles was examined. The service price would be TL 2.50 ($1), and a profit of TL 0.50 ($0.20) per capita would be made in the event that the rate of occupancy was around 50%.

**Questionnaire II**
A map showing the travel times by I-Service, obtained from the route travel times data, was used (Figure 2) to assist the respondents with Questionnaire II. A total of 377 people participated in the second survey. The travel times and travel costs for I-Service were determined by modeling the I-Service. The current transport characteristics and the new transport characteristics that would occur if the respondent used I-Service, general information on I-Service, and a questionnaire form (Questionnaire II) containing two questions were emailed to the respondents of Questionnaire I (Table 2).
Estimation of Modal Shift Potential for a New Form of Dial-A-Ride Service

FIGURE 2. Map showing travel times if I-Service used

TABLE 2. Questionnaire II

<table>
<thead>
<tr>
<th>Question</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Would you prefer I-Service?</td>
<td>Yes, every weekday (…)</td>
</tr>
<tr>
<td></td>
<td>Sometimes, a few days (…)</td>
</tr>
<tr>
<td></td>
<td>No (…)</td>
</tr>
<tr>
<td>If your answer is No, why?</td>
<td>(...)</td>
</tr>
<tr>
<td>2. Do you find the projected price of I-Service appropriate?</td>
<td>Yes (…)</td>
</tr>
<tr>
<td></td>
<td>No (…)</td>
</tr>
<tr>
<td>If your answer is No, how much would you pay for this service?</td>
<td>(...)</td>
</tr>
</tbody>
</table>

Summary of Surveys

In summary, the first survey, 606 people were asked about their age, gender, occupation, email address, residential address, existing modes of commuting transport, time spent for commuting, travel schedules, satisfaction levels, desired modes of commuting transport, etc. Based on the address and travel schedule information provided, a hypothetical model was developed for these particular individuals to determine if the proposed I-Service would offer shorter travel times between the same origins.
and destinations at competitive costs. Also in the first survey, we determined the number of people who would use an existing subscription bus service if introduced. To be conservative, in the model, this demand was reduced by 50% to be able to accommodate potential survey uncertainties. After calculating one-way fares using the model, a second survey was conducted with these 606 respondents, and 560 people expressed whether they would use the proposed I-Service at a particular fare and a commuting travel time between their origins and destinations.

**Findings**

According to the results obtained from Questionnaire I, the distribution of the participants was academic staff (40%), other staff (24%), and students (36%). When the distribution was examined by modes of transport, automobile (48%) was the most preferred mode (Table 3). When the results of both surveys were analyzed, it was found that automobile users had the largest potential to change mode, followed by public transport users; 44% of public transport users and 34% of automobile users continued to favor the automobile.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile</td>
<td>48%</td>
</tr>
<tr>
<td>Public transport</td>
<td>26%</td>
</tr>
<tr>
<td>Pedestrian</td>
<td>18%</td>
</tr>
<tr>
<td>Bicycle</td>
<td>5%</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>3%</td>
</tr>
</tbody>
</table>

According to the travel maps with time dimensions (e.g., Figure 3), it can be seen that the need for transport to the campus is denser during morning hours.
FIGURE 3. Example of demand for transport to campus in different time slices and arbitrarily-selected routes for demonstration purposes.
As a result of the data entered onto the map, the speeds of traffic in different links within the desired time zones can be seen. A sample of these maps is provided in Figure 4.

FIGURE 4. Sample of GIS map for speed range

In total, 20% of the public transport users and 26% of the automobile users preferred the new service. Reasons why the service was not preferred are presented in Table 4. It was determined that there would be a 49% modal shift in total (from 48% to 23% mode share), which shows the effect on the shift between modes. The service would lead to a 52% reduction in the use of automobiles, a 59% reduction in public transport, and a 26% reduction in pedestrians.

<table>
<thead>
<tr>
<th>Reason</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Familial reasons</td>
<td>10%</td>
</tr>
<tr>
<td>Comfort</td>
<td>1%</td>
</tr>
<tr>
<td>Need for a private car</td>
<td>12%</td>
</tr>
<tr>
<td>Health</td>
<td>16%</td>
</tr>
<tr>
<td>Fare</td>
<td>23%</td>
</tr>
<tr>
<td>Proximity</td>
<td>25%</td>
</tr>
<tr>
<td>Time</td>
<td>13%</td>
</tr>
</tbody>
</table>

TABLE 4. Reasons Why I-Service Not Preferred Among Participants
When the effect of the distribution of occupation on the modal shift caused by the I-Service for Akdeniz University campus was examined, it was seen that 51% of academic staff, 71% of other staff, and 44% of students shifted their mode.

Finally, the estimated distributions of the modes before and after the I-Service were compared. As seen in Table 5, the rate of use of automobiles was 48% before the survey, which dropped to 23% (second) after the introduction of I-Service, which ranked first (49%). This indicates that this alternative transport service would be an essential step towards tackling traffic problems.

<table>
<thead>
<tr>
<th>Mode of Transport</th>
<th>Participant Distribution before I-Service</th>
<th>Participant Distribution after I-Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-Service</td>
<td></td>
<td>49%</td>
</tr>
<tr>
<td>Automobile</td>
<td>48%</td>
<td>23%</td>
</tr>
<tr>
<td>Public transport</td>
<td>26%</td>
<td>11%</td>
</tr>
<tr>
<td>Pedestrian</td>
<td>18%</td>
<td>13%</td>
</tr>
<tr>
<td>Bicycle</td>
<td>5%</td>
<td>3%</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>3%</td>
<td>1%</td>
</tr>
</tbody>
</table>

These rates indicate that I-Service has a high potential for being preferred. Although these auto trips to/from the university are but a small percentage of total trips in the area and the impact on traffic reduction would be minimal, putting similar services into practice in places such as universities, factories, shopping centers, and airports could impact overall traffic. Also, the scheme may have positive implications on campus parking, where there are currently serious parking issues. All of these potentials will be the subject of further research.

Private car users would financially save 23% if using I-Service but would experience 16% longer travel times. Public transport users, however, would pay 45% more and shorten their travel times by 64%. This shows that the I-Service, as presumed, would be an alternative that is quicker than ordinary public transport and cheaper than private car use.

A sensitivity analysis was carried out on the reliability of the responses to the questionnaire about the willingness to use the I-Service. The results showed that the most effective factors in user choice are the new travel times and fare costs (by 85–95%); age, gender, occupation, and satisfaction level with existing mode of transport contributed 10–40%. These figures imply that the acceptability potential of the I-Service in application areas other than the study area is likely to be similar.

**Discussion and Conclusion**

Today, new modes of transport are being introduced to reduce traffic density and encourage people to use public transport instead of automobiles. Seeking private car-based solutions does not solve the problem but merely defers it to some future time. Conventional public transport remains insufficient for making people switch from their private cars to public transport. Hence, more innovative modes of transport to reduce
the use of private cars will contribute towards easing the traffic problem. An intelligent transport service with a reservation system that provides a flexible and dynamic public service based on minimum travel times was introduced and modeled in this study. The new I-Service was designed to provide an economical service that offers comfort close to that of a private car, and its effect on the mode of transport was investigated. Information from 606 participants was obtained through two questionnaires conducted on the Internet within the campus of Akdeniz University. The study estimated the required number of vehicles and drivers if respondents were to use the service. Optimum routes, travel times, and kilometers for these routes were determined, as were one-way fares and travel times for each passenger. A total of 49% of the respondents to Questionnaire II stated that they would use this service at a 2.5 TL ($1) single fare.

Examining the reasons why 51% of participants did not prefer the I-Service, many factors were influential. The most common reasons included living near the campus, health, and fare. Pedestrians and bicycle users did not prefer this service because they lived near the campus; automobile users did not prefer it because they use their automobile for more than commuting to and from campus; and the public transport users did not prefer it because they thought the fare was high. There was estimated to be a 52% modal shift from the use of automobiles to the use of I-Service; it would provide a more comfortable service than conventional public transport, which would lead to a 59% shift from public transport and a 26% shift from pedestrians. When automobile and motorcycle users were evaluated collectively, the mode shift rose from 52% to 54%. In total, 51% of academic staff, 70% of other staff, and 44% of students contributed to the mode shift caused by I-Service. These rates indicate that I-Service has a high potential for the future and deserves further and special research attention.

Acknowledgments

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Transforming Bus Service Planning Using Integrated Electronic Data Sources at NYC Transit

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New York City Transit

Abstract

The installation of an Automatic Vehicle Location (AVL) system alongside existing Automated Fare Collection (AFC) data spurred development of an inferred bus boarding and alighting ridership model at New York City Transit (NYCT), allowing for 100% passenger origin-destination (O-D) data citywide. Analysis techniques that relied primarily on professional judgment due to lack of data were replaced by more sophisticated statistical techniques. This paper describes two case studies and the resulting service planning potential from having access to fully-integrated big data sources: a neighborhood-wide analysis of performance and ridership, where 100% data allowed planners to pinpoint specific, low-cost reroutes and stop changes to better serve riders, and identification of an optimal route split location for a long route with poor performance by minimizing passenger impact using modeled O-D data. In both examples, new data sources allowed for novel analysis throughout problem investigation as well as forecasting ridership and cost impacts of proposed service adjustments. As the agency’s ability to leverage these data improves, it will support Title VI obligations as well as performance monitoring.

Key Words: Automatic vehicle location, AVL, automated fare collection, AFC, transit performance, O-D data, ridership forecasting, service adjustments

Introduction

MTA (Metropolitan Transportation Authority), New York City Transit (NYCT), and the MTA Bus Company operate 316 routes across the 5 boroughs of New York City (NYC). The transit network operates 24 hours per day and serves almost 3 million bus riders and 6 million subway riders daily. Scheduling, headway determination, and route planning historically have been conducted using sampled data collected by traffic surveyors whose primary role is to collect boarding and alighting for bus trips as well as timings for schedule-making and performance measurement. The rollout of the MTA
Bus Time Automatic Vehicle Location (AVL) system across NYC allows for continuous monitoring of performance and running time for every route, with data approaching 100% completeness. Furthermore, by integrating Automated Fare Collection (AFC) data with AVL data, an inference model that produces passenger boarding and alighting locations was developed, yielding trip level loads and passenger origin-destination (O-D) data at both the trip and neighborhood levels on single-mode and inter-modal trips.

Due to budgetary constraints with traffic surveyors, MTA Board guidelines required ridership and running time analysis of weekday bus service every two years, with weekend service checked every four years. Similarly, for operating performance reporting, only 42 key routes were analyzed using a stratified sample. This yielded limited amounts of data to be used as input into the service planning process and high reliance on professional judgment and community input. Now, with AFC and AVL data collected daily for every route, the problem has shifted to determining how to use these data to make sound decisions based on quantitative evidence. This paper discusses the resulting service planning potential from having access to fully-integrated, rich, big data sources. This planning potential is contingent on the availability of high-quality, validated ridership data sources. The specific ridership data sources were developed in-house by Zeng et al. (2015) at NYCT. The development and validation of these data sources are significant efforts and have been detailed in separate papers and, therefore, are not in the scope of this paper. The focus is on two case studies that illustrate how these data sources were combined to analyze the following topics: route performance, running time, dispatcher-initiated service changes, boarding and alighting locations, average passenger trip length, passenger transfers, passenger type analysis, O-D patterns, and ridership impacts. The first case-study describes a neighborhood-wide bus service analysis in the Co-op City section of the Bronx, and the second details the passenger-optimal re-design of a Manhattan bus route with performance problems.

Background

The in-house-developed MTA Bus Time AVL system was installed gradually on the fleet of more than 6,000 buses between 2012 and 2014. The system’s primary function is a customer information system, but from the project’s inception, Operations Planning has been involved in testing and using AVL data for internal planning purposes. Data were used primarily to track vehicle locations and match actual movements to schedule to report On-Time Performance (OTP) and Wait Assessment, NYCT’s main publicly-reported headway-based performance indicator (a measure of the number of headways that pass an acceptable waiting threshold) defines on-time as arriving within -1 to +5 minutes of schedule time, and a headway passing wait assessment is within +3 (peak) or +5 (off-peak) of scheduled headway (Cramer et al. 2009). Schedule matching was accomplished via several algorithms, tying 30-second reported AVL data to scheduled times at timepoint locations along the route and later refined to include depot pull-in/pull-out information, bus status, and route dispatcher-initiated service changes from other sources to report 100% data on all buses with a high degree of accuracy (Levine et al. 2014). AVL data replaced a system of manual traffic surveys, providing sample data for performance reporting conducted on just 42 key routes.
Following the success of matching AVL data to schedule, these data were used for running-time calculations to feed the schedule-making process. This greatly improved the accuracy of schedules while providing a mechanism to analyze bus running times associated with: stop and route modifications, temporal traffic variability, roadway construction, bus lane implementations, traffic signal timing, special events, and shuttle operations.

NYCT took significant steps in expanding usage of AVL data by developing a model connecting AVL with AFC data to estimate boarding and alighting locations of all passengers riding buses (Zeng et al. 2015). The model relies on matching payment time and bus position provided every 30 seconds from AVL data to locate customer boardings. An algorithm was developed to determine customers’ transfer or alighting locations from subsequent swipes of the same MetroCard. The tap-on only structure of the NYCT fare payment systems requires that alighting locations be inferred from subsequent farecard activity; thus, there is no guarantee that the modeled journey is precisely the one actually made. The small minority of ridership that uses cash and other non-MetroCard payment methods are assigned travel distributions that mirror that larger MetroCard population. Although this breakthrough provided O-D and route-choice information for nearly three million passenger bus trips on a daily basis, this ridership detail is best suited for higher-level analysis of ridership patterns. Other agencies and academic researchers have developed similar methodologies for estimating bus passengers’ boarding and alighting locations from AVL and AFC data (Munizaga et al. 2011; Alsger et al. 2015; Lu et al. 2011; Reddy et al. 2009). This breakthrough provided O-D and route-choice information for nearly three million passenger bus trips on a daily basis. Ridership information inferred from the integrated AFC and AVL model was validated against manually-collected ride check data, which was the previous source for scheduling and planning ridership information. An in-house reporting server was enabled to automate comparisons of load profiles reported by each data source to ensure that automated model results were credible. This further enabled simple identification of when bus route model results that deviated from manual checks to determine if algorithm adjustments were warranted, while also acknowledging that manual data sources were also subject to uncertainty. Greater detail surrounding the development and validation of the boarding and alighting model used for NYC buses can be found in Zeng et al. (2015).

Transit agencies deriving similar information with Automated Passenger Count (APC) data are able to use those data to support numerous planning and operational objectives (Hammerle et al. 2005). Boarding and alighting data developed from AFC models are derived from passenger-specific travel patterns and can be connected with transfers to other bus services or subways. APC data do not connect boardings with alightings and require an iterative fit process or other approach to gather O-D detail (Furth et al. 2005; Mishalani and McCord 2013).

Other agencies have leveraged boarding and alighting information for improved understanding of passenger usage within a transit network (Gokasar et al. 2015). NYCT began using these data for similar purposes along with incorporating them into the entire planning process, beginning with problem investigation through forecasting.
ridership and cost implications of proposed service adjustments. As big data sources and boarding and alighting inference models become more commonplace at transit agencies, there is significant potential for peer agencies to use them as valuable tools in planning projects. By using multi-day averages to estimate typical ridership, the information obtained is more current and no longer subject to single-day ridership variations due to weather, local events, and road disruptions. Multi-day results are more representative of the total population of riders that use the system over the collection period, thus improving the statistical validity of any subsequent analyses performed with the output data. Increased data sophistication allows for new planning approaches at NYCT, ranging from route modifications for operational improvement to neighborhood-wide studies of customer travel patterns.

**Neighborhood Bus Service Planning Using AVL and AFC Data**

With complete operational and ridership data available for all routes, the assessment of bus performance and potential improvements to service supplying the needs of an entire neighborhood could be evaluated. With manual surveys, complete data at this scale and temporal consistency were not previously feasible, prohibiting investigation of neighborhood-level service as well as comparability across routes. Integration of AFC and AVL data not only allowed for on-board ridership estimation, but a deep dive into AFC data also enabled tracking of passenger journeys across multiple unlinked trips. This is dependent upon consistent passenger use of the same MetroCard, which includes a unique serial number in the transaction record. The fraction of passenger trips for which fare payment is cash is known and used to scale-up results that are dependent on electronic media only. To serve the needs of residents of the community, full journey patterns were tracked based on anonymized AFC data with estimated boarding and alighting locations.

**Case Study: Co-op City Neighborhood Analysis**

Co-op City is a neighborhood of high-rise apartments in eastern Bronx with a population of about 35,000 people and consisting of 5 residential sections, 3 shopping centers, and additional commercial facilities throughout. It has a mix of students, workers, families and retirees, and a large number of older adults live in the residential towers but account for just under 20% of the population. There are three distinct, contiguous areas; approximately 75% of the population lives in the northern part, which is encircled by a large loop of primary roadways and accessed by several smaller loop, and the remaining 25% of the population lives in the southeast corner of the neighborhood. The Bay Plaza Shopping Center, a large regional shopping center, occupies the area between the two major residential areas. In 2010, as a result of a significant shortfall in the MTA budget, a comprehensive cost reduction program, including staff reductions, renegotiation of contracts, and service cuts, was undertaken. Changes in Co-op City were substantial and included re-routing several routes and discontinuing one. The service changes reduced operating costs; however, they also provided more direct access to traffic generators outside of Co-op City (MTA NYCT 2011, 2014). In the years following cuts, community dissatisfaction with bus service was voiced. The 2013 Co-op City bus map is presented as Figure 1.
At the request of community leaders, a complete bus service planning study for Co-op City was undertaken in 2013 to evaluate bus service in the neighborhood. The timing of the study coincided with completion of NYCT’s bus ridership estimation model, allowing for these data to be used for planning and route change analysis for the first time (MTA NYCT 2014). A key study goal was to evaluate current service on 100% ridership data for Co-op City, as well as to track journeys of passengers to/from Co-op City. Automated ridership data, comprising about 17,500 average weekday records for an entire month, were used in the study alongside a passenger interview survey with about 1,300 respondents conducted over several days. Although vocal community members had clarified the bus service they felt would best serve Co-op City, complete ridership data revealed potential service that would benefit the entire community. Previous service planning managed through community complaints or
requests potentially could result in service that is advantageous to a small population but not the greatest number of riders. Planning with 100% ridership data presents a more complete and unbiased reality of the existing ridership needs and, by extension, community needs. Costly and timely stop-intercept surveys have a low sample rate, as well as selection bias of respondents (Doxsey 1984). Planning initiatives also may change substantially from original to final proposals, making surveys a poor source of data.

The study objectives were organized into several broad categories:

- Analyze whether existing service was provided as scheduled and assess the quality of service being provided.
- Determine if bus routing within Co-op City provided sufficient intra-neighborhood travel options.
- Study bus boardings and alightings to identify key stops and areas that were under or overserved.
- Analyze O-D patterns of residents and visitors to determine if service was designed optimally to meet their needs and whether a high number of passengers were forced to make several transfers to reach their destinations.

AVL data revealed that bus service in Co-op City was provided at or above service standards within the Bronx. By collecting a statistically-significant number of running time records via an AVL system, the mean as well as 15th and 85th percentiles of actual running times for routes could be compared for every time of day with what was provided in the schedule. Some routes were identified for inaccurate running times by comparing with averages and ranges of the actuals and adjusted in the next schedule.

To study ridership patterns of Co-op City residents and visitors, only passengers boarding or alighting within Co-op City boundaries were considered. This subset was further split into residents and visitors by determining if the first fare payment of the day was made within Co-op City boundaries (classified as a resident) versus elsewhere in the system (classified as a visitor). O-D pairs of residents helped determine the most important areas to serve. Figure 2a, visualized by the widths of the travel arcs presented, shows the frequencies of O-D pairs for destinations outside of Co-op City, and Figure 2b shows frequencies for travel within Co-op City. Visualizing major O-D links made it clear that the primary function of transit in this neighborhood is delivering residents to destinations outside the neighborhood, functioning as feeders to subways. By tracking passenger journeys, it was estimated that 92% of all passenger trips beginning in Co-op City were bound for destinations outside Co-op City. From morning rush through evening rush, there were more than 10,000 bus–subway and subway–bus transfers coming from Co-op City, highlighting the significance of subways as traffic generators for Co-op City and the importance of providing connectivity via the bus network. This finding, corroborated by survey results, was valuable, as it departed from community feedback that indicated that a route providing better service within the neighborhood was the primary need (Cruz 2013). This highlighted the benefit of electronic data to better communicate actual needs, and the matching of O-D pairs provided from survey results to estimations provided by the ridership model highlighted the ability of the data to provide representations of ridership and service patterns.
FIGURE 2. Origin-destination arcs in and around Co-op City and proposed re-route
Although most Co-op City passenger trips had O-Ds outside the neighborhood, trips made within Co-op City were examined to determine if improvements on behalf of the community were possible. A pattern of trips from the south end of the neighborhood towards Asch Loop (in the center of Co-op City), proximate to several commercial areas such as the Bartow and Bay Plaza malls (Figure 2b), emerges from the data, which would not have been uncovered with manual ridecheck data, as they lack O-D components. A minor service revision resulted, with six more stops along four routes, including the re-route of one route through the loop to better serve demand highlighted by this data (Figure 2c).

**Inter and Intra-modal O-D and Transfer Analysis**

O-D patterns of riders leaving Co-op City were studied to determine if service provided matched observed journeys, and particularly if they were served under a single fare by NYCT’s fare policy. Current transfer policy allows one free bus-bus or bus-subway transfer within two hours of initial fare payment, and community complaints indicated that many riders were negatively affected by service changes that introduced double-transfer trips. Although the ridership estimation model makes use of subsequent AFC transactions to determine a passenger’s boarding and alighting stops on a single trip, tracking a user’s transactions throughout the two-hour transfer window can determine true O-Ds of a continuous journey with potentially multiple modes. Tracking journeys identified that only 8% of Co-op City residents’ journeys began and ended within Co-op City, another 55% were bound for Bronx destinations outside of Co-op City, 35% were bound for other boroughs, and the remainder were bound for neighboring counties (Figure 3a). This analysis illustrated that many residents were undertaking very long trips, often with transfers. Since a large proportion of weekday morning peak commuting trips were bound for subway lines close to the neighborhood (1, 2, 4, 5, 6, A, D), bus-subway transfers were analyzed (Figure 3b).

The analysis found that new double transfer trips created by the 2010 service changes impacted fewer than 50 riders. These journeys could have been satisfied by a single transfer and a very moderate increase in walking distance. The analysis also showed that customers originating or destined to stops along Dreiser Loop in northern Co-op City were using a transfer with the Q50 bus, which did not serve Dreiser Loop. Customers were making an extra transfer to go to/from the Pelham Bay Park subway station or other destinations in the Bronx or Queens served by the Q50. In response, a new Q50 stop was created at Dreiser Loop to serve those customers on a single fare and without a transfer.
FIGURE 3.
Co-op City borough destinations and weekday morning bus to subway transfers
Positive Reception and Future Neighborhood Analyses

Service changes were communicated to the community with the expectation that service would improve within Co-op City (Rocchio 2014). The positive reception to the conclusions of the Co-op City study generated interest in extending this process to other NYC areas with even larger geographic and ridership scopes (Rivoli 2014). Expanding to an area of Northeast Queens with more than 35 bus routes, multiple subway connections, and daily ridership in excess of 300,000, both challenged the processes used in Co-op City and highlighted the benefit of big data sources. Passenger trip detail was quickly taken from individual passenger and route-level detail to macro detail for evaluating the quality of service in large areas. Figure 4 shows inter-neighborhood O-D arcs in excess of 1,000 average daily weekday riders. Neighborhood boundaries were defined by the NYC Department of City Planning (DCP), and stop-level ridership was aggregated to larger areas via geographic information systems (GIS). The significant travel subway stations generate confirmed the expectation that providing subway feeder service in this region is one of the most important objectives for NYCT to meet in this area.

FIGURE 4. Significant Northeast Queens neighborhood O-D arcs
NYCT’s ability to analyze big data has permitted for scaling up the size of such studies, along with the ability to be more responsive to community complaints regarding service. Future plans will expand the scope of neighborhood bus studies to the entire borough of Staten Island (Barone 2015).

**Single Route and Redesign and Analysis Using AVL and AFC Data**

Along with the success of the Co-op City study, a single route in Manhattan, the M5, was analyzed at a more micro level of detail. The M5 bus route runs from the George Washington Bridge Terminal (Broadway and W 178 St) in Upper Manhattan to South Ferry in Lower Manhattan. Average weekday ridership exceeds 13,000 riders and is one of the longest bus routes in Manhattan (12 miles). The M5 operates limited-stop service on weekdays and local service overnights and weekends. The same service cuts that resulted in changes to Co-op City in 2010 included discontinuing service on one southern Manhattan route, M6, and extending the M5 to the southern end of Manhattan to cover the gap in service. Figure 5 shows the route profile and location of original Houston Street terminal with average weekday estimated boarding and alightings.

![FIGURE 5. M5 Ridership profile with route path](image)

After the M5 was extended to South Ferry in June 2010, the Department of Buses’ Manhattan Road Operations reported that the route experienced significant delays. Additionally, there has been an increasing number of concerns from the community and elected officials about lateness, gaps in service, and the number of buses being short-turned at various points along the route. OTP issues would have caused surface line dispatchers (SLDs) to short-turn certain bus trips to provide service in the opposite
direction, thus not serving certain stops with scheduled frequency. Operational
difficulties and community concerns identified the M5 as a potential candidate to
explore the novel ways in which service could be redesigned using big data.

Performance Reporting
After community complaints regarding service quality had been raised on the M5,
they were confirmed using AVL data. The existing performance-measuring framework
developed in tandem with the AVL rollout at NYCT confirmed that the M5 was
consistently one of the lowest-performing buses in the network. Over an entire month,
en-route OTP at pre-determined timepoints was below 50% for limited (rush-hour and
midday) service. Wait Assessment at these stops was just over 70%. At Houston Street,
buses were late 53.5% of the time in southbound direction, and at 9 AM were late over
70% of the time. Poor performance drove the decisions to short-turn buses to maintain
service in the opposite direction by the SLDs.

Service Changes
A majority of the real-time service adjustments made by SLDs to improve service
reliability are short turns, dark-to movements (beginning service a later stop than the
schedule origin), or skipping stops through part of the bus trip. These actions are done
to address lateness and maintain even spacing, as problems arise frequently and tend to
persist between trips. The service changes reported by passengers were also validated
through a novel application of AVL records. By tracing the movement of a specific bus
trip along its path and identifying cases when arrivals at expected stops were absent
for the remainder of the trip, the dispatcher intervention to short-turn a bus and the
approximate location at which it happened could be identified. The associated dark-to
movements in the opposite direction of short turns were also identified through this
process. An electronic booking system (EBS) exists for manually-recording service
changes such as short turns and records of other unplanned events. However, the most
important information from this system would be expected to be logged during periods
of greatest system duress and is then dependent on consistency of input by hundreds
of dispatchers during the busiest periods of managing bus service. When cross-checking
the inferred service changes from AVL data with EBS records, it was found that AVL
data provided a more reliable and more thorough source of service interventions. These
data are also consistently queriable and comparable across a large number of records,
which is not true of manually-entered data.

This process identified that over the course of four months, 9.8% of weekday
southbound scheduled trips on the M5 were short-turned at some point along the
course of their journey. An unequal distribution of service interventions by time of day
led to the 8 AM service hour having 18.2% of scheduled trips short-turned. Although
an external system for tracking service changes existed, the more comprehensive AVL
system discovered that there were almost one-third more service changes than initially
thought. In this hour, the combination of short turns and low operational performance
would lead to a significantly higher headway experienced by passengers than is
scheduled for this service. In the absence of the processed AVL data, NYCT would have
underestimated the extent of the performance problems that resulted from short turns.
This process proved that passengers voiced credible concerns.
Boarding and Alighting Estimation
To address passenger concerns on service changes and gaps in service, ridership data inferred from AFC and AVL data were used to guide the planning process. Due to the length of the M5, thorough checks of ridership for every stop on the route formerly were cost-prohibitive, even for a single day. Point checks at a limited number of stops cost-effectively collect the requisite data for service planning, but do not provide the same level of accuracy. Automated ridership model data quickly provided an overview of route usage and identified important service areas, as shown in Figure 5. Distinct maximum load points in different sections of the route, as well as areas of high turnover, highlighted areas of important service delivery and also served to confirm the appropriateness of the short-turn locations in the southbound direction.

Repeating an analysis procedure done for Co-op City, the most popular O-D pairs were identified. Although the M5 traverses most of Manhattan, 75% of the ridership was found to be making trips that extended no more than two neighborhoods beyond the boarding location. Neighborhoods were defined by the DCP and grouped or divided as appropriate so they contained approximately the same number of stops, about 20–25 blocks long. With specific boarding and alighting information available, average passenger trip length could be estimated easily. It was found that the passenger trip length distribution skewed heavily towards shorter trips, with the most common trip length 0.4 miles and the average trip length 2.2 miles. The ratio of average trip length to total route length for the M5 was 0.179, meaning an average rider uses only 18% of the route. The typical ratio for Manhattan routes is 0.27 and is 0.28 for all NYC. The M5 ratio was the fifth smallest of the 38 Manhattan routes, implying that the M5 length may be out of proportion, but also that other Manhattan routes may benefit from route rationalization. From this, it was determined that the M5 could be split while still satisfying most rider needs.

Passenger Types
AFC data capture the nature of the farecard purchased (e.g., pay per ride, 7-day unlimited, 30-day unlimited, etc.) along with details about discounted fares (e.g., senior, disabled) and are included in ridership data. This allows for targeted analysis of older adult riders who may require specialized bus service. This can also be extended to understanding the nature of different riders such as tourists or infrequent riders using single rides as opposed to unlimited rides.

Although a large majority of M5 riders took short trips, there were some long trips that traversed a majority of the route despite the fact that the M5 has a maximum run time of almost two hours and is redundant with the faster subway for most of its path. Analyzing rider behavior based on the few attributes present in AFC data is another improvement enabled by automated data sources. It was hypothesized that older adult or disabled riders may prefer or require a bus trip due to a preference to avoid stairs and longer access distance to underground subways. Analyzing riders with senior or disabled discounted fare structures found a slightly larger average trip distance was found for these riders, but at only 0.1 mile longer than the average population, it was determined that these riders trips were similar with the general population and would also benefit from a rationalized M5 route. This hypothesis could be disproved with minor data
Passenger Transfers

AFC data reveal that approximately one-quarter of the ridership of the M5 transfers to or from the subway as part of their journey. In the part of NYC that the M5 operates, local subway service is spaced about every 10 blocks or closer and almost always is parallel to the direction of them M5. These are presumably journeys that could be replaced easily by walking, but free transfers permit a faster or more comfortable journey to the subway via bus. This may explain why the mode for travel distance is only 0.4 miles.

The most common bus-subway transfer points for the M5 accounted for less than 8% of all bus-subway transfers for the route, implying that subway feeder passenger trips are spread throughout the route with no one station dominant in bus-subway transfers, as indicated in Figure 6a. In the case of the M5, understanding the geographic distribution of subway transfers does not change the planning decisions inferred from single-trip data, although it does serve to explain M5 ridership mode choices and trip lengths given other transit options available.

FIGURE 6. M5 subway transfers and optimal split point
**Route Split Approach**

To address operational issues associated with running a long route through a city environment, splitting the route was proposed. With complete boarding and alighting trip information for each passenger, the negative impacts of a route split could be quantified by determining those passengers that would need to transfer to complete their journey (induced transfers). Although boarding counts and average loading may help guide a split point, this fails to consider the full journeys of passengers and does not minimize the number of induced transfers.

A short shuttle route with few stops may achieve high performance, but would not serve passengers in a practical manner. An optimal solution could be approximated from these data in the absence of other operational considerations such as depot location, operational feasibility, existence of layover space, etc., by setting an objective function to minimize the number of riders that would require a transfer under the new route design. A non-linear Excel solver was used to iterate through each set of potential new terminals, with stops defined by their relative stop order. The nature of the solver used does not guarantee that a mathematical minimum is reached, although for this application the finite number of feasible combinations gives confidence that the returned solution is the optimal split point. Different objectives could be defined, such as distributing ridership evenly. To solve this objective function, three constraints were defined, including northern boundary for southern split of route, southern boundary for northern split of route, and allowable size of overlap (Figure 6b). Any solution that minimizes induced transfers will include a solution for which the maximum allowable overlap of two routes is a limiting constraint.

Defining the new route terminal locations and allowable size of route overlap yielded optimal split points in midtown Manhattan. Under these constraints, a new southern terminal was found that would induce new transfers for 6.9% of riders, exhibiting uneven length ratios (1.8:1) and ridership ratios (4.7:1). The optimization was repeated with new terminal constraints moved north and the same size of route overlap, producing a new optimal split in the Upper West Side. This solution impacted 11.2% of riders, but distributed ridership between the new routes in more equal ratios (1.3:1).

This approach considers only the optimal solution with respect to ridership. In practice, the bus planning process must address other considerations beyond just optimal ridership solutions. While attempting to minimize passenger impacts, operational and cost considerations also were noted, and a proposed split point for the M5 was identified nearby layover space in midtown Manhattan within the first-pass optimal split bounds. Considering operational constraints and a more cost-effective constraint of a single stop overlap, ridership impacts were recalculated. The change in the tolerable route overlap constraint and the assignment of the split point resulted in an impact on 10.2% of riders. Operational feasibility would have to take precedence over solutions minimizing ridership impacts. In the absence of this input to the planning process, professional judgment or anecdotal evidence may have guided where the split location should occur with limited manual data sources to support conclusions. The inclusion of a robust ridership data set helps balance professional judgment along with historic precedent and community input. The data supporting these conclusions had the
additional benefit of being free, as they were a usable byproduct of fare collection and customer-facing AVL data. This is in notable comparison with what may formerly have been necessary, such as an intercept survey to understand passenger travel patterns.

**Estimating New Route Running Time**

Schedule implications and running times could be predicted from existing bus data. Ridership in the northern section of the route had governed frequency, and a new schedule for the southern route could be written from ridership data. Historic AVL data could be used to predict the expected running time for the new routes. Running time and schedule frequency predictions allowed the proposed service change to be evaluated on the basis of cost in addition to performance and ridership impacts.

The M5 currently operates a limited service for most of the day but overnight has a local service pattern. Feedback that the limited and local divide was confusing prompted the idea to rationalize service patterns while the route length was being modified. Although AVL data could be used to estimate running times of two new routes from existing service, no such data existed for a local-only route traversing this path. By measuring local running times on segments of other routes overlapping the M5, limited pattern running times for a proposed new route path and service pattern could be estimated, including the new bus and cost requirements. The new northern route would overlap with other routes that run local-only service the entire day. This allowed for the predicted running times of a local-stopping pattern to be predicted for the M5. For northbound service, the M7 and M5 have overlapping service patterns from Sixth Avenue and 37th Street to Broadway and 70th Street; the difference in limited and local running time could be evaluated from AVL data. A similar overlap existed with the M5 and M4 so that an average increase in running time of 8.3 minutes or 12% was determined for the new northern route. This process was repeated with the M1, M2, M3, M4, and M7 routes to produce southbound estimates, which suggested a 9% increase in running times. Figure 7 better clarifies where local running time data were recorded to produce new running time estimates. The predicted increase in travel time due to the service change led to the abandonment of the proposed idea as planning moved forward.

Big data sources were important in every step of the proposed route modification—problem declaration, optimal solution from a passenger perspective, performance improvements, schedule, running time, and resulting cost implications of the proposed change. In the absence of big data, none of these processes would have been supported and would have involved far greater uncertainty and data of a much greater cost.
Conclusions and Next Steps

Big data sources at NYCT allow for improved bus service planning capabilities in several areas. Most significant was the new information about rider boarding and alighting locations, allowing for estimations of passenger impacts on route re-designs and other route characteristics. The data provide a more complete picture of ridership without relying on intuition or anecdotal or incomplete sources. Replacing manual data with automated data improved the confidence in the information being communicated, and freed up staff time to use and analyze data rather than processing it. Specific rider detail can be obtained without costly and time-consuming surveys or checks while also getting a more robust picture. This allows for more studies to be undertaken and scaled to higher-level network analyses, going from route to neighborhood to borough-level detail. Novel data sources were able to result in service and operational improvements in a Bronx neighborhood, including a re-route and stop addition. This also allowed for a ridership-optimal Manhattan route split at 38th street while supporting the Community Board and MTA Board procedural pieces of route modification.
Integrating ridership with demographic data will also enhance NYCT’s ability to perform Title VI analyses that currently rely on outside data sources such as the Census Journey to Work surveys to infer travel patterns. The different geographic and ridership sizes of the bus planning projects undertaken and planned by NYCT means that most bus-transit providers could extend these kinds of approaches to their planning processes.

Most of the data that supported these efforts have been incorporated into web-based reports, meaning that an analytical intermediate is not required to facilitate this kind of planning work. Boarding-alighting, O-D pairs, performance, running time, and others can be queried via these web-based reports by route, date, and time without intimate knowledge of the data or technologies used, increasing the applicability, flexibility and ease with which these analyses are conducted. This allows for the work described in this paper to be repeated on an ongoing basis, while development of other potentially useful data sources such as linked-trip O-Ds or non-revenue service analysis can be explored.

References


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Usability Evaluation of Access Ramps in Transit Buses: Preliminary Findings

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Abstract

The research literature on access ramps used in transit vehicles is undermined by inconsistent methodologies used across studies, thus providing an inconclusive evidence base for proposed Federal guidelines that would impose a maximum 1:6 slope for all deployment situations. The current study assessed the usability of ramp slope for mobility aid users. Four access ramp slopes were evaluated, with 27 adults representing three populations: manual wheelchair users, power wheelchair users, and people with vision impairment who use a cane or service animal. The dependent variables included five usability measures. The 1:8 and 1:12 slopes were usable and acceptable for most participants. The data indicate that the 1:4 slope is too steep for safe unassisted boarding and disembarking. Many manual wheelchair users lacked the strength needed for unassisted ascent. Power wheelchair users and people with vision impairment expressed safety concerns about descent of steeper slopes. Conclusive interpretations should be cautiously drawn because the sample size was relatively small and did not include users of scooters or ambulation aids.

Key Words: Transit, Americans with Disabilities Act, ADA, access ramp, wheelchair access, visual impairment, mobility impairment, access slope

Introduction

Many people with mobility impairments are dependent on public transportation for completing instrumental activities of daily living, participating in social activities, or engaging in recreational opportunities (Carlsson 2002; Carp 1988; Iwarsson and Stahl...
Community integration and overall quality of life are thus diminished if they encounter barriers to access and use of public transportation (Ståhl 1987). People with disabilities are 2.5 times more likely to experience transportation difficulties than able-bodied people (National Council on Disability 2005). Recent studies substantiate ongoing problems with boarding and disembarking that are experienced by transit bus riders with mobility impairments (Albertson and Falkmer 2005; National Highway Traffic Safety Administration 1997; Nelson\Nygaard Consulting Associates 2008; Frost, Bertocci, and Smallley 2015; Frost, Bertocci, and Sison 2010).

Among wheeled mobility equipment users living in areas served by public transit, 40% indicate that they have wheelchair or scooter access problems with public transit (LaPlante and Kaye 2010). Frost and Bertocci (2010) evaluated 115 adverse incidents involving wheeled mobility devices on large accessible transit buses over a 6-year period in Louisville, Kentucky, and found that 42.6% \((n=49)\) were associated with ingress/egress. Among these, 12 of 49 involved the wheeled mobility device tipping forward or rearward while ascending or descending the access ramp, prompting the authors to conclude that “research is needed to examine the adequacy of existing federal legislation and guidelines for accessible ramps used in public transportation” (Frost and Bertocci 2010, 236). A subsequent study of boarding and alighting (Frost, Bertocci, and Smallley 2015) found that 5% of wheeled mobility device users experience a ramp-related incident when accessing public transit buses and that these incidents were more than five times more likely when the ramp slope exceeded 9.5° (1:6).

The need for the current study is driven by a proposed Federal policy that would mandate a 1:6 slope maximum from the bus floor to street level, replacing the current 1:4 maximum. Some stakeholders have expressed concerns that the proposed policy would be problematic for riders with disabilities, and others have argued that the proposal is too stringent from the industry perspective (U.S. Access Board and Department of Transportation 2007b). The research literature on access ramp usability is undermined by inconsistent methodological elements across studies (Nelson\Nygaard Consulting Associates 2008), thus providing an inconclusive basis for either supporting or refuting the proposed guidelines (Nelson\Nygaard Consulting Associates 2008, U.S. Access Board and Department of Transportation 2007a). The current study partially addresses this knowledge gap by evaluating the usability of four access ramp slopes with three populations of mobility-aid users in a laboratory setting.

**Background**

Historically, step entrances in transit buses presented a barrier to boarding and disembarking for wheeled mobility users. Electromechanical lifts initially were used to address this accessibility barrier; however, lifts are considered unsatisfactory because they are prone to breakdown, require bus driver assistance, create long loading and unloading delay, and are not helpful for ambulation aid users. The emergence of low-floor bus designs in the late 1980s lowered the entry and exit height by 3–4 inches (Blennemann 1991), thus reducing physical demands and tripping risks (Schneider and Brechbuhl 1991; Rutenberg 1995). Many low-floor buses also “kneel” at stops, further
reducing the initial step height by 3–4 inches. The overall reduction in ground-to-bus floor height has made it feasible to replace lifts with access ramps (Rutenberg 1995).

Compared to wheelchair lifts, access ramps have a simpler design that is less prone to breakdown and requires less maintenance (Blennemann 1991; Schneider and Brechbuhl 1991; Rutenberg 1995). Ramps enable wheeled mobility users to board vehicles more discreetly and in less time (Blennemann 1991; Rutenberg 1995). For drivers, ramps are simpler to deploy and do not require them to leave their seat (Rutenberg 1995; Schneider and Brechbuhl 1991). Ramps can also be used by ambulation aid users, parents pushing strollers, and riders with rolling suitcases or shopping carts, allowing a greater percentage of passengers to enter and exit the bus with reduced effort and assistance (Schneider and Brechbuhl 1991).

However, access ramps are not without drawbacks. Drivers must alert those waiting outside that ramp deployment is imminent. Ramps require substantial horizontal space when deployed, which creates a design challenge for ramp storage. The latter design issue creates a potential tension for policymakers, who must attempt to balance the accessibility needs of people with mobility impairments with the pragmatics of ramp design for manufacturers. People with mobility impairment naturally prefer gentler slopes; however, ramps with gentler slopes create a design challenge for manufacturers of ramps and buses, who must attempt to create ramps of increasing length that can be electromechanically folded and stowed in a space that is inherently constrained by the available floor space in the entrance area of the bus.

The accessibility of access ramps is affected by their slope, which is often described by a ratio, \(a:b\), indicating a rise of \(a\) inches for every \(b\) inches in run. Table 1 summarizes common slopes in terms of rise:run, percentage gradient, and angle. The Americans with Disabilities Act Accessibility Guidelines (ADAAG) for Transportation Vehicles stipulate that ramp slope may vary from 1:4 to 1:12, depending on the overall rise (U.S. Access Board and Department of Transportation 1998). The U.S. Access Board has proposed a guideline (Architectural and Transportation Barriers Compliance Board 2010) that would establish a maximum slope of 1:6 for all deployment scenarios.

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<td>2.9</td>
</tr>
</tbody>
</table>
People with disabilities have expressed concerns that a 1:6 slope is too steep, potentially increasing the need for driver assistance (Nelson\Nygaard Consulting Associates 2008). Bus and ramp manufacturers who commented on the drafts of the proposed rule provided varied information on this proposed change. Some stated that the proposed 1:6 maximum slope to the roadway is feasible; others stated that the proposed slope would involve significant structural changes to buses or may not be feasible for certain model buses (Architectural and Transportation Barriers Compliance Board 2010).

Public transit agencies that commented on the drafts of the proposed rule expressed concern that longer ramps with more complicated mechanical systems (e.g., bi-fold ramps) will be more costly to maintain. They also expressed operational concerns about deploying longer ramps in urban environments with narrow sidewalks and streets. Ramp manufacturers expressed concerns that a 1:6 slope would necessitate longer ramps that would pose design challenges given existing space constraints in the forward section of transit buses (U.S. Access Board and Department of Transportation 2007b). The American Public Transit Association (APTA) asserted that the research literature does not conclusively justify the 1:6 maximum (U.S. Access Board and Department of Transportation 2007b).

Previous Ramp Research

The accessibility of ramps for buildings was first evaluated in the late 1970s (Steinfeld, Schroeder, and Bishop 1979), which led to the 1:12 slope standard now required for accessible buildings. For transit vehicles, an early study was contracted by the Urban Mass Transportation Administration (UMTA, now the Federal Transit Administration, FTA) (RRC International 1977), which reported findings based on an unspecified number of mobility aid users who evaluated ramp slopes ranging from 1:9 to 1:2. For wheelchair users, slopes of 1:3 could not be negotiated without assistance; unassisted entry was possible for some with slopes between 1:4 and 1:6; and ramp slopes shallower than 1:6 were substantially easier to traverse independently. Ambulation aid users found it very difficult to maintain standing balance at the 1:3 slope and thus necessitated assistance, slopes of 1:4 and 1:6 could be independently traversed with difficulty and often required assistance to exit the bus, and slopes of 1:6 and shallower could be traversed unassisted and without difficulty. This was a groundbreaking study that, nonetheless, had three key limitations: the participant sample was vaguely described in terms of device used and functional ability, the measurement tools were not described, and the research design and procedure were not described in a manner that would support replicability. Since 1977, there have also been some significant advances in wheelchair seating and mobility technology, notably the introduction of midwheel-drive power chairs, seating and positioning systems that allow more severely-impaired individuals to travel independently, and wheelchair frames that accommodate larger and heavier people (Steinfeld et al. 2010).

Sweeney et al. (1989) evaluated 13 portable ramps ranging from 1:12 to 1:3 with 45 participants representing a diverse age range, wheeled mobility devices, and functional levels. The authors reported that ramp slopes of 1:12 to 1:7 could be negotiated with "relative ease" by 88% of the self-propelling manual wheelchair users (n=18), compared
to 52% of the same group for the 1:6 slope. All seven power wheelchair users traversed the 1:12 to 1:7 slopes with relative ease, compared to 66% of the same group for the 1:6 slope. Nuanced interpretation of these findings is difficult because the measurement scales were not described for assessing ease of use, and the data were aggregated for slopes ranging from 1:12 to 1:7.

Blennemann (1991) evaluated ramp gradients from 1:16 to 1:5. The findings were based on “workshops” involving an unreported number of wheelchair users, their caregivers, and older adults. Manual wheelchair users navigated the 1:10 slope without difficulty, reported some difficulty with slopes between 1:10 and 1:6, and were unable to negotiate ramps of 1:5 without assistance. Power wheelchair users negotiated slopes as steep as 1:6 without difficulty; however they reported a fear of overturning at a slope of 1:5. Definitive interpretations of these data are not possible because the user groups were not well articulated, the data collection procedures were not described, and the measurement scales were not described.

Sanford, Story, and Jones (1996) evaluated the usability of 6 slopes ranging from 1:8 to 1:20 for 171 participants who used a range of mobility aids. The authors concluded that ramps steeper than 1:12 and longer than 30 feet are difficult to use by manual wheelchair users. Although these findings provide an excellent starting point, the data reflect an experimental ramp length (30’) that is not directly comparable to the typical length (~6’) of access ramps in transit vehicles.

It is difficult to derive conclusive slope guidelines from the above literature because key factors (e.g., ramp length, ramp slope, population studied, and measurement tools) are quite disparate and often vaguely described. Because the proposed guidelines have substantial implications for bus manufacturers, access ramp manufacturers, transit operators, and people with disabilities, a more rigorous and systematic study is needed to assure that any new ramp slope guidelines are data-driven. In response to this need, the current study was launched as the initial stage of a two-phase study to assess four access ramp slopes with multiple populations of mobility aid users. The four ramp slopes range from the steepest ramp slope (1:4) allowed by previous U.S. public transit accessibility standards to the slope standard for access to buildings (1:12).

Methodology

Study Design

A 3×4 mixed factorial design was used to evaluate four ramp slopes (1:4, 1:6, 1:8, and 1:12) with three participant groups (manual wheelchair users, power wheelchair users, and persons with vision impairment using a cane or service animal). The range of slopes from 4.8 degrees (1:12) to 14 degrees (1:4) is comparable with the range identified by Bertocci et al. (2014) in their in situ measurement of access ramp slopes as deployed in everyday transit bus use. The dependent variables included five domains of usability: time to ascend the ramp, perceived exertion, perceived difficulty, perceived acceptability, and comparative difficulty of ascent versus descent.
Participants

The three user groups represented a range of mobility device users, as suggested by previous authors who emphasized the need for researchers to include diverse disability populations (Hunter-Zaworski and Hron 1993; Rutenberg 1995). The inclusion criteria included age (18–85) and the ability to navigate a 1:12 ramp without assistance. A convenience sample was recruited from a registry of consumers who had previously participated in research at the Center for Inclusive Design & Environmental Access at the University at Buffalo. Participants were also recruited through the local offices of vocational rehabilitation. As the study progressed, participants were encouraged to distribute recruitment flyers to peers and colleagues. In all, 27 participants were enrolled: 8 manual wheelchair users, 8 powered wheelchair users, and 11 people with vision impairment who used a cane or service animal. Human subjects approval was obtained from an Institutional Review Board at the university. Participants received $50 in consideration for their time.

Instruments

Ascent Time

The time required for ramp ascent was measured using a stopwatch. Consistent time measurements were fostered by taping a starting line at the base of the ramp and a finish line on the platform. Timing was initiated when the forward-most point of the wheelchair crossed the starting line and stopped when the rear-most wheel crossed the finish line.

Borg Rating of Perceived Exertion (RPE) Scale

Level of perceived exertion was measured using the Borg RPE scale, a 15-point psychophysical scale that captures subjective feelings of physical exertion with scores ranging from 6 (no exertion at all) to 20 (maximal exertion). The validity and reliability of the RPE are well-established (Borg 1998; Chen, Xitao, and Moe 2002; Lagally, Robertson, and Gallagher 2002; Ozcan and Kin-Islar 2007).

Difficulty Rating Scale and Acceptability Rating Scale

The Difficulty Rating Scale (DRS) and Acceptability Rating Scale (ARS) were developed as measures of environmental usability (Steinfeld and Danford 2000; Danford and Steinfeld 1999). The DRS (Figure 1) measures perceived ease or difficulty of task performance using a 7-point ordinal scale ranging from -3 (very difficult) to +3 (very easy). Respondents rate perceived task difficulty in two steps: (a) indicate if a completed task was “difficult,” “moderate.” or “easy”; and (b) choose a final rating from three possible options based on the general rating provide in the first step. For example, a respondent who initially indicates that a task was “difficult” would then choose a final rating of barely difficult (-1), moderately difficult (-2), or very difficult (-3).
The ARS (Figure 2) measures acceptability of a task using a similarly worded 7-point ordinal scale and two-step rating process. Although the psychometric properties of each have not been rigorously evaluated, there is preliminary evidence of their convergent validity with other functional measures (Steinfeld and Danford 2000).

**Comparison of Ascent and Descent**

A study-specific rating scale was created (Figure 3) because it was hypothesized that ramp ascent and ramp descent would not be rated at equal difficulty levels by all participant groups. The 5-point ordinal response options ranged from -2 (descent much more difficult) to +2 (ascent much more difficult).

**Apparatus**

The experimental apparatus consisted of a wooden ramp (6’ long, 40” wide) attached by hinge to a height adjustable, 8’ × 8’ platform. The ramp length is consistent with current 1:6 access ramp designs. The width and large landing area were chosen to isolate the effects of slope on ramp usability and minimize the potentially confounding effects of a narrower ramp width and confined landing area for those using larger wheeled
mobility devices. Four hydraulic jacks, each rated to support 1500 lbs, supported the platform. The ramp slope was adjusted by changing the height of the platform from the floor. Four adjustable jack stands were placed underneath the platform as a precaution against jack failure, and a 4-inch yellow curb was mounted along the edges of the platform and the ramp.

**Procedure**

Four research assistants performed the data collection protocol. One was primarily responsible for interacting with participants, and the other three served as spotters and changed the ramp slope between trials. The order in which the ramp slopes were presented was counterbalanced within and between groups to minimize order effects. Rest periods were provided as needed throughout the protocol to minimize the effects of fatigue.

Participants were instructed to move as quickly and safely as possible to mimic everyday ramp use. For each slope, participants were given one practice trial and one measurement trial. Thus, each participant experienced a total of eight ascent and descent tasks. One participant requested to propel backwards up the ramp. All other participants propelled themselves in a forward-facing direction for all trials.

The RPE was administered after the ascent task for each slope. The remaining self-report measures (e.g., DRS ARS, and comparison of ascent and descent difficulty) were administered immediately upon completion of each measurement trial. Participants also were queried for open-ended comments upon completion of each trial.

**Statistical Analysis**

Categorical variables were summarized using frequencies and cumulative frequencies. Continuous variables were summarized using means, standard deviations, and medians. A 3x4 mixed factorial ANOVA model with subject as a blocking variable was used to evaluate the effect of disability group, ramp slope, and disability group by ramp slope interaction on ascent time, RPE, DRS, and ARS. In cases in which the interaction between group and slope was significant, post-hoc tests with a Bonferroni adjustment were conducted to evaluate the pairwise differences. Ordinal regression was used with subject as a blocking variable to study the effect of disability group, ramp slope, and disability group by ramp slope interaction on participants’ comparison of ascent and descent difficulty. Spearman correlation was used to evaluate the association among the six dependent variables, ascent time, RPE, DRS, ARS, and comparison of ascent versus descent. A 0.05 nominal significance level was used in all analyses, which were conducted using SAS v.9.2.

**Results**

Table 2 summarizes demographics of the 27 participants. The mean age was 47.9 (SD=14.4, range: 22–75) years, and the majority (58.1%) was male. More than 80% (n=22) used public transportation at least several times per year, and more than half (n=14) use public transit at least several times per month. All 27 participants attempted each of the four ramp slopes for a total of 108 possible trials. Among these, 14 trials could not be
completed because of difficulty—nine at the 1:4 slope, four at the 1:6 slope, and one for the 1:8 slope. Manual wheelchair users accounted for 10 of the unsuccessful attempts, and power wheelchairs users accounted for the remaining four.

Table 3 summarizes the results of the five 3×4 factorial ANOVAs that were conducted to evaluate the effects of three mobility aids and four ramp slopes on the respective usability indicators. Each is described below.

**Ascent Time**
The means and standard deviations for ascent time are presented in Table 4, and Figure 4 depicts the mean values for each group-slope combination. The assumptions for ANOVA were met using a natural log transformation to stabilize the variance. The ANOVA results indicated significant main effects for group (p=0.0019) and slope.
Usability Evaluation of Access Ramps in Transit Buses: Preliminary Findings

(p<0.0001) and a significant interaction between group and slope (p=0.0005). The post-hoc analysis indicated that the interaction was driven by the longer ascent time experienced by manual wheelchair users at the steepest slopes (1:4 and 1:6) compared to the shallowest slopes (1:8 and 1:12) – in contrast with the relatively consistent ascent times experienced by the other two groups across all four slopes.

TABLE 4. Mean Ascent Time (in seconds) for Each User Group and Slope Combination

<table>
<thead>
<tr>
<th>Ramp Slope</th>
<th>Manual WC Mean (SD)</th>
<th>Power WC Mean (SD)</th>
<th>Visually-Impaired Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:4 (n=18)*</td>
<td>16.25 (.35)</td>
<td>8.20 (3.35)</td>
<td>9.32 (3.17)</td>
</tr>
<tr>
<td>1:6 (n=23)</td>
<td>15.80 (7.26)</td>
<td>7.86 (2.97)</td>
<td>8.64 (2.75)</td>
</tr>
<tr>
<td>1:8 (n=26)</td>
<td>13.43 (6.90)</td>
<td>8.00 (3.12)</td>
<td>8.14 (2.18)</td>
</tr>
<tr>
<td>1:12 (n=27)</td>
<td>13.13 (10.62)</td>
<td>8.31 (4.04)</td>
<td>7.95 (2.13)</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope

FIGURE 4. Mean ascent time for each user group across slopes

Rating of Perceived Exertion

The means and standard deviations for the RPE are presented in Table 5. Figure 5 depicts the mean values for each group-slope combination. The assumptions for ANOVA were met using a weighted least squares procedure to stabilize the variance. The ANOVA results indicated significant main effects for group (p<0.0001) and slope (p<0.0001) and a significant interaction between group and slope (p=0.0001). The post-hoc analysis indicated that the interaction was driven by the difference in RPE ratings reported by manual wheelchair users, compared to the other two groups, for the steeper slopes (1:4 and 1:6), which narrowed for the 1:8 slope and diminished substantially for the 1:12 slope.

TABLE 5. Mean RPE Scores for Each User Group and Slope Combination

<table>
<thead>
<tr>
<th>Ramp Slope</th>
<th>Manual WC Users Mean (SD)</th>
<th>Power WC Users Mean (SD)</th>
<th>Visually-Impaired Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:4 (n=18)*</td>
<td>15.5 (2.12)</td>
<td>7.8 (2.95)</td>
<td>10.82 (3.68)</td>
</tr>
<tr>
<td>1:6 (n=23)</td>
<td>13.6 (3.29)</td>
<td>7.68 (2.91)</td>
<td>10.09 (4.04)</td>
</tr>
<tr>
<td>1:8 (n=26)</td>
<td>9.86 (3.08)</td>
<td>6.38 (1.06)</td>
<td>7.18 (3.28)</td>
</tr>
<tr>
<td>1:12 (n=27)</td>
<td>7.75 (1.75)</td>
<td>6.13 (0.35)</td>
<td>6.73 (2.1)</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope
Usability Evaluation of Access Ramps in Transit Buses: Preliminary Findings

Higher scores indicate greater perceived exertion.

**Difficulty Rating Scale**
The means and standard deviations for the DRS are presented in Table 6. Figure 6 depicts the mean values for each group-slope combination. The studentized residuals plots were satisfactory to meet ANOVA assumptions. The ANOVA results indicated significant main effects for group (p=0.0063) and slope (p<0.0001) and a significant interaction between group and slope (p=0.0032). The post-hoc analysis indicated that the interaction was driven by the difference in DRS ratings reported by manual wheelchair users, compared to the other two groups, for the steeper slopes (1:4 and 1:6), which diminish substantially for the 1:12 slope.

**TABLE 6.**

<table>
<thead>
<tr>
<th>Ramp slope</th>
<th>Manual WC Users (Mean (SD))</th>
<th>Power WC Users (Mean (SD))</th>
<th>Visually-Impaired (Mean (SD))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:4 (n=18)*</td>
<td>-2.75 (0.35)</td>
<td>-0.3 (1.79)</td>
<td>0.82 (1.99)</td>
</tr>
<tr>
<td>1:6 (n=23)</td>
<td>-0.9 (1.52)</td>
<td>1.79 (1.63)</td>
<td>1.41 (1.77)</td>
</tr>
<tr>
<td>1:8 (n=26)</td>
<td>1.57 (1.51)</td>
<td>2.94 (0.18)</td>
<td>2.36 (1.8)</td>
</tr>
<tr>
<td>1:12 (n=27)</td>
<td>2.75 (0.46)</td>
<td>3.0 (0)</td>
<td>2.64 (1.21)</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope.

Positive DRS ratings indicate relative ease of task; negative ratings reflect relative task difficulty.
Acceptability Rating Scale

The means and standard deviations for the ARS are presented in Table 7. Figure 7 depicts the mean values for each group-slope combination. The studentized residuals plots were satisfactory for meeting ANOVA assumptions. The ANOVA results indicated a non-significant main effect for group (p=0.1097) and a non-significant interaction between group and slope (p=0.3217). A significant main effect for slope (p<0.0001) was seen, indicating that there were significant differences in level of acceptability across slopes. Given that there was not a significant interaction between group and slope, no post hoc analysis was conducted for the ARS data.

<table>
<thead>
<tr>
<th>Ramp slope</th>
<th>Manual WC Users Mean (SD)</th>
<th>Power WC Users Mean (SD)</th>
<th>Visually-Impaired Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:4 (n=18)*</td>
<td>-1.25 (2.47)</td>
<td>-0.2 (1.79)</td>
<td>-0.18 (2.56)</td>
</tr>
<tr>
<td>1:6 (n=23)</td>
<td>0.50 (1.66)</td>
<td>2.64 (0.48)</td>
<td>1.82 (1.47)</td>
</tr>
<tr>
<td>1:8 (n=26)</td>
<td>1.93 (1.79)</td>
<td>3.0 (0)</td>
<td>2.45 (1.51)</td>
</tr>
<tr>
<td>1:12 (n=27)</td>
<td>3.0 (0)</td>
<td>2.88 (0.35)</td>
<td>3.0 (0)</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope

Comparison of Ascent and Descent

The means and standard deviations for ascent-versus-descent ratings are presented in Table 8. Figure 8 depicts the mean values of ascent vs. descent for each group-slope combination. Ordinal regression was used to analyze the results with subjects as a blocking variable. The results indicated a significant main effect for group (Chi-square=6.59, df=2, p=0.037), a non-significant main effect for slope (Chi-square=0.45, df=3, p=0.9305), and a non-significant interaction between group and slope (Chi-square=6.15, df=6, p=0.4066). Manual wheelchair users rated ascent to be more difficult than descent across all ramp slopes, whereas power wheelchair users and people with vision impairment rated descent to be slightly more difficult-to-neutral across all four slopes.
TABLE 8.  
Mean Scores on Scale Comparing Difficulty of Ascent and Descent

<table>
<thead>
<tr>
<th>Ramp slope</th>
<th>Manual WC Mean (SD)</th>
<th>Power WC Mean (SD)</th>
<th>Visually-Impaired Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:4 (n=18)*</td>
<td>1.5 (0.7)</td>
<td>-0.6 (1.1)</td>
<td>-0.27 (1.2)</td>
</tr>
<tr>
<td>1:6 (n=23)</td>
<td>1 (0.7)</td>
<td>-0.29 (1.0)</td>
<td>-0.18 (1.1)</td>
</tr>
<tr>
<td>1:8 (n=26)</td>
<td>0.86 (0.7)</td>
<td>0 (0.5)</td>
<td>-0.18 (0.8)</td>
</tr>
<tr>
<td>1:12 (n=27)</td>
<td>0.5 (0.5)</td>
<td>0 (0.5)</td>
<td>0 (0.5)</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope.  
Positive values indicate that ascent was rated to be more difficult than descent; negative values indicate that descent was rated to be more difficult than ascent.

FIGURE 8.  
Mean scores on scale comparing ascent and descent for each user group across slopes

Positive ratings indicate that ascent is more difficult; negative ratings indicate that descent is more difficult.

Associations among Key Dependent Measures
Table 9 shows correlations among ascent time, RPE, DRS, and ARS scales. There was a statistically-significant, negative correlation between RPE and DRS for all four slopes. The correlation was strong for all slopes except 1:12, which exhibited moderate correlation. There was a statistically-significant, negative correlation between RPE and ARS for all slopes except 1:12. The correlation between RPE and ARS was moderate for 1:4 (r = -0.525) and 1:8 (r = -0.673) and strong for 1:6 (r = -0.831, p < .0001). There was a statistically-significant, positive correlation between ARS and DRS for all the slopes except 1:12. The correlation between ARS and DRS was moderate for slope = 1:4 (r = 0.664) and strong for 1:6 (r = 0.834) and 1:8 (r = 0.879). For all slopes except 1:8, ascent time did not correlate with RPE, DRS, or ARS at a statistically-significant level.
### TABLE 9. Correlations among Key Dependent Variables

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Slopes</th>
<th>r</th>
<th>Significance (p value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPE and DRS</td>
<td>1:4 (n=18)*</td>
<td>-0.711</td>
<td>0.000**</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>-0.813</td>
<td>&lt;0.000**</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>-0.78</td>
<td>&lt;0.000**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>-0.557</td>
<td>0.003**</td>
</tr>
<tr>
<td>RPE and ARS</td>
<td>1:4 (n=18)</td>
<td>-0.525</td>
<td>0.025**</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>-0.831</td>
<td>&lt;0.000**</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>-0.673</td>
<td>0.000**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>0.136</td>
<td>0.499</td>
</tr>
<tr>
<td>DRS and ARS</td>
<td>1:4 (n=18)</td>
<td>0.664</td>
<td>0.003**</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>0.834</td>
<td>&lt;0.000**</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>0.879</td>
<td>&lt;0.000**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>0.069</td>
<td>0.732</td>
</tr>
<tr>
<td>Ascent time and RPE</td>
<td>1:4 (n=18)</td>
<td>0.276</td>
<td>0.268</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>0.252</td>
<td>0.245</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>0.414</td>
<td>0.035**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>0.333</td>
<td>0.09</td>
</tr>
<tr>
<td>Ascent time and DRS</td>
<td>1:4 (n=18)</td>
<td>-0.342</td>
<td>0.165</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>-0.138</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>-0.403</td>
<td>0.041**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>-0.03</td>
<td>0.883</td>
</tr>
<tr>
<td>Ascent time and ARS</td>
<td>1:4 (n=18)</td>
<td>-0.463</td>
<td>0.525</td>
</tr>
<tr>
<td></td>
<td>1:6 (n=23)</td>
<td>-0.159</td>
<td>0.469</td>
</tr>
<tr>
<td></td>
<td>1:8 (n=26)</td>
<td>-0.544</td>
<td>0.000**</td>
</tr>
<tr>
<td></td>
<td>1:12 (n=27)</td>
<td>0.063</td>
<td>0.754</td>
</tr>
</tbody>
</table>

* Indicates number of participants who completed each slope

**p<0.05, <0.01, <0.001

### Discussion

Data from multiple measures of usability indicate that the 1:4 access ramp slope is too steep for unassisted boarding and disembarking. Clearly, this slope is a potential barrier for manual wheelchair users who lack the strength to propel independently over the relatively short distance required by an access ramp. The ascent times for manual wheelchair users completing the 1:4 and 1:6 slopes were substantially greater than the comparison groups. This not only reflects the physical difficulty of the steeper slopes but also portends extended dwell times and needs for assistance that could also be problematic for bus operators striving to maintain timely fixed-route service and minimize occupational injuries for bus operators.

The 1:4 slope was intimidating for some power wheelchair users who declined to complete the ascent task because of concerns about their safety. Several expressed apprehension that their footrests might collide with the ramp and that their chair...
might tip over. For 1:4 and 1:6 slopes, we observed several power wheelchair users who deviated from straight-line propulsion and exhibited lurching wheelchair movements at the top-of-ramp grade transition, which introduced perturbations in upright trunk posture and reflected the challenge of maintaining a straight path and steady speed.

In contrast, people with visual impairment could ascend all ramp slope conditions independently. Similar to power wheelchair users, their ascent times and ratings of exertion were substantially similar across all slope conditions, though they rated descent to be slightly more difficult than ascent for the three steepest slopes. Most were emphatic that the 1:4 slope was too steep, and several exhibited momentarily unsteady standing balance at the top-of-ramp grade transition under the 1:4 and 1:6 slope conditions. Participants from all three groups conveyed unprompted comments expressing concern that their performance would be diminished under adverse weather conditions, e.g., rain, ice, or snow.

The 1:8 slope appears to be generally usable and acceptable for all three user groups. However, manual wheelchair users exhibited mean ascent times at 1:8 and 1:12 that were more than 5 seconds slower than the two comparison groups, which is not inconsequential to bus operators seeking to minimize dwell times. The 1:12 slope elicited the least differentiation among the three groups, who all completed the ascent independently, reported similar ratings of exertion and acceptability, did not exhibit any balance or tracking problems, and did not report any safety concerns. The performance of manual wheelchair users appear generally consistent with findings of Sweeney and colleagues (1989) and Blennemann (1991), although differences in research methods and slope conditions, make direct comparison impossible.

**Methodological Insights**

The results indicate that ramp usability is best evaluated through the lens of diverse disability populations and complementary usability measures. Excluding key populations or focusing on a single indicator of usability would risk loss of important insights regarding ramp usage. Whereas the usability for manual wheelchair users was most tellingly revealed by ascent times, the safety concerns of power wheelchair users and those with vision impairment were captured by their ratings of acceptability and comparison of ascent and descent. The comparability of ascent and descent difficulty for powered wheelchair users at all slopes contrasts the findings of Frost et al. (2015), whose safety data found that ascent was more challenging that descent. This difference might be caused by the confined interior space at the upper ramp landing and the narrower ramp width that are found in operational buses.

Data from the DRS and ARS demonstrate their promise. The DRS correlated well with the RPE, particularly for conditions involving moderate-to-high levels of effort. The DRS was less discerning for conditions involving low perceived effort. The ARS data were less strongly correlated with the DRS and RPE under conditions involving moderate-to-high effort, and did not distinguish participant groups under conditions of low effort. Although the DRS and ARS require further psychometric evaluation, the data suggest
that both are potentially valuable in studies for which the constructs of difficulty and acceptability of environments are relevant.

The study-specific measure comparing difficulty of ascent and descent uncovered key differences that were not otherwise revealed by the other measures. Manual wheelchair users felt ascent was much more difficult than descent because of the physical effort, whereas power wheelchair and vision impairment groups reported that descent was more difficult for them at 1:4 and 1:6 and neither more or less difficult at 1:8 and 1:12.

**Limitations**

The research methodology had several limitations. The relatively small sample did not include users of scooters and ambulation aids, which comprise the two largest populations of mobility aid users. Although further research is yet needed with these populations, several useful findings can be seen at this juncture from the data with wheelchair users and persons with vision impairment, especially regarding the usability challenges presented by 1:4 and 1:6 ramp slopes. In addition, the data were collected in a lab setting that featured two idealized performance conditions: (a) the indoor setting does not reflect the performance degradation that occurs with outdoor climatic conditions (e.g., temperature, rain, ice, snow, wind) that influence usability of ramps in northern climates (Ripat, Brown, and Ethans 2015); and (b) the ramp apparatus was 40 inches wide, a wider-than-typical dimension that was chosen in order to eliminate the potentially confounding effects of narrower ramp widths on the ability to navigate different grades. The data from these conditions thus suggest a baseline of best-case performance that can be a useful basis for comparison with future data captured in real-world environments. We also used several measurement tools (e.g., DRS, ARS, and comparison of ascent and descent) that had limited use in previous studies. These measures were nonetheless chosen for their relevance to our research objectives and low response burden. The correlations found among DRS, ARS, ascent times, and RPE data suggest that the measures behaved largely as hoped and merit continued deployment in future usability studies.

**Conclusions**

The data indicate that the 1:4 slope is too steep for safe unassisted boarding and disembarking. Many manual wheelchair users lacked the strength needed for unassisted ascent. Power wheelchair users and people with vision impairment expressed safety concerns about descent of steeper slopes. Additional interpretations should be cautiously drawn because the sample size was relatively small and did not include users of scooters or ambulation aids. It should be emphasized that deployed ramp slope is not purely a design issue for bus manufacturers. A variety of environmental design factors may also contribute to the ramp slopes achievable everyday situations, e.g., availability of raised platforms, accessibility of bus stops and sidewalks leading to bus stop areas, illegally parked cars that block sidewalk deployment of ramps at bus stop areas, and accumulations of snow at bus stop areas during winter months.

Future research on access ramp usability is needed in three areas: (a) evaluation of additional populations of mobility aid users, including those who use ambulation aids
and scooters; (b) evaluation of the usability of ramps with 1:6 and 1:8 slopes using a configuration of width and landing area that more closely approximates the dimensions found on operational buses; and (c) evaluation under environmental conditions that reflect outdoor winter weather.

References


Usability Evaluation of Access Ramps in Transit Buses: Preliminary Findings


Usability Evaluation of Access Ramps in Transit Buses: Preliminary Findings


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A Composite Index for Evaluating Transit Service Quality across Different User Profiles

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Abstract

This paper evaluates the quality of service of the metropolitan Metro of Seville (Spain) across different user profiles, as determined through cluster analysis. Service quality evaluation is performed using a composite index that combines the user point of view with the service operator point of view. The combination of these two types of service quality measurement fulfills the need to provide a reliable measurement tool for transit performance. Six user profiles were identified, and it was ascertained that they have different opinions about the service, with heterogeneous gaps between the points of view among the six user profiles.

Key words: Transit quality; cluster analysis; user profiles; composite index

Introduction

One way for public transport (PT) to achieve more competitiveness with private vehicles is to improve the service quality (SQ) (De Oña and De Oña 2015; Wen and Lai 2010, Dell’Olio et al. 2010). Evaluating the various aspects of PT could highlight the areas in which it has poor performance to improve service and thereby obtain new users. SQ is a composite concept; it can be evaluated through the perceptions and opinions of the users or through a range of simple disaggregated performance measures collected by the service operators (Federal Transit Administration et al. 1999; Eboli and Mazzulla 2011). Therefore, there are two different agents that measure SQ. First, the service operators provide a quantitative indicator (Objective Indicator) that can be compared with a standard or past performance, but this indicator provides no information in itself regarding how “good” or “bad” a specific result is. Second, the measure of the users (Subjective Indicator) is derived from customer satisfaction surveys (CSS), which provide
qualitative measures of transit SQ related to the perceived discrepancy between the actual and ideal levels of service (Nathanail 2008).

Both indicators are crucial to evaluate the performance of a transit service; if either is not considered, there will be missing information, and the results will not effectively reflect reality. A useful and reliable measurement tool of transit performance could be obtained by combining these two types of measures (Tyrinopoulos and Aifadopoulou 2008; Nathanail 2008; Yeh et al. 2000). The use of a combination methodology allows the assessment of a concrete public transportation service and the solution of cost problems and constraints of service operators. The measurement tool is composed of the Subjective Indicator (S), which shares the crucial aspects that accurately reflect the needs of customers and potential customers, and the Objective Indicator (O), which quantitatively evaluates the performance of the service in comparison with previously established standards of performance in a previous period (Eboli and Mazzulla 2011; Federal Transit Administration et al. 1999; Nathanail 2008).

When S is calculated, it is necessary to consider that the quality of the PT is perceived by many different types of users who have different needs and personal characteristics that require individual attention (Zhou et al. 2004; Paez 2006; Button and Hensher 2001). If these variations are not addressed, it can lead to biased results and conclusions that might not identify some relationships between the data and, thus, might not reflect reality (De Oña et al. 2013; De Oña et al. 2014). In the area of data mining, there are advanced segmentation techniques, such as Cluster Analysis (CA), which enable the reduction of such heterogeneity. This technique has been applied in transport engineering and other fields (e.g., Wen and Lai 2010; Shiftan et al. 2008; Prebensen 2005) with satisfactory results.

The goal of this paper is to apply a methodology that considers different typologies of passengers to evaluate how SQ is perceived and to understand the differences in the SQ gap obtained. An improved formulation of the composite indicator proposed by Eboli and Mazzulla (2011), which combines the subjective data with the objective data, is used and adapted to the specific case study represented by the metropolitan Metro of Seville (Spain). The proposed methodology introduces the use of CA to assemble more homogeneous groups of users and to calculate the composite indicator for different types of users. In this manner, a comparative analysis between the assessments of each obtained group was conducted to extract specific conclusions regarding the aspects that are most critical for each group of users and the main causes and solutions thereof.

The paper is structured as follows: the next section shows the methodology used to evaluate SQ through the composite indicators and define the different groups of users by CA and is followed by a description of the data used for the analysis—specifically, the data used to calculate the objective indicators—and the results of a CSS conducted to calculate the subjective indicators. In addition, this section describes the results of the CA that were applied to stratify the sample and define the different groups of users. The results obtained by applying the composite indicators to the whole sample and to each cluster are explained, and finally, the conclusions are reported.
Methodology

Composite Indicator

The main aim of a composite indicator is to obtain a measure of SQ that combines the service operator point of view and the PT user point of view. The methodology is based on developing an indicator that takes an intermediate value between the quality measurements of service, considering the slope of each one. This process provides a significant quality measurement of the service that is governed by two basic concepts: 1) both indicators have equal importance in evaluating SQ, and 2) an indicator with less heterogeneity or variance has greater repercussions on the composite indicator (Eboli and Mazzulla 2011).

Each attribute is measured by an S and an O, with S calculated by the average of the satisfaction rates expressed by a sample of users with respect to a service attribute (Parasuraman et al. 1985) and O calculated by the average of the estimated value that is assigned to performance indicators about the attribute by service operators or by mystery shopper surveys and compared with standards (Nakanishi 2003).

Many O values were calculated by comparing the value of the predefined parameter (P) with a standard of quality (Q). To obtain these indicators, the criterion proposed by Nathanail (2008) and used by Eboli and Mazzula (2011) was adopted. A grade of zero is given to the indicator (O) in the event that the parameter is greater than or equal to double the standard, and 10 is given when it is less than the standard. Intermediate grades were calculated according to the following formula (1):

\[
O = \left[ \frac{2*Q-P}{Q} \right] \times 10
\]  

(1)

Subsequently, an optimization process based on the variances S and O results in a composite indicator (X) for each attribute. X, similar to indicators S and O, is expressed on a cardinal scale from 0 to 10, where 0 represents the lowest level of quality and 10 is the highest level of quality.

The mathematical formulation proposed by Eboli and Mazzulla (2011) and adopted in this paper is described in the following.

Let \( S_k \) denote the average rate of satisfaction or user perception about generic service attribute k expressed by a user in a survey according to the specific scale of evaluation. \( S_k \) denotes the actual value of the indicator, and the distance between the actual value and the estimated value for indicator k is denoted by \( \varepsilon_k^{PER} \), which represents the average error of the perception of the indicator due to heterogeneity in the judgment of different users (2):

\[
\bar{S}_k = S_k + \varepsilon_k^{PER}
\]  

(2)

Let \( O_k \) denote the estimated value of the objective performance indicator of generic service attribute k calculated based on service operator information and converted to the same scale of evaluation adopted for the satisfaction rates. In the same manner, \( O_k \) denotes the actual value of the indicator, and the distance between the actual value and the estimated value of indicator k is denoted by \( \varepsilon_k^{OBS} \), which represents the
average error in the measure of the indicator caused by measurements that are made by instruments and equipment (e.g., the length of a line path) that are calculated as an average of elements that can have different values that vary in time, space and so on on (3):

\[ \bar{O}_k = O_k + \varepsilon_k^{OBS} \]  
(3)

If \( m \) is considered to be service attributes adopted to describe the SQ of a transit system, the expressions of the indicators in terms of vectors are (4), (5) and (6):

\[ \bar{S} = S + \varepsilon^{PER} \]  
(4)

\[ \bar{O} = O + \varepsilon^{OBS} \]  
(5)

\[ S = 0 = X \]  
(6)

where the number of dimensions of all vectors is \([m \times 1]\).

One problem of optimization with a constraint is how to obtain vector \( X \). This constraint consists of maximizing an objective function \( Z(X) \) with a constraint that is sum of functions \( Z_1(\bar{S}, X) \) and \( Z_2(\bar{O}, X) \). Thus, a measure between vectors \( S \) and \( O \) can be considered vector \( X \), which can be obtained through (7):

\[ X^* = \arg\min_{X \geq 0} [Z(X)] = \arg\min_{X \geq 0} [Z_1(\bar{S}, X) + Z_2(\bar{O}, X)] \]  
(7)

The functional structure of \( Z_1(\bar{S}, X) \) and \( Z_2(\bar{O}, X) \) varies with the nature of the information. In this case, the methodology to obtain information is from experimental surveys, so a statistical theory is adopted, specifically the generalized least squares method, which provides an estimation of a parameter vector starting from a system of linear stochastic equations (8).

\[ X^{GLS} = \arg\min_{X \geq 0} [Z(X)] = \arg\min_{X \geq 0} \left[ \sum_{k=1}^{m} \frac{(S_k - X_k)^2}{\text{var}(S_k)} + \sum_{k=1}^{m} \frac{(O_k - X_k)^2}{\text{var}(O_k)} \right] \]  
(8)

This expression means that the estimate of vector \( X \) is vector \( X^{GLS} \), which minimizes the sum of the standard deviations of vectors \( S \) and \( O \) and sample estimates \( \bar{S} \) and \( \bar{O} \). The standard deviations are weighted in inverse proportion to the variances of the errors; this fact indicates that the deviation of the sample estimation from a component of vector \( X \) will apply a greater weight with greater variability of the sample values from the mean values.

However, if the variance of an indicator, e.g., \( O_k \), is very low (near 0), the value of \( X_k \) would be the same as that of the indicator. This occurs because the weight associated with \( O_k \) tends to infinity, and the second indicator (\( \bar{S}_k \)) would be ignored. The same would occur in the opposite case. This is the most inconvenient aspect of this optimization factor because subjective components usually have higher variances than objective components, for which the variance is sometimes null. Consequently, for many evaluated attributes of service, the composite indicator could tend to be a solely objective indicator, totally ignoring the subjective values. To solve this problem, the optimization function has been slightly modified to avoid the indicator \( X \) tending to the indicator with null variance by weighting indicators with the variance of the indicator’s errors plus one. The new formulation of the composite indicator is the following (9):
A Composite Index for Evaluating Transit Service Quality across Different User Profiles

\[ X^{GLS} = \arg\min_{X \geq 0} [Z(X)] = \arg\min_{X \geq 0} \left[ \sum_{k=1}^{m} \frac{(S_k - X)^2}{1 + \text{var}(e_k)} + \sum_{k=1}^{m} \frac{(O_k - X)^2}{1 + \text{var}(e_k)} \right] \]  

(9)

There may be cases in which the variance for both indicators (S and O) is zero; thus, they would be weighed equally, and X would be a value halfway between them. Moreover, if S and O have the same value, it would be the ideal situation in which S = X = O. However, this is not the usual case. The more homogeneous the judgments expressed by the passengers are, the more reliable the estimated value of S. The values are generally more reliable than S because the O indicators are calculated based on almost accurate measurements effected in different periods but not very variable among the periods (Eboli and Mazzulla 2011). Therefore, following formulation (9), the normal value of X is slightly more weighted toward O than S.

Cluster Analysis

CA is a technique that is used to segment a group of data (e.g., numbers, things, or events), and it is based on heuristic techniques that attempt to maximize the similarity among items in a group and obtain the maximum differences between items in distinct groups (Fraley and Raftery 1998; De Oña et al. 2013).

To conduct a CA, all methodologies that can be used to achieve clustering segmentation are similarly valid. There is no universal measurement that can compare diverse cluster techniques and classifications because these methodologies are merely exploratory and are used primarily to analyze the groups that are obtained (DeSarbo and Mahajan 1984). However, the Latent Class Clustering (LCC) methodology has significant advantages over the others (Alarcon-del-Amo et al. 2011; de Oña et al. 2013; Hair et al. 2010; Magidson and Vermunt 2002; Vermunt and Magidson 2005):

- It is possible to consider different variables without the need for a priori standardization that could influence the results.
- LCC allows classification of probabilities through the use of the membership probabilities of each item, which have previously been classified using the maximum likelihood.
- LCC uses measures that are not based on the distance between data, so the standardization of data has no effect on the final clusters.
- It does not demand a large space in the memory of a computer, allowing the construction of models with large amounts of data.
- The models can usually incorporate independent variables, known as covariates, or grouping variables, that can be used to describe the latent classes rather than defining them.

The formal definition of LCC is as follows: Consider a data sample of N data measured with a set of observed variables, Y1...Yj, which are considered indicators of a latent variable X and form an LCM with T classes. If each observed value contains a specific number of categories, where Yi contains li categories, within =1...j, then the manifest variables form a multiple contingency table with \( \prod_{i=1}^{l_i} l_i \) response patterns. If \( \pi \) denotes
the probability, \( \pi(X_t) \) represents the probability that a randomly-selected case belongs to latent class \( t \), \( t \in 1, 2, \ldots, T \). The regular expression of LCMs is given by (10):

\[
\pi_{Y_i} = \sum_{t=1}^{T} \pi_{X_t} \ast \pi_{Y_i|X_t}.
\]

where \( Y_i \) is the response pattern vector of case \( i \); \( \pi(X_t) \) is the prior probability of membership in cluster \( t \); and \( \pi_{Y_i|X_t} \) is the conditional probability that a randomly selected case has response pattern \( Y_i=(y_1 \ldots y_J) \), given its membership in class \( t \) of latent variable \( X \). Local independence is the underlying assumption to be verified, so Equation (9) is rewritten (11):

\[
\pi_{Y_i} = \sum_{t=1}^{T} \pi_{X_t} \ast \prod_{i=1}^{J} \pi_{Y_{ij}|X(t)} \text{with } \sum_{i=1}^{J} \pi_{Y_{ij}|X(t)} = 1 \text{ and } \sum_{t=1}^{T} \pi_{X_t} = 1
\]

The estimation of the model is based on the nature of the manifest variables because it is assumed that the conditional probabilities may follow different formal functions (Vermunt and Magidson 2005). The method of maximum likelihood is the most widely-used method for estimating the model parameters. Once the model has been estimated, the cases are classified into different classes by using the Bayes rule to calculate the \( a \) \text{ posteriori} probability that each subject \( n \) comes from class \( t \) (the model’s estimated values) (12):

\[
\pi_{X_t|Y_i} = \frac{\pi_{X_t} \ast \pi_{Y_i|X_t}}{\pi_{Y_i}}
\]

In practice, a set of probabilities is calculated for each response pattern, and the case is assigned to the latent case in which the probability is the highest. Thus, a specific user may belong to different latent cases with specific probabilities of membership (with 100\% being the sum total of the membership probabilities). Magidson and Vermunt (2002) and Vermunt and Magidson (2005) provide a detailed explanation of LCC analysis.

The objective in this methodology is to find the optimal number of clusters to align the database with the model. The criteria of selection are based on three information criteria: the Bayesian information criterion (BIC) (Raftery 1986), the Akaike information criterion (AIC) (Akaike 1987), and the consistent Akaike information criterion (CAIC) (Fraley and Raftery 1998). The information criteria and criteria of representativeness and of characterization are used to evaluate the optimal number of clusters because it is important that the obtained groups have remarkable characteristics and be easily characterized. The optimal number of clusters is the one that minimizes the score of these criteria, thus making them more parsimonious and better adapted to the study data (De Oña et al. 2014).

**Application**

**Study Case**

The transit system analyzed in this paper is the Metro transit service of Seville, a city located in the south of Spain. The municipality of Seville has a population of approximately 700,000 inhabitants in an area of 140.8 km\(^2\). The population density is approximately 4,950 inhabitants/km\(^2\). In 2014, the numbers of private cars and
motorcycles per 1,000 inhabitants were 466 and 131, respectively. The most recent mobility household survey was conducted in 2007, when the analyzed transit system still was not in operation. Nevertheless, in 2007, the modal split showed a predominance of private vehicle (53.9%) against the public transport modes (10.4%) and walking and cycling modes (35.7%).

The analyzed new Metro system entered operation in 2009 and currently consists of a sole line characterized by a length of 18 km (10.08 km underground) and 21 stations that connect 4 of the main municipalities in the metropolitan area of Seville. These four boroughs register a population of approximately 850,000 people. In 2013, the Metro carried more than 13.7 million users. This Metro system coexists with other transit alternatives in the city of Seville, such as a suburban train (5 lines), metropolitan buses (64 lines), urban buses (51 lines), a tram (1 line), and public bicycles (250 facilities and more than 2,500 bicycles for hire), all of which are coordinated by the Transport Consortium of Seville. Moreover, bicycles have significantly increased their importance following the construction of numerous cycle paths (80 km) and the creation of some parking for bicycles. In fact, most Metro stations have parking facilities for bicycles in their vicinity (distances less than 250 m).

An online CSS was addressed to a sample of 3,198 users of Line 1 of Metro de Sevilla in June 2014. Previously, a face-to-face pilot survey was carried out to check the soundness of the questionnaire and perform some modifications, reformulating the way some attributes were introduced, removing inappropriate questions, changing the order of the sections, and so on. The questionnaire adopted for conducting the CSS was then divided into four main sections:

- **Part A – attitude of users towards Metro service.** In this section, the user rates the different aspects related to their experience with the Metro service. The questions are measured on an 11-numeric scale defined as 0 = totally disagree and 10 = totally agree.

- **Part B – perceptions of users about service characteristics.** In this section, the user directly rates the different service aspects that they use in Metro Sevilla and provides a global score for the service. This part was developed according to an extensive literature review and the European Norm CEN 320/TC–EN 13816:2002 and contains 37 questions related to various aspects of the Metro service, such as availability of the service, accessibility, information, timeliness, attention to clients, comfort, safety and environmental pollution. The perceived level of quality of each of the 37 attributes was surveyed on an 11-numeric scale from 0 to 10 (0 = poorest quality and 10 = highest quality). Respondents also rated their overall perceived level of quality of the Metro service according to the same scale. In this paper, 18 of these service attributes were used for the analysis by a composite indicator; the other 19 were not considered because there were no elements for the calculation of their respective objective indicators and it was impossible to calculate the composite indicator with only their subjective indicators. User perceptions about the 18 service attributes were adopted to define the subjective indicators for the calculation of the composite index.
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- Part C – general information on the trip. In this section, the users score their travel.
- Part D – socioeconomic characteristics. This part has 11 questions related to age, gender, income, level of study, and labor situation. The different typologies of questions used are categorical answer, comment box, and multiple choice.

Service Quality Attributes and Objective Indicators

The majority of the objective indicators related to service attributes were calculated by adopting the criteria of Nathanail (2008), Cascetta and Carteni (2014), and Eboli and Mazzulla (2012). In the following, we propose a detailed description of the calculation of the indicators, providing an objective measure of the 18 analyzed SQ attributes. These attributes concern six different service aspects (Table 1).

<table>
<thead>
<tr>
<th>Service Aspects</th>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability</td>
<td>A1. Time of performance</td>
</tr>
<tr>
<td></td>
<td>A2. Number of trains per day (frequency of service)</td>
</tr>
<tr>
<td></td>
<td>A3. Proximity of stop to origin and/or destination</td>
</tr>
<tr>
<td></td>
<td>A4. Regularity of service (absence of interruptions caused by breakdown or incidents)</td>
</tr>
<tr>
<td>Accessibility</td>
<td>A5. Easy connection with other transportation modes such as bike rental, bikes, buses, etc.</td>
</tr>
<tr>
<td></td>
<td>A6. Performance of lifts and escalators</td>
</tr>
<tr>
<td></td>
<td>A7. Ease for persons with disabilities to access Metro</td>
</tr>
<tr>
<td></td>
<td>A8. Performance of validating tickets machines</td>
</tr>
<tr>
<td>Time</td>
<td>A9. Punctuality</td>
</tr>
<tr>
<td></td>
<td>A10. Speed of trip</td>
</tr>
<tr>
<td>Customer Care</td>
<td>A11. Performance of customer service (offices, website, contact by phone, etc.)</td>
</tr>
<tr>
<td>Comfort and Amenities</td>
<td>A12. Cleanliness of stations</td>
</tr>
<tr>
<td></td>
<td>A13. Cleanliness of vehicle</td>
</tr>
<tr>
<td></td>
<td>A14. Lighting in stations</td>
</tr>
<tr>
<td></td>
<td>A15. Lighting on vehicle</td>
</tr>
<tr>
<td></td>
<td>A16. Availability of Internet and phone service in stations and on vehicle</td>
</tr>
<tr>
<td>Safety and Security</td>
<td>A17. Sense of security against theft and aggression in stations and on vehicles</td>
</tr>
<tr>
<td></td>
<td>A18. Sense of security against slipping, falling, accidents at vehicle doors and escalators</td>
</tr>
</tbody>
</table>

Availability

This aspect is described by four attributes that represent the availability of the service in time and space.

“Time of performance” is the number of hours during a day that Metro service is provided. It is calculated as the average value of the number of hours per day in all considered months. It is compared with 20 h, which is the target reference schedule for other Metro services in Spain.

“Frequency” measures how often the transit service is provided. It is calculated with respect to the frequency interval per half hour. It is provided by the Metro Seville.
operator and is compared with two target references: 5 min for peak hours and 7.5 min for the rest of the day. These target references are contractual conditions for Metro Seville.

“Proximity to origin and/or destination of users” measures the average distance (or time) between origins, destinations, and Metro stations. It is evaluated based on two average times: the time between origin and Metro station, and the time between Metro station and destination. The target reference for both quantities is 7.5 min (Nakanishi 2003).

“Regularity of service (absence of interruptions caused by breakdown or incidents)” is the evenness of the intervals between transit vehicles. It is calculated with respect to the number of kilometers per breakdown. This ratio was obtained for each month, and the target reference is the minimum percentage in the interval of the month that was considered. This target reference is a contractual condition for Metro Seville.

**Accessibility**

This aspect is explained by four attributes that represent the facility’s access to stations and connection with others transports.

“Easy connection with other transportation modes such as bike rental, bikes, and buses” was evaluated with respect to the number of connections (C). It considers nine connections: taxi, urban bus, interurban bus, bicycle, tramway, surface and underground parking for private cars, train, and parking for bicycles. The final value is obtained through a logarithm equation (Eq. 13): if the number is 0, 0.5 is obtained, because walking will always be possible. The number but 1 is obtained if all of the connections are available at this station. Thus, the target reference is nine connections.

\[
y = 0.5 + 0.228 \times \ln(C)
\]  

(13)

“Performance of lifts and escalators” measures the functionality of the lifts and escalators in all stations of Metro Seville. This is evaluated with respect to the average effective performance of lifts and escalators for each month. Through comparison between the target time of performance and the real time of performance, an average is obtained. The target reference is the considered contractual target time.

“Ease for persons with disabilities to access Metro” measures the functionality of the lifts, which is the only way for a person with disabilities to access the station. Therefore, it is evaluated based on the comparison between the target time of the lift performance and real time. In the same way, “Performance of validating ticket machines,” which measures the functioning of the validating machines, is evaluated based on the comparison between the target time of the validating machine performance and real time. In both cases, the target reference is the considered contractual target time.

**Time**

This aspect is described by two attributes that represent the wait time between one train and the next and the speed of traveling by metro.

“Punctuality” measures the number of runs that arrive/depart on time. It is evaluated with respect to the percentage of regular trains. This concept is defined by Metro Seville as the time between a train’s departure from a station and that of the preceding train if
lower than its scheduled headway plus 10% (i to i+10%×i). Metro Sevilla use a definition of regularity indicator similar to that of a bus operator, Lisbon Carris (Trompet et al. 2011). The Metro Sevilla operator provides different tables with the percentage for each day at each station. Thus, an average of the values for all months and stations is considered, and this is adopted as the value for this indicator.

“Speed of the trip” measures the average speed that is provided per day. This is evaluated based on the ratio (Eq. 14) between the total commercial kilometers (L) traveled and the performance effective hours (T_e). It is weighted by the number of trains (N_i) and the ratio between its intervals of time performed (T_{ei}) and the sum of the total target hours (T_t).

\[ V_C = \frac{L}{T_e} * \left( \sum_{i=1}^{N} N_i * \frac{T_{ei}}{T_t} \right) \]  

(14)

The average commercial speed in three other Spanish undergrounds is taken as the target reference.

**Customer Care**

This aspect consists of one attribute that represents the speed with which employees answer the passenger applications/suggestions.

“Performance of customer service (office, website, contact by phone, dealing with complaints, etc.)” measures the performance of the customer service system through the average answer times for the total number of complaints and suggestions. The average answer time from the previous six months is compared with the target reference, which is the average answer time for the previous three years. The methodology used to establish the target reference is similar to that used by Nathanail (2008), who examined safety aspects.

**Comfort and Amenities**

This aspect is described by five attributes that represent the cleanliness and lighting of vehicles and stations and smartphone (phone and Internet) coverage.

“Cleanliness of vehicle” and “Cleanliness of station” are evaluated based on a rate provided by an inspector from Administration. This ratio measures the level of dirt in the Metro interior and exterior, and its range is from 0 to 3, where 0 = total filth and 3 = perfect cleanliness and, hence, the target reference. These attributes are contractual conditions for Metro Seville.

“Lighting on vehicle” and “Lighting in stations” were evaluated based on a rate provided by an inspector from Administration. This ratio measures the visual clarity in the Metro interior and exterior, and its range is from 0 to 1, where 0 = total darkness and 1 = perfect clarity and, hence, the target reference. These attributes are contractual conditions of Metro Seville.

“Availability of Internet and phone service in stations and on vehicle” is evaluated based on the rate between the line length where telephonic coverage is available and the total length of the line. Compared with other metros in Spain, where there is phone coverage and 3G along the total length of the line, the target reference is established as the total length of Metro Seville.
Safety and Security
This aspect is explained by two attributes that represent safety and security issues.

It is necessary to differentiate between two typologies in this section (Carr and Spring 1993; Eboli and Mazzulla 2008). Safety refers to involvement in an accident of transport—in this case, a Metro accident—and is measured by the “Sense of security against slipping, falling, and accidents at vehicle doors and escalators.” It is calculated based on the average number of Metro accidents during the first half of the previous year and is compared with a target reference, the average number of Metro accidents during the first halves of the previous three years (Nathanail 2008).

In contrast, security refers to victimhood of a crime or a robbery and is measured by the “Sense of security against theft and aggression in stations and on vehicles.” It is calculated based on the mean number of complaints registered during the first half of the previous year, which is compared with a target reference, the average number of Metro complaints registered during the previous three years (Eboli and Mazzulla 2011).

Sample Characteristics
The general characteristics of the collected sample are shown in Table 2. It is made up of more females (53.30%) than males (46.70%). The majority of respondents were ages 18–25 (41.70%), and the next largest groups were 26–40 (28.90%) and 41–65 (25.60%). There is an underrepresentation of the groups younger than age 18 and older than age 65 (2.80% and 1.00%, respectively). The main reasons for traveling are studies (38.80%) and work (35.50%), with leisure and other reasons showing a similar percentage (15.30% and 10.30%, respectively). Most users travel daily (52.10%). Users generally have a high school diploma (41.90%) or are university graduates (48.50%), but there is also a small group who have only secondary obligatory education (8.40%). Most of the sample has a low household monthly family income (less than 1,800 euros). The sample of users is fairly equally distributed between those who have a private vehicle available to make the trip and those who do not (54.78% and 45.22%, respectively). The users in the sample are sufficiently satisfied with the overall service (average rate of 7.6).

<table>
<thead>
<tr>
<th>TABLE 2. Distribution of Complete Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>-------------------------------</td>
</tr>
<tr>
<td>Trip purpose</td>
</tr>
<tr>
<td>Frequency of use</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Availability of:</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Level of studies completed</td>
</tr>
<tr>
<td>Household monthly income</td>
</tr>
<tr>
<td>Satisfaction with Overall SQ</td>
</tr>
</tbody>
</table>
Stratification of Sample by Cluster Analysis

The methodology applied to obtain the optimal number of clusters consists of four steps.

**Step 1: Selection of variables.** In total, 17 variables were included in the CA. (The used variables and their sample distribution for each cluster are reported in Table 5.)

**Step 2: Identification of optimal solution.** This is an iterative process in which the number of clusters was selected and refined by the variables. The Latent GOLD software program was used to obtain the optimal number of clusters. This step was necessary because not all variables were valid for use in the CA. Therefore, the objective was to achieve homogeneity of variables in all clusters to be compared between them.

First, all variables were input to the software, and 1–10 clusters were simulated. Using the Wald Test, it was possible to determine which variable should be deleted or changed into a covariable. A covariable can describe or predict (instead of defining or measuring) the latent class and reduce the classification error (Vermunt and Magidson 2005). When no variable was rejected by all clusters, the optimal number of clusters was selected. For this objective, the information criteria (BIC, AIC, CAIC), representativeness, and simplicity of the structure criteria were used. Although the information criteria (when the variation of BIC, AIC, and CAIC in % is less than 1%, it is the optimal number of clusters (De Oña et al. 2013)) noted that the optimum was five clusters, by following the representativeness and simplicity of the structure criteria, six clusters were selected. The main reason for this conclusion was that the representativeness of the six clusters was better than that of the five clusters because more heterogeneous profiles of users among clusters and, in turn, greater homogeneity within clusters were obtained. Furthermore, the model provided six additional clusters of user profiles that were sufficiently differentiable from the standpoint of characterization. Moreover, the selection of six clusters improved the information indicators that were considered, and the complexity of the model did not substantially increase (Table 3).

### Table 3.
Variation of Information Criteria

<table>
<thead>
<tr>
<th>Nº Clusters</th>
<th>BIC (%)</th>
<th>AIC (%)</th>
<th>CAIC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>1.85%</td>
<td>2.11%</td>
<td>1.81%</td>
</tr>
<tr>
<td>4</td>
<td>0.83%</td>
<td>1.09%</td>
<td>0.79%</td>
</tr>
<tr>
<td>5</td>
<td>0.33%</td>
<td>0.59%</td>
<td>0.29%</td>
</tr>
<tr>
<td>6</td>
<td>0.25%</td>
<td>0.51%</td>
<td>0.20%</td>
</tr>
<tr>
<td>7</td>
<td>0.16%</td>
<td>0.43%</td>
<td>0.12%</td>
</tr>
</tbody>
</table>

**Step 3: Development of the cluster model.** Once the number of clusters was chosen, cluster depuration was performed. In this case, the variables in this specific group were deleted or changed, regardless of whether they were in other groups. The process was similar to that of Step 2. The adjustment parameters obtained for this cluster model are shown in Table 4. It was observed that the information criteria (BIC, AIC, and CAIC) improved significantly from the model obtained in Step 2 of the CA (Table 3). Finally, the model calibration of six clusters showed an entropy value of 0.88, indicating good separation of the clusters and interpretability (De Oña et al. 2013; Depaire et al. 2008).
Additionally, it is important to emphasize the classification of error, which did not exceed 0.082 and was within the range reported in the other studies (Vermunt and Magidson 2002; Reyna and Brussino 2011). Additionally, the correlation coefficient showed a value of 0.85, near the value of a perfect setting 1, which indicated a good model fit (Rondán-Catalan et al. 2007).

### Table 4. Model Parameters

<table>
<thead>
<tr>
<th>Model Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of cases</strong></td>
<td>3198</td>
</tr>
<tr>
<td><strong>Number of parameters (Npar)</strong></td>
<td>352</td>
</tr>
<tr>
<td><strong>Statistics of Cluster Classification</strong></td>
<td></td>
</tr>
<tr>
<td>Error classification</td>
<td>0.082</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.883</td>
</tr>
<tr>
<td>R</td>
<td>0.854</td>
</tr>
</tbody>
</table>

**Step 4: Cluster characterization.** To characterize each cluster, a ratio based on the frequency distribution (in %) of the categories of all the variables considered in the analysis is used. This ratio compares, in percentages, the distribution of frequency of a category of a variable in a cluster with the distribution of the frequency of that category in the total sample. Following this indicator, the categories of variables that are overrepresented in each group can be identified. If the ratio is more than 1.5 for a category, the category is considered to be highly over-represented; if it is between 1.4 and 1.5, it is moderately over-represented; if it is between 1.3 to 1.4, it is slightly over-represented; and if it is less than 1.3, nothing can be said about this category because it follows a similar distribution to the total sample.

The results are described in the following, and the characteristics of the identified groups of users are summarized in Table 5:

- **Cluster 1 (CL1)** can be named “High-income users with predisposition to use private cars” and comprises 26.46% of the whole sample. It is predominantly made of users from ages 26–65 whose employment status is employed or less predominantly retired and who hold a university degree. Users belonging to CL1 predominantly show the availability of a personal vehicle and driver license and make sporadic trips for work or other reasons, with Metro stations not near the origin or destination of their trip. Moreover, a notable proportion of these users jointly use a car and the Metro service for their trip, and they mainly consider the car an alternative to the Metro. Finally, CL1 users show a greater level of agreement in considering the lack of parking, traffic congestion, and, less frequently, the unavailability of their vehicle as the main reasons to use the Metro. This cluster is characterized by a predominant household monthly income of more than 2,401€.

- **Cluster 2 (CL2)** represents 18.26% of the complete sample and comprises “High-income users with predisposition to use the Metro.” This cluster contains a higher proportion of users over age 26 whose status is employed or retired; university-level studies predominate. These users notably show the availability of private
cars and bicycles; they mainly make sporadic and short trips for work, other reasons, and leisure. Additionally, they consider walking, tram, and motorcycle as alternatives to the Metro more frequently than the general trend of the sample. A notably higher proportion of CL2 users consider speed, comfort, and fare as the main reasons for using the Metro; thus, we can consider this group of users as those who have a predisposition to use the Metro and are attracted by service characteristics. Moreover, this group shows the highest average perception of the overall SQ. Additionally, in this case, a monthly household income level of more than 2,401€ is more predominant than in the complete sample.

- Cluster 3 (CL3) comprises 16.73% of the sample and is named “Captive young students.” This cluster predominantly comprises users younger than age 26 who are students seeking a high school or professional education degree. This cluster shows a higher proportion of captive users (who have no alternative mode of transportation to the Metro for their trip) and users with no driver license or personal vehicle available; more than 20% of CL3 users live in large families and habitually use the Metro to reach places of study.

- Cluster 4 (CL4) comprises 14.92% of the whole sample and predominantly includes “Captive university students” who are mainly users ages 18–25 and are students seeking a high school or professional education degree. This cluster contains a distinctively higher proportion of users who used the Metro because they are captive to the Metro service, unable to drive (no private vehicle available, although they have a driver license), and who habitually take long trips for studies. Moreover, users in the CL4 cluster show the lowest assessment of the overall SQ.

- Cluster 5 (CL5) represents 12.32% of the sample and can be named “Non-captive university students.” This cluster mainly consists of users aged ages 18–25 years and are students seeking a high school or professional education degree and travel daily for studying. In contrast to CL4, this cluster did not show a proportion of captive users higher than the general trend; almost 90% of users had access to a private car. Furthermore, compared with the complete sample, these users more frequently stated that they were using the Metro service due to traffic congestion, lack of parking, or unavailability of a private vehicle; a relevant part of these users reach the Metro station by car.

- Cluster 6 (CL6) is the last cluster and comprises 11.41% of the whole sample. They are “Users with low income and high predisposition to use the PT” who more frequently declared that urban and metropolitan buses and trams are transport alternatives to the Metro service and that they use the Metro service mainly due to a lack of a driver license and the unavailability of a private vehicle. Approximately 40% of the users have no transport means available. However, they show a relatively higher average perception of the overall SQ. CL6 contains a high proportion of users over age 26 who are without education. There is a higher proportion of employed or, less prominently, retired users, and the percentage of women (65%) is considerable compared with the other clusters. They mainly travel for work or other reasons. CL6 shows a predominant monthly household income level less than €1,200.
### TABLE 5.

**Distribution of Clusters according to 17 Variables Adopted in Cluster Analysis**

<table>
<thead>
<tr>
<th>Variable</th>
<th>CL1 (842*)</th>
<th>CL2 (584*)</th>
<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>V1. Average overall SQ (Overall SQ)</strong></td>
<td>7.5</td>
<td>8.3</td>
<td>7.6</td>
<td>7.1</td>
<td>7.4</td>
<td>7.7</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(1.6)</td>
<td>(1.1)</td>
<td>(1.5)</td>
<td>(1.5)</td>
<td>(1.5)</td>
<td>(1.4)</td>
</tr>
<tr>
<td><strong>V2. I use the metro service because of</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fare</td>
<td>7.5</td>
<td>14.7</td>
<td>10.7</td>
<td>7.1</td>
<td>13.2</td>
<td>9.0</td>
</tr>
<tr>
<td>Comfort</td>
<td>54.7</td>
<td>62.7</td>
<td>46.0</td>
<td>37.1</td>
<td>49.2</td>
<td>42.5</td>
</tr>
<tr>
<td>Quickness</td>
<td>59.2</td>
<td>84.2</td>
<td>65.8</td>
<td>58.3</td>
<td>66.0</td>
<td>68.5</td>
</tr>
<tr>
<td>Frequency</td>
<td>22.8</td>
<td>28.6</td>
<td>32.1</td>
<td>27.0</td>
<td>36.3</td>
<td>33.2</td>
</tr>
<tr>
<td>Ecologic reasons</td>
<td>21.2</td>
<td>19.0</td>
<td>14.2</td>
<td>8.2</td>
<td>18.5</td>
<td>14.2</td>
</tr>
<tr>
<td>I do not have a driver license</td>
<td>0.1</td>
<td>0.0</td>
<td>63.2</td>
<td>1.3</td>
<td>0.0</td>
<td>32.9</td>
</tr>
<tr>
<td>I do not own private car</td>
<td>1.8</td>
<td>3.4</td>
<td>46.5</td>
<td>53.5</td>
<td>2.0</td>
<td>52.6</td>
</tr>
<tr>
<td>It is my unique alternative</td>
<td>3.2</td>
<td>1.0</td>
<td>32.9</td>
<td>30.2</td>
<td>7.1</td>
<td>14.5</td>
</tr>
<tr>
<td>Lack of parking</td>
<td>57.5</td>
<td>38.9</td>
<td>6.2</td>
<td>6.3</td>
<td>59.6</td>
<td>5.2</td>
</tr>
<tr>
<td>Traffic jam</td>
<td>40.3</td>
<td>27.6</td>
<td>8.0</td>
<td>7.3</td>
<td>48.0</td>
<td>6.8</td>
</tr>
<tr>
<td>I can use my own private car for any reason</td>
<td>8.1</td>
<td>3.4</td>
<td>0.7</td>
<td>10.1</td>
<td>10.9</td>
<td>2.7</td>
</tr>
<tr>
<td><strong>V3. Trip purpose</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work</td>
<td>61.9</td>
<td>56.8</td>
<td>2.8</td>
<td>4.8</td>
<td>4.1</td>
<td>62.5</td>
</tr>
<tr>
<td>Studies</td>
<td>5.3</td>
<td>4.3</td>
<td>77.7</td>
<td>83.9</td>
<td>88.1</td>
<td>2.7</td>
</tr>
<tr>
<td>Leisure</td>
<td>18.8</td>
<td>21.1</td>
<td>15.4</td>
<td>8.6</td>
<td>5.1</td>
<td>17.8</td>
</tr>
<tr>
<td>Other</td>
<td>14.0</td>
<td>17.8</td>
<td>4.1</td>
<td>2.7</td>
<td>2.8</td>
<td>17.0</td>
</tr>
<tr>
<td><strong>V4. Arrival transport from origin to station</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On foot</td>
<td>43.5</td>
<td>80.0</td>
<td>69.3</td>
<td>70.0</td>
<td>53.3</td>
<td>68.5</td>
</tr>
<tr>
<td>Other</td>
<td>5.5</td>
<td>2.2</td>
<td>6.4</td>
<td>10.3</td>
<td>1.8</td>
<td>7.9</td>
</tr>
<tr>
<td>Bus</td>
<td>5.1</td>
<td>1.0</td>
<td>13.8</td>
<td>16.6</td>
<td>9.4</td>
<td>18.9</td>
</tr>
<tr>
<td>Car</td>
<td>45.9</td>
<td>16.8</td>
<td>10.5</td>
<td>3.1</td>
<td>35.5</td>
<td>4.7</td>
</tr>
<tr>
<td><strong>V5. Length from origin to station</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 10 min</td>
<td>45.4</td>
<td>91.1</td>
<td>57.6</td>
<td>55.3</td>
<td>63.5</td>
<td>54.0</td>
</tr>
<tr>
<td>10–15 min</td>
<td>26.7</td>
<td>8.0</td>
<td>17.9</td>
<td>18.9</td>
<td>18.8</td>
<td>21.1</td>
</tr>
<tr>
<td>&gt; 15 min</td>
<td>27.9</td>
<td>0.9</td>
<td>24.5</td>
<td>25.8</td>
<td>17.8</td>
<td>24.9</td>
</tr>
<tr>
<td><strong>V6. Arrival transport from station to destination</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On foot</td>
<td>83.6</td>
<td>93.8</td>
<td>85.0</td>
<td>86.6</td>
<td>90.6</td>
<td>77.5</td>
</tr>
<tr>
<td>Other</td>
<td>4.4</td>
<td>1.9</td>
<td>2.6</td>
<td>4.6</td>
<td>0.0</td>
<td>7.7</td>
</tr>
<tr>
<td>Bus</td>
<td>5.3</td>
<td>1.5</td>
<td>8.4</td>
<td>7.1</td>
<td>4.3</td>
<td>11.5</td>
</tr>
<tr>
<td>Car</td>
<td>6.6</td>
<td>2.7</td>
<td>3.9</td>
<td>1.7</td>
<td>5.1</td>
<td>3.3</td>
</tr>
<tr>
<td><strong>V7. Length from station to destination</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 5 min</td>
<td>26.2</td>
<td>70.9</td>
<td>39.4</td>
<td>37.1</td>
<td>61.7</td>
<td>32.3</td>
</tr>
<tr>
<td>5–10 min</td>
<td>34.2</td>
<td>26.0</td>
<td>31.8</td>
<td>36.1</td>
<td>20.8</td>
<td>26.8</td>
</tr>
<tr>
<td>&gt; 10 min</td>
<td>39.6</td>
<td>3.1</td>
<td>28.8</td>
<td>26.8</td>
<td>17.5</td>
<td>40.8</td>
</tr>
</tbody>
</table>
### Variable: Total Length

<table>
<thead>
<tr>
<th>Variable</th>
<th>CL1 (842*)</th>
<th>CL2 (584*)</th>
<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 25 min</td>
<td>6.9</td>
<td>87.3</td>
<td>33.3</td>
<td>28.5</td>
<td>34.0</td>
<td>27.1</td>
</tr>
<tr>
<td>25–40 min</td>
<td>57.7</td>
<td>12.7</td>
<td>36.6</td>
<td>37.5</td>
<td>41.9</td>
<td>40.5</td>
</tr>
<tr>
<td>&gt; 40 min</td>
<td>35.5</td>
<td>0.0</td>
<td>30.1</td>
<td>34.0</td>
<td>24.1</td>
<td>32.3</td>
</tr>
</tbody>
</table>

### Variable: Type of Ticket

<table>
<thead>
<tr>
<th>Variable</th>
<th>CL1 (842*)</th>
<th>CL2 (584*)</th>
<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day ticket</td>
<td>8.9</td>
<td>10.3</td>
<td>12.0</td>
<td>9.4</td>
<td>7.1</td>
<td>10.4</td>
</tr>
<tr>
<td>Bonometro</td>
<td>39.1</td>
<td>41.1</td>
<td>24.9</td>
<td>22.9</td>
<td>25.1</td>
<td>26.8</td>
</tr>
<tr>
<td>Consortium card</td>
<td>52.0</td>
<td>48.6</td>
<td>63.2</td>
<td>67.7</td>
<td>67.8</td>
<td>62.7</td>
</tr>
</tbody>
</table>

### Variable: Frequency of Use

<table>
<thead>
<tr>
<th>Variable</th>
<th>CL1 (842*)</th>
<th>CL2 (584*)</th>
<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;4 days/week</td>
<td>43.5</td>
<td>42.3</td>
<td>59.4</td>
<td>59.9</td>
<td>66.0</td>
<td>51.2</td>
</tr>
<tr>
<td>3–4 days/week</td>
<td>17.2</td>
<td>15.2</td>
<td>17.2</td>
<td>21.1</td>
<td>18.3</td>
<td>20.5</td>
</tr>
<tr>
<td>1–2 days/week</td>
<td>17.6</td>
<td>17.5</td>
<td>11.6</td>
<td>10.9</td>
<td>6.3</td>
<td>13.2</td>
</tr>
<tr>
<td>Occasionally</td>
<td>21.7</td>
<td>25.0</td>
<td>11.8</td>
<td>8.1</td>
<td>9.4</td>
<td>15.1</td>
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</tbody>
</table>

### Variable: If You Could Not Use Your Own Car, What Alternative Do You Use?

<table>
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<tr>
<th>Variable</th>
<th>CL1 (842*)</th>
<th>CL2 (584*)</th>
<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>On foot</td>
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<td>6.7</td>
<td>5.0</td>
<td>2.1</td>
<td>3.8</td>
<td>3.0</td>
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<tr>
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<td>5.2</td>
<td>8.6</td>
<td>10.3</td>
<td>11.9</td>
<td>3.0</td>
<td>7.9</td>
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<tr>
<td>Urban Bus (Tussam)</td>
<td>12.9</td>
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<td>18.3</td>
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<td>17.9</td>
<td>18.0</td>
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<tr>
<td>Private Car</td>
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<td>13.0</td>
<td>49.7</td>
<td>4.1</td>
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<td>Combination of vehicles</td>
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### Variable: Gender

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<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
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<td>48.2</td>
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<tr>
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### Variable: Availability of

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<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>99.6</td>
<td>97.5</td>
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<tr>
<td>Access to private car</td>
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<td>20.0</td>
<td>87.8</td>
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<td>11.0</td>
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<td>4.6</td>
<td>8.4</td>
<td>4.1</td>
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<td>53.6</td>
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<td>0.0</td>
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### Variable: Age

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<th>CL3 (534*)</th>
<th>CL4 (479*)</th>
<th>CL5 (394*)</th>
<th>CL6 (365*)</th>
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<td>89.1</td>
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<td>47.1</td>
<td>5.2</td>
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<tr>
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<td>0.3</td>
<td>0.2</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
Variable | CL1 (842*) | CL2 (584*) | CL3 (534*) | CL4 (479*) | CL5 (394*) | CL6 (365*)
--- | --- | --- | --- | --- | --- | ---
V15. Level of studies completed
None or secondary School | 6.7 | 10.3 | 14.6 | 1.3 | 1.3 | 22.7
High school or professional education | 26.1 | 23.3 | 66.1 | 63.3 | 61.2 | 24.4
Bachelor’s or higher | 66.6 | 65.6 | 18.4 | 35.5 | 37.3 | 52.3
No response | 0.6 | 0.9 | 0.9 | 0.0 | 0.3 | 0.5
V16. Employment situation
Employee | 80.4 | 76.0 | 0.2 | 3.6 | 2.3 | 67.9
Student | 0.5 | 0.9 | 97.0 | 90.6 | 92.6 | 0.8
Retired | 3.6 | 6.3 | 0.2 | 0.0 | 0.0 | 3.8
Other | 15.5 | 16.8 | 2.6 | 5.9 | 5.1 | 27.4
V17. People who live at your home
1–2 people | 33.9 | 39.0 | 9.3 | 9.4 | 3.8 | 39.7
3–4 people | 54.7 | 52.7 | 68.2 | 70.6 | 72.1 | 48.8
More than 4 people | 11.4 | 8.2 | 22.4 | 19.9 | 24.1 | 11.5

Results and Discussion

Composite Indicator for Each Cluster
The composite indicator was calculated for each cluster, and some interesting differences were found among the clusters. It must be emphasized that in this analysis, only subjective indicators change across clusters, whereas the objective indicators are always the same for all cases, with the only exception of the third attribute “Proximity of stop to origin and/or destination,” which changes due to its measurement methodology. Table 6 shows the results for each cluster and the results for the overall sample, which are compared and discussed with each cluster. Figure 1 shows the results for each cluster.
## TABLE 6. Calculation of Composite Indicators of Clusters (CL1, CL2, CL3, CL4, CL5, CL6)

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Overall Sample</th>
<th>CL1</th>
<th>CL2</th>
<th>CL3</th>
<th>CL4</th>
<th>CL5</th>
<th>CL6</th>
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<th>CL2</th>
<th>CL3</th>
<th>CL4</th>
<th>CL5</th>
<th>CL6</th>
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<td>Var</td>
<td>Var</td>
<td>Var</td>
<td>Var</td>
<td>Var</td>
<td>Var</td>
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<td>3.12</td>
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<td>4.92</td>
<td>7.01</td>
<td>4.23</td>
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<td>8.22</td>
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<td>4.50</td>
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FIGURE 1.
Value of S (blue), O (red), and X (green) for all clusters
The main characteristic of CL1 (“High-income users with predisposition to use a private car”) is that the values are lower than in the complete sample, with all subjective values showing differences of less than 1 point, and the variance is slightly lower as well. Specifically, the “Proximity of stop to origin and/or destination” shows the worst subjective (5.67) and objective (2.60) evaluation and lower variance than the complete sample (9.28). These results might indicate that the origins/destinations are commonly farther than a 7.5-min walk from the Metro service. Furthermore, compared with the complete sample, in this cluster, more users prefer using their cars, but they must sporadically use the Metro due to limitations such as traffic jams and a lack of parking. Thus, despite the inconvenient distance from/to the origin/destination, the use of Metro by this cluster is an obligation, so they are critical.

In this cluster, aspects related to accessibility present worse subjective values than the complete sample. In the case of composite indicators, “Proximity of stop to origin and/or destination” is beneath the satisfactory threshold (5.00). Therefore, transit operators should consider this attribute to be a critical aspect to improve the perceived service quality of users in this cluster.

The main characteristic of CL2 (“High-income users with predisposition to use the metro”) is that it shows the highest level of perceived overall SQ evaluation and the best evaluation of the single service attributes. All subjective values have a higher value (average of 7.85) than the complete sample (7.37) and a lower variance (average of 3.38, one point below the corresponding value of the total sample). This shows that this cluster had homogeneous positive opinions about the service of the Metro. Furthermore, in contrast to CL1, the indicator related to proximity objectively (6.75) and subjectively (7.51) shows a notable improvement, a positive difference of 2.50 and 0.70, respectively, compared with the complete sample. This is the group of users for which stations are nearest their origins/destinations. The second indicator with a notable improvement is “Connections between metro stations with other transports” (almost 0.40 positive differences). This could be justified by arguing that in this cluster, users with private cars but who prefer to use the Metro for reasons of fare are over-represented. This predisposition to use the Metro jointly with the proximity of the stations to their origins/destinations could lead this cluster to perceive a very satisfactory level of SQ of the Metro. In this group, the subjective and objective indicators are very close, and there are some indicators related to accessibility aspects that have a greater subjective value than objective value; however, this difference is negligible. Thus, the perceptions and expectations of service of this group are similar to those provided by the service operator. Finally, with regard to the composite indicators, “Availability of Internet and phone service in stations and on vehicle” is the only indicator that is below the satisfactory level (4.30). This attribute is critical in all clusters and could be improved by installing phone and 3G coverage along a greater extension of the line.

CL3 (“Young and captive students”) has subjective values (average of 7.38) and an objective value (only B3 indicator) similar to those of the complete sample (average of 7.37). However, it has a slightly greater variance (average of 4.71). Therefore, this group has more heterogeneous opinions about the service, and it is more difficult to find agreement on specific aspects. There are possibly more extreme values that, on average,
have the same mean as the complete sample. However, in this cluster, young students whose age is under 18 or who are 18–25 are over-represented. They show the same opinions as the complete sample. They consider the time performance of the Metro to be unsatisfactory, probably because they like to use it during extreme schedules such as on weekends. This aspect is accentuated in this group because captive users are over-represented and because the only way to move across Seville is PT, similar to the Metro service. Furthermore, it is currently highly important for this demographic of user to be connected to the Internet everywhere; therefore, this aspect is also observed to be critical based on the results of the corresponding composite indicator.

The main characteristic of CL4 ("Captive university students") is the lowest level of perceived overall SQ evaluation and of several service attributes, although this group of users is also satisfied with the service, given that the satisfaction with the overall service is equal to 7.1 and that most attributes are satisfactory for the users. This cluster shows a high level of variance (average of 4.50). As in CL3, users have more heterogeneous opinions about the service, but they are generally low. The objective value of "Proximity of stop to origin and/or destination" is 0.5 (3.73), below the corresponding value observed in the complete sample (4.13). Young students, whose age is 18–25, are over-represented in this cluster. They perceive that the provided service is slightly less satisfactory than the complete sample, and there are two aspects that they consider to have an especially lower level of quality—phone coverage ("Availability of Internet and phone service in stations and on vehicle") and security ("Sense of security against slipping, falling, and accidents at vehicle doors and escalators"). The first may be a common necessity among young people who must be connected to the Internet at all times. The second is probably because in this group, people with a temporal disability are over-represented and they might not feel secure with the automatic doors or feel that they can fall down in some areas. Therefore, a strategy could be to provide users with a personal assistant service to help them if necessary, and their assessment of the security of the service might thus improve. However, the "Sense of security against slipping, falling, and accidents at vehicle doors and escalators" presents a limitation, similar to "Sense of security against theft and aggression in stations and on vehicle" and "Performance of customer Service," showing a possible potential disconnect between S and O values. For instance, passengers could be unsatisfied with their sense of security; however, the objective score receives full marks because the actual number of reported crimes has not increased compared with past performance.

Finally, with regard to the composite indicators, "Availability of Internet and phone service in stations and on vehicles" (4.30), which is critical in all clusters, and "Proximity of stop to origin and/or destination" are the indicators that are beneath the satisfactory level. Students who must take long trips are over-represented, so it is important for them that the stations are near their origins/destinations. This aspect is accentuated in this group because captive students are over-represented.

It was worth noting that CL5 ("Non-captive university students") is similar to both CL4 and the complete sample. Subjective values are slightly greater (average of 7.22), but they also show a greater variance (average of 4.70) than the complete sample (average of 4.38). However, non-captive users are over-represented in this group, although they
regard the use of the Metro as an obligation, probably because they do not use private cars due to traffic jams, lack of parking, and so on. Thus, they express their disapproval with the service. Singularly, the value of “Proximity of stop to origin and/or destination” is 5.85, near the critical level, which shows that users have stations nearer their origins/destinations than CL4 and the complete sample.

CL6 (“Users with low income and high predisposition to use the PT”) users have subjective values (average of 7.45) and variance similar to the complete sample (average of 7.37 and 4.38, respectively). In the case of the objective value of “Proximity of stop to origin and/or destination,” it presents a lower value than the complete sample. Therefore, this indicates that the stations are farther than for the complete sample. However, in this cluster, users over age 26 are over-represented. They show the same point of view as the complete sample. They regard the time performance of the Metro as unsatisfactory because they like to use the Metro in extreme schedules, possibly because they work at night. This aspect is accentuated in this group because captive people are over-represented, and the only way to move across Seville is by PT.

Conclusions

The exclusive use of either subjectively- or objectively-measured indicators could be insufficient to achieve a comprehensive assessment of the quality of a PT because of its diffuse, complex, and heterogeneous nature. This could provide a biased representation of reality. Therefore, it is necessary to combine all information collected from users and provided by transit agencies (subjective and objective data). The methodology that is proposed is quite adequate to achieve a composite indicator, equally considering both indicators and awarding indicators that present less heterogeneity in their assessments. The subjective data were provided by means of a CSS, and the objective data were calculated by adopting different criteria based on a comparison of the actual performance with standards. This point presents a limitation; indicators that have a standard based on past performance (e.g., “Performance of customer service,” “Sense of security against theft and aggression in stations and on vehicles”) present a possible potential disconnect between the S and O values. For instance, passengers could be unsatisfied with their sense of security; however, the objective score receives full marks because the actual number of reported crimes has not increased compared with past performance.

Another aspect that should be taken into account when considering opinions on the quality of service is that currently there is a great diversity of users with different needs who depend on such factors as their socioeconomic characteristics and travel patterns. Therefore, a segmentation of the sample was made to identify different groups of users and analyze their opinions about the service.

Because the conventional methods of segmenting categories according to some socioeconomic variables have disadvantages of under-representation or lack of different parameters, it is necessary to use cluster analysis as an effective segmentation procedure to facilitate the achievement of these objectives. Among the different CA techniques, it is noteworthy that there is no universal measure that serves to determine the best
technique because they are exploratory techniques. However, Latent Class Clustering has several advantages over other procedures, the main one of which is that several types of variables that are not segmentation-based measurements of the data can be used.

The combined use of these techniques was applied to the case of Metro Seville, and the benefits were 1) allowing the characterization of the different typologies of users, 2) enabling the study of each attribute for each cluster and, consequently, identifying the attributes that present the lowest and highest values, and 3) explaining and contextualizing for each of them the composite indicators and results, which allows agencies and consortiums of PT to provide different strategies for marketing for specific demographics of users.

Specifically, six different groups of users who have relatively different perceptions of the service were identified. Two groups of users are characterized by a wide presence of adults who travel for work and have a relatively high income level. These two groups differ regarding their opinions about the Metro service and the transportation modes in general: one group comprises people who are more disposed to use private cars, and the other group is more inclined to use Metro. The second cluster clearly shows better opinions of the service.

In addition to the two groups of adults, three groups of students were identified that differ according to the availability of driver licenses and private cars as alternative mode to the Metro. Specifically, there is one group of captive young students and one group of captive university students who use the Metro because they have no other alternatives; this last group expressed the worst opinions about the service. The third cluster of students mainly comprises non-captive university students who use the Metro because they want to use it; the last identified cluster is made up of users with low income and high predisposition to use PT who expressed higher rates of satisfaction regarding several attributes compared with other clusters.

Thus, it can be concluded that users who choose to travel by Metro but who have the option to travel by private car are more satisfied with the service, whereas users who use only the Metro because they do not have other alternatives (captive users) are more critical towards the service. This is a comforting result, which suggests that if transit operators offer services characterized by high levels of quality, public transport can become a real alternative to private cars. This is an important point for solving environmental and social problems resulting from the excessive use of private cars.

From a practical perspective of this research for service operators, the number of cases in which the objective and subjective rankings are not similar could be identified. If the target values for these indicators could be adjusted, then service operators may be able to simply measure the objective indicators, supplemented by less frequent customer surveys to ensure that the two types of measures are still aligned. This would facilitate a purely objective measurement of passenger satisfaction. Moreover, this would allow for more frequent measurement and incorporation into a service operator’s performance management program while reducing measurement costs.
Acknowledgments

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Older Adult Transportation in Rural Communities: Results of an Agency Survey

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Abstract

The proportion of people over age 65 is higher in U.S. rural and small communities than in urban or suburban areas. When older adults who reside in these communities retire from driving, they may need to rely on alternative transportation options that exist in urban settings but that might not be provided, might be less accessible, or might be available in a different form in their communities. This paper uses a survey of service providers to identify the types of public transportation options available to older adults residing in these communities, as well as the strategies employed to finance, operate, and/or market these services. The survey results highlight a need for more careful investigation of the nature of service partnerships, the effectiveness of service strategies, and the actual use of services by older adults.

Keywords: Public transportation, older adults, rural and small communities, finance

Introduction

The older adult (aged 65 or older) population in the United States is projected to increase by half in the next 25 years, from 14.1% of the population in 2014 to 21% by 2040 (U.S. Census Bureau 2014). Recent studies have shown that the proportion of people (approximately one in five) over age 65 is higher in rural and small communities than in urban or suburban areas, and is expected to grow significantly over the next decade (Baernholdt et al 2012; Bennet et al 2013). For the purposes of this project, rural and small communities are those defined by the Federal Transit Administration (FTA) as having a population less than 50,000 (FTA 2015a).

The growth in the older adult population of these communities can be attributed to two distinct yet interrelated factors. First, the sheer number of Americans over the age of 65 is increasing due to advances in medical care, greater longevity overall, and the impending transition of a major birth cohort—the Baby Boomers—into this age range (Blanton and Bowen 2013; Glasgow and Brown 2012; Myers and Sung-Ho 2008).
Second, older adults are becoming an increasingly large proportion of those areas’ total population, due to a host of economic and migration factors. As explored in the literature review, “aging in place” is a dominant force in aging policy, and many older adults are encouraged (or compelled by financial constraints) to remain in their homes even as other age cohorts leave rural and small communities (Morken and Warner 2012). These communities also tend to suffer from “brain drain” forces that compel young people to more urban areas for higher education or better career opportunities (Carr and Kefalas, 2010; Scales et al. 2013), leaving behind a disproportionate number of older residents who continue to age in that setting.

Like the rest of the adult population, older adults living in rural and small communities rely on the personal automobile as a primary means of mobility (AARP 2012). However, when they cease driving, they may need to rely on alternative transportation options that exist in urban settings but that might not be provided, might be less accessible, or might be available in a starkly different form in rural and small communities (Kerschner 2006). Given the pending growth of older adults living in rural and small communities, more information about the kinds of transportation services currently available in these communities is needed.

This paper examines the state of rural and small community transportation programs from an administrative and operations perspective to better understand how such programs, particularly those serving older adults, provide services and perceive their role in the broader transportation and human-service environment. Using a survey, the authors found that service providers in rural and small communities offer a diverse array of transportation options for older adults and frequently partner with social services, government, and other entities to finance, operate, and/or market services. The survey results also indicate that providers in rural and small communities perceive themselves to have been successful in marketing services, building trust, and leveraging resources in an environment that presents a unique set of challenges for transit providers and policymakers. The findings suggest a need for more careful investigation of the nature of service partnerships, the effectiveness of service strategies, and the actual use of services by older adults.

Literature Review

The unique transportation needs of older adults have been explored at length in recent years, often through the lens of aging in place initiatives. The focus is often on the promotion of transportation as a means of maintaining independence for older adults who wish to maintain community ties while remaining in their own homes (AARP 2012; Rosenbloom 2003, 2004), though other streams of analysis have focused on the availability and structure of existing alternatives to driving in rural and suburban areas (KFH Group 2001, 2004, 2008). Commonly-cited destinations popular among the 65 and older population include shopping centers, medical offices, places of worship, and community centers, but in rural and small community settings, such destinations often are inaccessible by transit. This compels older adults living in such areas to rely on the personal automobile to a greater degree than their urban counterparts (Giuliano 2004; Rosenbloom 2004).
As such, the need for reliable alternative transportation options becomes particularly pronounced once older adults voluntarily or involuntarily cease driving (Safe Mobility for Life Coalition 2011; AARP Public Policy Institute 2011). In recent years, the gerontological literature has focused on the physiological and cognitive impairments that often accompany aging and how these can have a deliterious effect on driving (Alsnih and Hensher 2003; McKnight 2003). Policies designed to help older adults transition from driving to using specialized transportation are limited, but the emergence of these topics in the literature suggests the need for studies such as this one that may help to bridge the knowledge gap to aid practitioners in using such policies to increase ridership and accessibility of older adults.

The types of public transportation services available in rural and small communities vary widely from place to place, but may consist of ordinary automobiles rather than large buses, operations that make individualized trips via appointment rather than on a scheduled fixed route, and/or shuttle-like services to specific destinations such as major medical complexes (KFH Group 2004). Service providers that operate rural- and small-community-focused transportation programs in the U.S. receive funding from federal authorities to provide transportation. In FY2014, FTA devoted more than $600 million to rural-area programs under the §5311 Formula Grants for Other than Urbanized Areas Program (FTA 2015b). Some providers also receive funding through the §5310 Transportation for Elderly Persons and Persons with Disabilities Grant Program that funds services for older adults and individuals with disabilities (FTA 2015a). Although there is no funding program specifically geared toward serving older adults in rural and small communities, the agencies that receive funding under both FTA programs most likely provide services for both constituencies in tandem. In fact, the set of funding recipients for the two programs often overlaps considerably, which suggests that providers have easily been able to secure funding for one, or both, priorities.

Rural and small communities tend to have smaller tax bases as a consequence of the decreased economic opportunities and lower living standards of their communities as compared to their urban counterparts. These smaller tax bases typically produce insufficient local government fiscal resources to support a permanent public transportation program (The White House 2010). Because of these resource challenges, service providers have been said to exist in a “culture of innovation” (KFH Group 2001). The economic circumstances of many rural service areas requires providers in that setting to be creative and adopt unique funding streams, institutional partnerships, or other strategies related to service delivery, management, and administration (Hosen and Powell 2011; Koffman 2004). The desire to gain more knowledge about the purpose and extent of these strategies was a primary motivation for this research.

**Research Design and Case Selection**

This study examined two questions: What kinds of transportation services are available to older adults living in rural and small communities? How are these transportation services organized and delivered by transportation service providers?
To answer these questions, the authors designed a survey distributed to administrators of 108 agencies that serve older adults living in rural and small communities. The survey used a web-based platform with open-ended questions and was administered in the spring and summer of 2015. The survey respondents were drawn from the 2014 National Transit Database (NTD) of transit agencies that received some combination of funding designed to service older adults and/or persons with disabilities (§5310 funds) and individuals living in non-urbanized areas (§5311 funds) (FTA 2015c). The authors used the combined (urban and rural) NTD as a survey pool and focused on agencies that applied grant monies to operational and/or capital expenses, with preference given to agencies using the funds for operating expenses. This allowed the authors to communicate specifically with rural and small community-serving organizations that devoted at least some resources to serving older adults. Because this was a targeted and non-random survey, responses were not anonymous. As discussed in the results below, responses were received from a national distribution of agencies, roughly two-thirds of which were public transportation or aging-related agencies. The remaining third were private non-profit organizations, most of which identified a primary focus on aging-related issues. Survey materials were addressed to administrators or those individuals within the organization who could best discuss the issues identified.

The authors asked respondents a set of 13 questions that ranged from general topics such as organization, location, and communities served to more administrative-focused topics such as agency mission, results of ridership surveys, and noteworthy opportunities or challenges to future growth of the older adult rider market. A copy of the survey is included as Appendix A. The general-topic questions helped to establish the context in which these programs operate. The administrative questions shed light on issues more directly related to service provision by allowing respondents to explain how their organization works with older clients as well as how their agency’s stated mission connects with its current and long-range activities.

The survey responses fit into a few broad categories, from which some general points of consensus emerged regarding the operation and growth potential for transit providers in rural areas and small communities. For example, nearly all respondents identified either inadequate funding or the difficulties in communicating effectively with independent older adults as their organization’s single greatest challenge. Nearly all respondents identified either financial or collaboration/partnership ties with government agencies and/or local non-profit organizations, usually those organizations related to healthcare or education services. The survey also revealed that even though a large number of respondents stated that their organization explicitly targets older adults and/or receives funding to serve their needs, the language of the agencies’ published mission statements was far less likely to contain references to older adults or their needs.

**Survey Results**

In total, 40 responses were received from agencies located throughout the United States, with a large number of respondents from the Pacific Northwest (see Figure 1). Although the number of responses may appear small for a national survey, these 40
were from the aforementioned list of 108 agencies that received both §5310 and §5311 funds, indicating a response rate of just under 40%. This is a reasonable response rate for this kind of survey.

Of the 40 individuals who completed the survey, 38 occupied a position of senior management, such as executive director, mobility manager, transportation director, or a similar title. One respondent self-identified as a dispatcher, and one identified as a service specialist. Most responding agencies were formed or administered by a local government body, as opposed to being non-profit organizations or private companies. The discussion that follows focuses on eight key survey questions about service provision (see Appendix A for the full question set).

Mission Statement Language Rarely Matches Day-to-day Operations
The authors asked respondents whether their organization has a specific mission related to transportation service provision. From the 33 agency mission statements supplied by respondents, it was found that general terms such as “transportation,” “provide,” and “service” appeared more frequently in the statements (30, 28, and 17 appearances, respectively) than aging-oriented terms such as “independence,” “seniors,” and “safe,” (7, 5, and 4 appearances, respectively). This was observed despite the fact that every agency surveyed received some funding from FTA to provide services specifically for older adults and individuals living with disabilities. Although the terminology used in mission statements is not generally required to match an organization’s daily operations, the fact that many agencies received federal dollars to serve these two groups, yet maintained mission statements that generally did not contain explicit references to them, may indicate either an outdated set of guidance documents or a functional disconnect between formal policy and daily operations.
Surveyed Organizations Provide a Diverse Range of Services

Respondents were asked to list the specific transportation services their agencies provide to client populations. Given the wide range of terms used to describe agency services, the responses were reviewed and classified into a number of basic service categories, as is shown in Table 1.

Nearly every respondent listed multiple service types, but the most common, by far, was demand-response or “curb-to-curb” service. A majority of respondents stated that they offer an on-call or demand-responsive service, and a smaller number reported providing traditional fixed-route services such as those that accept or discharge passengers at predetermined stops or operate on a set schedule. This finding mirrors what the literature has noted regarding rural areas with dispersed populations—many rural transit riders use these services only for medical or infrequent trips (Kerschner 2006; National Rural Health Association 2013). Whereas all 40 responding agencies accepted §5310 monies to serve passengers living with mobility impairments as classified by the terms of the Americans with Disabilities Act (ADA), 12 respondents reported providing ADA-specialized service on a regular basis. They distinguished this from “demand-response service,” as discussed in the next paragraph. According to federal regulation, transit agencies that operate fixed-route services are required to offer ADA-compliant paratransit services within a set distance of their routes to meet the needs of individuals with disabilities who might be unable to use the fixed-route services. The §5310 program is intended to provide paratransit services as a supplement to fixed-route service for those agencies that operate fixed routes. Since the agencies surveyed also received §5311 funds, meaning they serve rural and small communities, most do not operate fixed-route transit within their service areas. Overall, this suggests that the 12 responding agencies that explicitly mentioned providing ADA-compliant service operate some level of fixed-route service and are accustomed to the service-supplementing requirements of the §5310 program, which was confirmed in a post-survey review of responding agencies.
One issue that arose in coding and interpreting the survey results was that of terminology. Numerous terms are used within the industry to describe the services listed in Table 1, and some definitions overlap. For example, whereas some respondents explicitly distinguished between “paratransit service” and “demand-response service,” it is not clear from the data that all respondents made a distinction between the two services when they answered the survey question. Given this issue, the results did not easily indicate the degree to which individual agencies focus on passengers with disabilities versus older-adult passengers. This overlap in service-provision is made more difficult by the fact that §5310 monies are disbursed to serve both older adults (those age 65 and older) and individuals with disabilities (of all ages). A deeper examination of the issue may bear more solid findings on the specific makeup of §5310 funds allotted to each agency’s various services, but for this analysis, respondents’ statements were clear that demand-response services dominate the programming of rural and small community transportation providers.

**Observed Organizations Partner with a Vast Array of Government or Non-profit Agencies**

Respondents were asked if they partner with other organizations when providing services, and if so, to list those partners and to explain the purpose(s) for such partnerships. The responses, once categorized into the simple tally of partner types shown in Table 2, produced two central findings.

<table>
<thead>
<tr>
<th>Partner Agency Type</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local government</td>
<td>20</td>
</tr>
<tr>
<td>State government</td>
<td>16</td>
</tr>
<tr>
<td>Older adult service organizations</td>
<td>16</td>
</tr>
<tr>
<td>Health facilities</td>
<td>12</td>
</tr>
<tr>
<td>Education and workforce</td>
<td>11</td>
</tr>
<tr>
<td>Human service nonprofit</td>
<td>8</td>
</tr>
<tr>
<td>Private transportation companies</td>
<td>3</td>
</tr>
<tr>
<td>Veterans’ care organizations</td>
<td>2</td>
</tr>
<tr>
<td>Tribal transportation</td>
<td>1</td>
</tr>
</tbody>
</table>

In total, 34 respondents (85%) reported that they partner with at least one local, regional, or statewide entity to provide transportation services. Such intergovernmental partnerships are common among public transit agencies (KFH Group 2004). Local-government ties were more frequently reported than statewide ties. Most of these intergovernmental partnerships were of the sort defined by formal and/or financial arrangements such as contracted service, government grants, and pass-through monies. Locally-oriented human service non-profit organizations, particularly those related to older adult services and health, tend to dominate these working relationships. Assisted-living facilities, adult day-care facilities, and medical facilities were listed as the most frequent non-governmental partners. Many respondents also reported collaborating with school districts, local colleges, job-training nonprofits, and a few private companies.
to provide transportation to students and workers. Overall, the survey results suggest that transportation service providers are well-connected and in a unique position to provide clients with access to a vast array of services.

Despite being directly asked to discuss the nature of agency partnerships in the survey, only 14 out of 40 explicitly stated the purpose for the inter-agency partnerships in which their employer was engaged. The respondents that did explain the purpose(s) behind these partnerships described rationales such as fee-for-service contracts, state-required inter-agency coordination, or simply to share costs among local human-service agencies.

**Informal Marketing and Word-of-Mouth are the Most Common Tools Used by Providers**

Respondents were asked to assess the degree to which their agencies marketed transportation services to older adults, as well as the specific ways in which they did so. A total of 31 respondents reported that their agency targets older adults as a client population and devotes resources to marketing services to that population; 21 of those work directly with older-adult housing facilities and medical professionals to market transportation services at those locations and to educate potential riders of the benefits of said services.

Regarding the marketing of services, 24 out of 40 respondents stated that their agency’s outreach efforts depend to a large degree on informal recommendations and/or word-of-mouth communication among clients, due to a commonly-held belief among these providers that personal recommendations are the most effective marketing tools when working with older adults in smaller communities. Although traditional marketing and education tools such as advertisements and pamphlets were used by 25 respondents, the consensus among them was that informal marketing is vital to operational success. Many made the direct assertion that informal marketing is as common and as useful to their organization as formal marketing platforms. This indicates that a communicative and socially-oriented marketing approach is likely to be equally, if not more, successful at growing and retaining older adult ridership than traditional marketing formats such as printed or multimedia advertising.

**Customer Surveys are Common, and Conducted for a Variety of Purposes**

Respondents were asked whether they conducted surveys or other assessments to measure the effectiveness of their agency’s services in meeting older adult transportation needs, and if so, to discuss the results of such assessments. A total of 22 respondents stated that they conducted formal surveys, with most being for general customer-service or customer needs-assessment purposes. Of the 22, 3 claimed to conducted formal surveys as part of a comprehensive-plan update or as a legal/contract stipulation, 4 surveyed clients informally—for example, through in-person conversations with a client during or after a trip—and the remaining 13 respondents did not survey clients at all. Of the agencies conducting formal surveys, one stated that their agency does so solely as a requirement for receiving federal funding. As a whole, the survey responses indicate a client-oriented culture in many of these organizations, given their focus on gauging customer satisfaction and customer needs.
Overcoming Clients’ Fears and Securing Program Funding Represent Major Challenges

Respondents were asked what they perceived to be the greatest challenge(s) to encouraging greater older adult usage of transportation services. Responses were organized into a handful of broad but logically-grouped categories, as shown in Table 3.

<table>
<thead>
<tr>
<th>Challenges to Encouraging Older Adult Use</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inadequate funding/staff/vehicles</td>
<td>12</td>
</tr>
<tr>
<td>Maintaining older adults’ independence as they transition from driving to transit</td>
<td>11</td>
</tr>
<tr>
<td>Overcoming older adults’ fears and building trust</td>
<td>8</td>
</tr>
<tr>
<td>Limited schedules and dispersed clientele</td>
<td>4</td>
</tr>
<tr>
<td>Inadequate marketing of services</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Opportunities for More Older Adult Use</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion of existing service</td>
<td>8</td>
</tr>
<tr>
<td>Marketing/education for older riders</td>
<td>7</td>
</tr>
<tr>
<td>Strong ties to older adult services</td>
<td>7</td>
</tr>
<tr>
<td>Word-of-mouth among existing users</td>
<td>5</td>
</tr>
<tr>
<td>Popularity of service among older riders</td>
<td>2</td>
</tr>
<tr>
<td>Miscellaneous or unrelated response</td>
<td>7</td>
</tr>
</tbody>
</table>

The most common challenge identified by respondents was the set of issues related to funding for operations, equipment, and staffing. The second and third most frequent responses were actually more noteworthy for this project, as they related to respondents’ views about more effectively engaging older adult riders. Nearly one third of respondents stated that their agency’s greatest challenge was helping auto-dependent older adults transition from driving to transit. One-fifth of respondents reported that building trust and helping older adults overcome their fear of transit represented their greatest obstacle to success. Taken together, these responses show that nearly half of the respondents consider their agency’s interactions with older adults to be the single greatest challenge facing them. The remaining respondents felt their organization’s greatest challenge was either program-related (limited schedules and dispersed clientele) or a generally inadequate marketing of services. Thus, from the respondents’ perspective, issues of limited fiscal resources and the need for more effective older adult outreach and engagement are the biggest obstacles to future success.

Building Strong Networks and Ties to Older Adults are Key Opportunities for Growth

To supplement the question regarding challenges, respondents were asked to identify their agency’s best opportunities for encouraging greater older adult use of agency services. The responses to this question were grouped into a small number of broad categories, mainly as a means of simplifying the analysis.

First, as indicated in Table 3, respondents identified the expansion of existing services as representing the biggest opportunity for growth. Second, consistent with the
responses related to challenges, many responses were related to agency relationships with the older adult community. A number of respondents perceived opportunities for more marketing and outreach directly to older adults and for more partnerships with organizations serving that population. Many respondents also thought that their agency’s generally positive reputation among older riders provided an excellent opportunity for more informal, word-of-mouth marketing opportunities that might promote older adult use of the services. Indeed, some respondents perceived word-of-mouth as the most effective marketing strategy for this population in the rural and small community setting. The fact that nearly all relevant responses were in some way related to either funding/expansion of services or relations with older adult riders indicates that rural and small-town transportation providers understand the tremendous value that transportation services have in meeting the various practical, social, and emotional needs of older adults in rural and small communities.

Discussion

One important finding from the survey is that nearly all survey respondents work closely with a wide range of government and/or community partners to organize, finance, market, and/or deliver transportation services. Although the exact nature of these partnerships and their effectiveness in permitting or encouraging older adult use of transportation services is still to be determined, the importance of these partnerships is unquestioned by respondents and reflects the value of partnerships in overcoming many of the financial, technical, and/or organizational challenges that are especially challenging for providers working in rural and small communities.

A second important finding is the importance that survey respondents assigned to word-of-mouth marketing and direct personal outreach to the older adult population. The managers of these programs seem particularly attuned to the social and/or psychological challenges inherent in building trust with older adults and helping them transition from driving to transit. Their administrative experiences should be valuable for others who work with older adult populations in both rural and urban settings.

Conclusion

This study sought to identify the types of transportation services available in rural and small communities and to determine how these services were organized and delivered. Agencies in rural and small communities offer a diversity of service types, ranging from demand-responsive to fixed-route to highly-specialized services (for example, trips to medical providers). The managers of these programs have found partnerships with other organizations, informal marketing, and personalized contact with older adult populations to be critical to their agency’s ability to provide service and meet the transportation needs of older adult riders. These agencies have limited resources available to provide services, but program managers see tremendous potential to increase older adult ridership if they can expand service and enhance their marketing, education, and outreach efforts.

These findings have several important implications for policy, practice, and research. First, the finding that these agencies rely on a range of partners, both as sources of
funding and as co-providers of human services, shows a resilience and entrepreneurial spirit that has helped them to provide much-needed services to passengers in a resource-challenged environment. Second, the degree to which these providers are attuned to the psychological and social needs of transit-hesitant older adults proves they might be an invaluable source of insight for service providers of all sizes in better tailoring their outreach and services to more effectively meet the needs and expectations of older riders. Finally, the significant degree to which these agencies seem to function more based on community ties and local perceptions than broader technical or political concerns suggests that planning transit for rural and small communities is likely to take a different approach from the technically-savvy operations and administration climate in urban transit agencies.

The logical next step is to examine transit in rural and small communities from the perspective of the older adults who use these transportation services. An investigation of how older adults perceive these services and how they perceive the barriers and opportunities to their use would be informative. In addition, further research into how older adults actually use transportation services, why they use them, and in what numbers they use them would provide more insight to planners, policymakers, and scholars concerned about rural and small community transportation and the importance of addressing the transportation needs of America’s aging population. Such an investigation would be an invaluable complement to the preliminary findings presented here.

Acknowledgments

The authors are grateful to the agency representatives who participated in the survey whose results are discussed in the article. The authors also thank the Center for Accessibility and Safety for an Aging Population at Florida State University for its financial support of this research.

References


Appendix A: List of Questions Used in Agency Survey

**General Questions**

1. What is the name of your organization or agency?
2. Where is your organization or agency located?
3. What is your organization or agency’s service area?
4. What is your position in the organization or agency?

**Content-Focused Questions**

5. Does your organization or agency have a specific mission with respect to the provision of transportation services? If so, what is it?
6. What kinds of transportation services do you provide?
7. Do you partner with any other organization or agency when providing services? If so, what are their names? For what purpose(s) do you partner with those organizations?

8. Are older adults a targeted user market for your programs or services? Why or why not?

9. If they are, how do you market your programs or services to older adults?

10. Have you conducted any assessments of the effectiveness of the services you provide in meeting the transportation needs of older adults? If so, what were the results?

11. What do you see as the greatest challenge(s) to encouraging greater usage of your services by older adults?

12. What do you see as the greatest opportunities for encouraging greater usage of your services by older adults?

13. Do you think your organization or agency would be a good candidate for a more detailed study? Why or why not?

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Examining Bus Lost Time Dynamics for a Bus Rapid Transit Station

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Abstract

Bus Rapid Transit (BRT) systems are considered to be the most effective alternative for solving urban transportation problems for both developed and developing countries. The conventional approach to estimate dwell time (DT) is based on traditional DT models derived for normal bus stops, but not for modern BRT stations. BRT stations are different from bus stops in terms of length of platform, multiple loading areas, and number of passengers handled. Therefore, understanding dwell time dynamics, including the recently-introduced component of Bus Lost Time (BLT), is important to improve the operations of BRT systems. This research introduces various possible scenarios of alighting and boarding using video data collected at the Shivranjini BRT station in Ahmedabad, India.

In total, 877 observations of BLT and DT were extracted from 17 hours of video data recorded for one full-service time of the day. The possibility of BLT occurrence was examined and explained with the help of conceptual line diagrams, and the probability distribution of BLT was fitted for two loading area platforms by considering 401 observations from the BRT platform video data of the entire service period. A comparative evaluation was made between observed and estimated BLT values. This study estimated station capacities before and after, including BLT as a DT component to observe the effect of BLT on BRT stop capacity. It was observed from the results that including BLT in dwell time reduced BRT capacity by 11%. This study provides ready-to-use BLT values for correct estimation of dwell time, thus improving accurate estimation of BRT station capacity.

Keywords: Bus rapid transit, BRT, bus lost time, bus lost time dynamics
Introduction
A large number of cities in the world are facing rapid urbanization and development, which is leading to increased demand for travel by private modes and resulting in congestion (Zimmerman and Agarwal 2012). Light rail transit (LRT) and mass rapid transit systems (MRTS) are two high-investment public transport alternatives for significantly reducing congestion on roads. Bus Rapid Transit (BRT) systems are becoming popular all over the world because of their low initial investment (Gupta 2014; Carey 2002). They are considered to be reliable, cheap, and effective and regarded as a widespread option for public transportation (Jiang et al. 2012). Satiennam et al. (2013) identified BRT as a system that can bring about a modal shift from private vehicles. Currie (2005) reported BRT to be as effective as a rail system in generating patronage when developed to replace conventional bus service. Deng and Nelson (2011) reported the acceptance and popularity of BRT, which has increased attractiveness because it is an integrated system of facilities, amenities, services, intelligent transportation systems (ITS), and operations (Levinson et al. 2002). Vuchic (2002) conducted a comparison between bus semi-rapid transit and LRT and found out that the former is better in terms of initial investment and implementation time.

Although not quite a decade old in India, BRT systems are running in eight cities of India. Therefore, understanding system capacity and its components is now becoming very crucial. One of the major components of BRT system capacity is dwell time (DT).

The traditional approach of estimating bus DT at a stop based on the number of passengers alighting and boarding is considered to be suitable for analysis of a suburban stop with a single marked bus loading area but not for a modern BRT station (Jaiswal et al. 2010). There are two commonly-adopted methods of DT estimation. One lengthy method is by field measurement, and the other, relatively less time-consuming method (used by planners) is by using already-available average per-passenger service time values, as indicated in the literature. Large amounts of time and money are involved in the field measurement method; therefore, planners use the second method, which requires the number of passengers boarding and alighting per bus in a station and the per-passenger alighting and boarding times. However, the problem here is that these default per-passenger service time values are estimated and reported (using regression models) for conventional bus stops (Guenthner and Hamat 1988; Levinson 1983). These conventional bus stops have negligible bus lost time (BLT) because the characteristics of a bus stop are different from a modern BRT station (Jaiswal et al. 2010). According to the Transit Capacity and Quality of Service Manual (TCQSM) (Transportation Research Board [TRB] 2013), BLT is defined as the “waiting time for bus, between when the bus comes to stop in its loading area and when the first passenger boards.” The average walking time for a passenger in a BRT station with multiple loading areas is more than that for a normal bus stop because of the long length of the platforms and more crowding (Jaiswal et al. 2010). Therefore, if the default per-passenger service time (from the regression model) of a normal bus stop is used in the DT estimation of a BRT station, then these values will underestimate the DT because negligible BLT would be included. Therefore, there is a need to add BLT to DT separately to take into account the
increased walking time in a BRT station. This concept with a model has been approved and include in the TCQSM, as shown in the literature.

The main objective of this research was to improve the estimation of DT by examining the dynamics of boarding and alighting (B&A) of single-door buses. The concept of BLT as a recently-introduced component of DT in the TCQSM was then studied for various scenarios of B&A occurring in series and simultaneously. Data from the busiest bus stops of the Ahmedabad BRT system in India were considered to examine the dynamics of DT. BLT values for two loading areas were included in the study, and the loading area capacity of stations was estimated before and after considering BLT.

**Review on Estimation of Dwell Time and Its Components**

In the literature, most studies consider linear regression models for DT estimation, and the main parameter considered in these models is the number of B&A passengers (Feder 1973; Levinson 1983; Guenthner and Hamat 1988). Previous researchers (Levinson 1983) estimated DT for buses and derived that it depended on two primary factors—number of passengers boarding and alighting and time required for the bus doors to open and close. This is shown in Equation 1:

\[
DT = tN + t_{oc}
\]  

where DT is the dwell time, t is the average B&A time per passenger (reported to be 2.75 sec), N is the total number of persons boarding and alighting, and \( t_{oc} \) is the bus door opening and closing time. Another DT model was proposed by Guenthner and Sinha (1983), as shown in Equation 2:

\[
\frac{DT}{Total} = 5.0 - 1.2\ln(\text{Total})
\]  

where DT is the dwell time and Total is the total number of passengers boarding and alighting.

Based on field observations, a link between DT estimation and fare collection systems was deduced for buses (Guenthner and Sinha 1983), which reported the average alighting and boarding time per passenger as 1.81 sec and 5.66 sec, respectively, considering 10 different types of fare collection systems. Lin and Wilson (1992) reported DT models for one- and two-car trains and reported average alighting and boarding time per passenger as 0.23–1.4 sec and average boarding time per passenger as 0.27–1.15 sec. Levin and Torng (1994) examined relationships between low-floor buses and DT, and a Transit Cooperative Research Program (TCRP) study (1996) relates DT savings to the layout of bus stops. Duekar et al. (2004) analyzed dwell times with respect to bus door widths, and Li et al. (1971) formulated a model to study DT based on preferences of doors among passengers. Rajbandari et al. (2003) studied DT on a large data set obtained by Automatic Vehicle Location (AVL) data, and Tirachini (2013) studied techniques for payment of fares to reduce DT in buses. Curie et al. (2013) studied the effects of crowding and its influence on dwell times, and TRB (2003, 2013), Vuchic
Examining Bus Lost Time Dynamics for a Bus Rapid Transit Station

(2005), and Sun et al. (2014) developed a model for DT estimation, as presented in Equation 3:

$$ DT = P_a t_a + P_b t_b + t_{oc} \quad (3) $$

where DT is dwell time, \( P_b \) and \( P_a \) are the number of passengers boarding and alighting, \( t_a \) and \( t_b \) are the per-person alighting and boarding times, and \( t_{oc} \) is the bus door opening and closing time. Because this model is applicable only when B&A are occurring in series, a different DT model for simultaneously-occurring B&A was reported in the literature, as presented in Equation 4 (Sun et al. 2014; Ashtiani and Iravani 2002; Larrain and Munoz 2008):

$$ DT = \max\{ P_a t_a, P_b t_b \} + t_{oc} \quad (4) $$

BLT was introduced as a new component of DT. TRB (2013) and Jaiswal et al. (2010) explain loss of station capacity due to BLT, and Jaiswal et al. (2010) reported BLT values for three linear loading areas for a BRT system in Brisbane, Australia. The proposed DT equation including BLT is mathematically expressed in Equation 5. An average of 4 sec of BLT is reported for three loading areas (TRB 2013):

$$ DT = P_a t_a + P_b t_b + t_{oc} + BLT \quad (5) $$

The literature summarizes various equations that were improved with time to estimate DT for both in-series and simultaneously-occurring B&A. The aforementioned DT equations including BLT are not understood based on different scenarios of B&A; in some scenarios, using the same equation might overestimate or underestimate DT. The literature reports an average BLT value for only three loading areas, but no values were reported for two or four loading areas. These values play an important role in estimating overall system capacity.

**Methodology Development**

Methods of B&A play a major role in estimating DT. Three ways are most commonly observed, namely, boarding and alighting from the front and back doors, alighting from the front door and boarding from the rear door, and boarding and alighting from a single door. The concept of B&A is briefly discussed in the following subsections.

**BLT Dynamics for In-Series B&A**

Four different scenarios to estimate dwell time \((T_o)\) in which in-series B&A takes place are illustrated in Figure 1. In the scenario a), alighting occurs before boarding, and in series b), boarding occurs before alighting. Further, in scenarios c) and d), either alighting or only boarding takes place. The main components for estimating DT are total alighting time \((T_a)\), boarding times \((T_b)\), bus lost time \((BLT)\), and bus door opening and closing time \((t_o \text{ and } t_c)\), as represented in Figure 1.
The TCQSM (TRB 2013) provides the following equation for estimation of DT for all these cases:

$$DT = P_a t_a + P_b t_b + t_{oc} + BLT$$ (6)

where DT is the dwell time, $P_b$ and $P_a$ are the number of passengers boarding and alighting, $t_a$ and $t_b$ are per-person alighting and boarding times, and $t_{oc}$ is the bus door opening and closing time. BLT was initially introduced by Jaiswal et al. (2010) and was considered further in the TCQSM (TRB 2013). Using the definition of BLT, scenarios a), b), and d) in Figure 1 will have BLT; in scenario c), BLT will not occur, as in this scenario, no boarding is taking place.

**BLT Dynamics for Simultaneously-Occurring B&A**

Eight different scenarios in which B&A occur simultaneously are presented in Figure 2. Here, $T_a$ is total time of alighting passengers, and $T_b$ is total time of boarding passengers. In scenario a), first alighting starts, and then boarding starts in between alightings; in scenario e), first boarding starts, and then alighting starts in between. In these scenarios, both boarding and alighting end at the same time. Scenario a) will not have any BLT because the first passenger will board the bus while alighting is occurring. On the other hand, scenario e) will have added BLT because the alighting is starting when few passengers have already boarded the bus. Hence, the BLT—the time taken by the first passenger to board the bus—will not overlap with the alighting time. In scenario b), boarding starts with alighting but ends before alighting; similarly, in scenario f), boarding starts with alighting, but ends before alighting. In both the scenarios, there will be no BLT, as both boarding and alighting start in parallel. Further, in scenario c), alighting starts before boarding and ends after boarding; in scenario g), boarding starts before alighting and ends after alighting: hence, BLT will exist in this condition. Finally, in scenarios d) and h), alighting starts before boarding and vice versa. In scenario h), BLT will be observed, as boarding is occurring before alighting and is not starting in parallel with alighting.
It is noteworthy that the TCQSM (TRB 2013) suggests considering a BLT value of 4–4.5 sec for all scenarios of DT for three loading areas, but it does not explain in which scenarios it should be considered. Therefore, based on this research, it is recommended that BLT be considered only for a few of the aforementioned scenarios. These BLT values are then used for DT estimation from the videography data in Equation 6 for in-series B&A and in an improved Equation 7 for simultaneously-occurring B&A:

\[ DT = \max\{ P_a t_a, P_b t_b \} + BLT + t_{oc} \] (7)

After understanding all the scenarios and the gap in the application of BLT, a modified definition of BLT is suggested—BLT is the time lost by a bus between when it stops and when the first passenger boards, given that this time does not overlap with the alighting time and bus door opening time. This improvement in the definition is necessary because directly adding the time taken by the first passenger to board the bus in the DT estimation without observing if it is overlapping with alighting time will overestimate DT.

**Study Area and Data Collection**

**Study Area**

In this study, the Ahmedabad BRT system was considered. This system started functioning in 2009 and is a closed BRT system with the following features:
- Entry of passengers to station supported by well-defined pedestrian mid-block crossing
- Broad single-door buses with level boarding and alighting
- Pre-board fare collection system using smartcards
- Segregated busways on majority of network length
- Location of bus station and busway on median
- Good integration of network of routes and corridors
- BRT stations that are covered, secure, comfortable, and protected from different kinds of weather
- Integration with feeder services
- Restricted entry to any other kind of bus rather than that prescribed
- Distinctive marketing identity comparable to MRT systems

These features satisfy it being called a closed BRT system (Mahadevia et al. 2012). The existing Ahmedabad BRT network is around 88.5kms with 127 BRT stations and 12 routes. Of the 127 stations, the Shivranjini BRT station was selected to study DT dynamics because it is one of the busiest stops; most major routes pass through this station, and dense commercial land use is observed around the station and on both the sides of the road. The BRT network and the physical characteristics and inside view of the bus station are shown in Figure 3. From the figure, it can be observed that the Shivranjini station has two linear loading areas for both directions (up/down).

**FIGURE 3.** Ahmedabad BRT network and location and view of Shivranjini station
Data Collection

Ahmedabad Janmarg Limited (AJL) monitors the total BRT system with the help of integrated GPS and GIS-based ITS techniques. In this study, video data collected by a BRT cell of AJL were considered. There were three closed-circuit televisions (CCTVs) installed in the station to capture the B&A on all four doors (see Figure 3). Of the three CCTVs, two were installed at the entry/exit doors of the station and one in the middle of the station. The operation and data management of CCTV are managed by Milestone Xprotect Video Management software, in which videos are recorded and saved to a digital video recorder (DVR) installed at the station. Video data were extracted for one working day (June 18, 2015) at the Shivranjini platform for a complete service period from 6:00 AM to 11:00 PM (0600–2300) using Klite software, including:

- Time when bus comes to a complete stop
- Bus door-opening time-stamp
- Time when first and last passengers board and alight bus
- Number of passengers boarding and alighting
- Time taken by first passenger to board
- Bus door-closing time-stamp

Passenger Behavior while Waiting at Two Loading BRT Stations

Figure 4 demonstrates waiting pattern of passengers at two loading areas of a BRT station. Passengers waiting at the platform stand more towards loading area 1 than loading area 2, as shown by the shaded portion with centroid y-y. The distances d1 and d2 are the distances of the bus doors at LA 1 and LA 2, respectively, from the centroid y-y of the shaded portion. For most cases, d1 would be less than d2 because the walking time of passengers to the bus door in loading area 1 would be less. Therefore, in the best-case scenario, the lost time would be less for loading area 1 and more for loading area 2. Also, passengers walking towards the bus door at loading area 1 would walk along the direction of the bus, but passengers walking towards the bus door at loading area 2 would walk against the direction of the bus. This overlap of time would cause a reduction in lost time for loading area 1.

![Figure 4. Waiting pattern and distance of bus door to loading area](image-url)

Estimation of BLT

BLT will be considered as a DT component only when either boarding occurs before alighting, boarding occurs after alighting (in a series), or only boarding is occurring
(as was shown in Figures 1 and 2). Observed BLT data were fitted by considering standard probability distributions. The observed and fitted probability and cumulative probability distributions for BLT data of loading areas 1 and 2 of the entire service period (0600–2300) are presented in Figure 5.

For loading areas 1 and 2, a lognormal distribution function fits best. For the total data set, BLT values for loading areas 1 and 2 were analyzed. The fitted probability distribution was validated statistically by considering goodness of fit measures such as KS and Chi-square tests. The significance of estimated values are presented in Table 1. These values are less than the critical values at a 5% level of significance. The significance
values of the KS and Chi square tests suggest that BLT during the day follows a lognormal distribution.

**TABLE 1.**

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Loading Area (LA)</th>
<th>Sample Size</th>
<th>KS Test Significance</th>
<th>Chi-Square Test Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lognormal</td>
<td>Lognormal</td>
</tr>
<tr>
<td>Total Service Period</td>
<td>0600–2300</td>
<td>LA 1</td>
<td>212</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LA 2</td>
<td>189</td>
<td>0.05</td>
</tr>
<tr>
<td>Morning Peak</td>
<td>1000–1100</td>
<td>LA 1</td>
<td>35</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LA 2</td>
<td>26</td>
<td>0.71</td>
</tr>
<tr>
<td>Off-Peak</td>
<td>1400–1500</td>
<td>LA 1</td>
<td>23</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LA 2</td>
<td>22</td>
<td>0.21</td>
</tr>
<tr>
<td>Evening Peak</td>
<td>1700–1800</td>
<td>LA 1</td>
<td>33</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LA 2</td>
<td>28</td>
<td>0.22</td>
</tr>
</tbody>
</table>

The average BLT value during the off-peak hour was more than both the morning and evening peak hours because during less crowded times, passengers tend to stand between loading areas 1 and 2 rather than near to the gate of loading area 1. The descriptive statistics of BLT for the entire service period, off-peak hour, and peak hours is presented in Table 2. These values are compared with the fitted distribution. It can be observed from the Table 2 that the average BLT values of loading areas 1 and 2 vary from 1.8 to 2.6 seconds, respectively, throughout the day.

**TABLE 2.**

<table>
<thead>
<tr>
<th>Loading Area</th>
<th>BLT (0600–2300)</th>
<th>BLT Morning Peak (1000–1100)</th>
<th>BLT Off-Peak (1400–1500)</th>
<th>BLT Evening Peak (1800–1900)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA 1 Sample Size</td>
<td>212</td>
<td>212</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>Mean (sec)</td>
<td>1.8</td>
<td>1.8</td>
<td>1.2</td>
<td>1.1</td>
</tr>
<tr>
<td>85th Percentile (sec)</td>
<td>2.1</td>
<td>2.3</td>
<td>1.3</td>
<td>1.5</td>
</tr>
<tr>
<td>Std Dev (sec)</td>
<td>0.6</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>LA 2 Sample Size</td>
<td>189</td>
<td>189</td>
<td>26</td>
<td>26</td>
</tr>
<tr>
<td>Mean (sec)</td>
<td>2.4</td>
<td>2.3</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>85th Percentile (sec)</td>
<td>2.7</td>
<td>3.0</td>
<td>1.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Std Dev (sec)</td>
<td>0.6</td>
<td>0.6</td>
<td>0.2</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Further, to observe the effect of geometric design of a BRT station, the BLT value of the two loading areas was compared with a study done for the Brisbane BRT system for three loading areas. The results were compared to show different BLT values with changes in geometric design in terms of number of loading areas. Comparing different geometric designs in terms of 85th percentile BLT for two and three loading areas of a BRT station, the following results were observed (Table 3).


**Table 3. Comparison of BLT Values for Different Geometric Designs**

<table>
<thead>
<tr>
<th></th>
<th>LA-1 (sec)</th>
<th>LA-2 (sec)</th>
<th>LA-3 (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mater Hill Busway Station, Brisbane, Australia</td>
<td>7.2</td>
<td>4.5</td>
<td>8.7</td>
</tr>
<tr>
<td>Shivranjini BRT Station, Ahmedabad, India</td>
<td>2.3</td>
<td>3.0</td>
<td></td>
</tr>
</tbody>
</table>

The above two results show that the BLT for three loading areas of a BRT station is higher for all loading areas. In this BRT station, passengers prefer standing near to the second loading area so they have an equal distance to walk towards both the first and third loading areas; therefore, the time taken by the first passenger to board the bus in the first and third loading areas is higher than the second loading area. On the other hand, for two loading areas in a BRT station, the BLT of loading area 1 is less than that of loading area 2 because the passengers stand closer to loading area 1. Overall, the BLT of a station with two loading areas is less than that with three loading areas because of the longer station length and crowding.

**Rule of Thumb for Considering BLT**

Viewing videos to observe the scenarios is a lengthy process; therefore, a rule of thumb for adding BLT was proposed in the present research based on closely observing 877 scenarios from the video data. It was determined from the observed data that in all scenarios in which BLT was occurring, 94% had critical boarding passengers, as follows:

1. Only boarding passengers (no alighting passengers)
2. Number of boarding passengers > number of alighting passengers

For all other scenarios in which BLT was not occurring, 91% had either critical alighting or the number of boarding passengers was equal to number of alighting passengers. Therefore, BLT can be added to the DT data of stations at which boarding is critical.

**Capacity Estimation**

The importance of BLT is explained through bus station capacity estimation. Bus stop capacities were estimated with and without considering BLT. The capacity estimation of a BRT station is determined by using Equation 8 (TRB 2013):

$$B_n = \frac{3600g}{t_c + DT_n(\frac{g}{c}) + zC_v(DT_n)}$$

where $B_n$ is the capacity of nth loading area (bus/hr), 3,600 is the number of seconds in 1 hour, $g/c$ is the green time ratio, $z$ is the standard normal variable corresponding to a desired failure rate, $t_c$ is clearance time, and $C_v$ is the coefficient of variation of DT. For estimation of capacity, standard values of parameters as given in the TCQSM (TRB 2013) were considered, leaving the coefficient of variation and DT, which were calculated using data. Therefore, the green time ratio ($g/c$) was taken as 1 (assuming an unsignalized lane and bus facility), $t_c$ as 10 sec, and a standard normal value ($z$) of 1.28, considering a 10% failure rate for both the loading areas. Using the video extracted data, the $C_v$ values with and without considering BLT were estimated for loading areas 1 and 2. These value
were estimated using 877 observation of DT that extracted for different scenarios of B&A from the BRT station video. Average DT values also were estimated considering the same data.

From Table 4, it can be observed that considering BLT resulted in increased average DT of 13% for loading area 1 and 15% for loading area 2, whereas the bus stop capacity was reduced by 11%. Therefore, not considering BLT will always lean towards an inflated value of capacity. Again, BLT should be considered only for certain scenarios of B&A.

### TABLE 4.

<table>
<thead>
<tr>
<th>Lost Time</th>
<th>C_V of Dwell Time</th>
<th>Average Bus Dwell Time(sec)</th>
<th>Bus Stop Capacity (buses/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loading Area 1</td>
<td>Loading Area 2</td>
<td>Loading Area 1</td>
</tr>
<tr>
<td>Without BLT</td>
<td>0.40</td>
<td>0.43</td>
<td>14.8</td>
</tr>
<tr>
<td>Including BLT</td>
<td>0.35</td>
<td>0.37</td>
<td>17.1</td>
</tr>
<tr>
<td>% Change</td>
<td>13%</td>
<td>14%</td>
<td>13%</td>
</tr>
</tbody>
</table>

### Conclusions

Understanding DT components and the related dynamics is useful for estimating system capacity of BRT in a structured manner. The main findings of the study are as follows:

- BLT is defined as the waiting time for a bus between when it comes to stop in its loading area and when the first passenger boards (TRB 2013).
- BLT should be considered for DT estimation only for 6 types of B&A scenarios out of total 12 possible scenarios. Adding BLT as a DT component to all other scenarios will result in overestimation of DT.
- The six scenarios in which BLT will occur are scenarios a), b), and d) for in-series B&A (Figure 1) and scenarios e), g), and h) for simultaneously-occurring B&A (Figure 2).
- A modified definition of BLT is suggested in this paper: BLT is the time lost by a bus between when it stops and when the first passenger boards, given that this time does not overlap with the alighting time and the bus door opening time.
- BLT values were estimated, and it was observed that the mean BLT values during the off-peak period are more than during the morning and evening peaks. Also, the average BLT of loading area 2 is more than that of loading area 1.
- BLT data followed lognormal distribution for both loading areas 1 and 2.
- This research suggests a BLT value of 2.3 sec for loading area 1 and 3.0 sec for loading area 2.
- Considering BLT as a DT component resulted in an approximately 13% and 15% increase in average DT for loading areas 1 and 2, respectively, and the bus stop capacity was reduced by 11%. Therefore, considering BLT in capacity calculation is necessary to avoid overestimation of BRT system capacity.
References


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