ARE WE GIVING BRT PASSENGERS WHAT THEY WANT? USER PREFERENCE AND MARKET SEGMENTATION IN JOHANNESBURG

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ABSTRACT

The public transport systems being implemented under the DOT's Integrated Public Transport Network (IPTN) programme generally have lower passenger demand, poorer financial performance and higher subsidy requirements than initially hoped. One cause of poor passenger attraction may be that IPTN systems do not offer sufficiently attractive services, given the other alternatives available to potential passengers. This paper examines the value proposition of IPTN systems against the stated needs and preferences of passengers, drawing on a recent combined revealed and stated preference survey of 1,200 people in the City of Johannesburg. Added validity and realism is obtained by studying actual (as opposed to hypothetical) choice behaviour in the existing BRT system. The analysis identifies distinct market segments with clearly different needs. About a quarter of current car users are persistent car captives, and opposed to using a good BRT option. Choice passengers have a very limited willingness to pay for the travel time savings procured with dedicated trunk lanes, but place much higher value on good access, higher frequencies, and, above all, the overall service quality of BRT. This suggests that future IPTN networks will maximise ridership by prioritising affordability, good network coverage, customer service, and perhaps differentiated price-service combinations – all elements that might require a shift away from the current infrastructure-heavy paradigm.

1. INTRODUCTION

Intelligence on the needs and preferences of potential users of new or improved transport modes is critically important for the design of systems that attract passengers and reach social goals. Stated preference (SP) surveys have commonly been used to gain such information while planning for improved public transport systems including Bus Rapid Transit (BRT) in South Africa (e.g. Van Zyl & Hugo, 2002). While these have been useful for testing the market and developing demand forecasting models *prior* to BRT deployment, a common shortcoming has been the hypothetical nature of the options offered during the SP choice experiment. By studying the preferences and choice behaviour of commuters in areas where BRT is actually operated, a more realistic understanding of the actual preferences and choice drivers may be obtained under real market conditions. This paper describes such an effort to examine preference in the market by employing advanced stated and revealed preference modelling among current and potential BRT users in the City of Johannesburg, where the first phases of a BRT network is already operational.

The study was conducted as a part of the development of an Integrated Transport Network strategy to guide further deployment of the BRT and related services in coming years. Apart from developing choice models for use in passenger forecasting, the study aimed at generating a broader understanding of what passengers want, and of how this might differ across user groups. This was achieved by segmenting the commuter market according to people's current choices and their willingness to consider new BRT alternatives. This segmentation leads to an enhanced understanding of mode captivity, of the limits of what BRT might realistically be able to achieve (in terms of attraction), and of which features are needed to make new public transport services attractive to different users. These insights are likely to be useful during the planning of enhanced public transport services elsewhere in South Africa.

The paper first describes the data collection and market segmentation analysis before discussing the approach to and results of the choice modelling exercise. Several implications emerge for the design of future BRT systems which might warrant rethinking the approach being followed in South Africa. Finally, some concluding remarks are offered.

2. DATA

The data source is a relatively large stated preference survey conducted in June to August 2014 in the City of Johannesburg. The survey was fairly extensive for an SP survey; key characteristics included:

- A wide geographic spread was achieved within COJ in order to capture sufficient variation in socio-demographic characteristics, network effects, and trip lengths. Surveys were clustered in eight areas ranging from the northern suburbs, Midrand, the Empire-Perth corridor, and Soweto, to Orange Farm in the far south.

- All major modes of transport were covered, to allow examination of user preferences by mode. Targets were specified per mode, and respondents recruited at modal facilities (like taxi ranks or Gautrain stations) or public facilities (e.g. shopping malls).

- Both work and non-work trips were covered to give a suitable reflection of a range of trip purposes.

- A total sample of 1208 interviews was completed.

The survey further incorporated several practices which are considered state of the practice in order to improve the validity of the ensuing models, including:

- Inclusion of Revealed Preference data: The survey contained a Revealed Preference (RP) section where respondents provided details about the most recent trip – termed the reference trip – that they made to a regular destination (including trip costs and time, walk and wait time, and transfers). Respondents were also asked for details about one alternative (but unused) mode that was available for the trip, or to indicate if no alternatives were available, information that could be used to measure their level of mode captivity and to enrich the mode choice model.

- Use of reference trip in SP alternatives: In the Stated Preference (SP) section, each respondent was presented with nine stated choice questions in the form of a choice between their current mode (at current attribute levels) and a BRT option with a range of attributes, for the reference trip. The attributes of the hypothetical option were automatically constructed as variations around the reference (actual) trip they made. By preserving the choice situation (e.g. constraints, preferences) that was actually faced during this trip, the realism and validity of the response could be maximised (Rose et al., 2008).

- Inclusion of current BRT users in sample: One of the criticisms against SP is that people may make unrealistic choices about hypothetical modes that they have no experience with. To counter this about a fifth of the sample was drawn from people who currently use Rea Vaya, while many of the rest of the surveys were conducted in areas where BRT is currently operating.

- Computer-Aided surveying: The entire questionnaire was executed using Android tablet computers. Use of the computer-aided questionnaire was the only way of implementing the pivot design with automatic generation of SP questions around the RP levels; it further enhanced data quality through multiple logic tests and elimination of coding errors.

The sample distribution in terms of incomes and current mode was as follows:

Table 1: Sample composition

		Number (%) of interviews
Monthly Household Income	0 – R2500 (Low)	100 (8.3%)
	R2501 – R8000 (Medium)	469 (38.8%)
	R8000 and more (High)	447 (37.0%)
	Refused/Unknown	192 (15.9%)
Current mode used (frequent trip)	Car (driver or passenger)	352 (29.1%)
	Minibus-taxi	300 (24.8%)
	Bus Rapid Transit	254 (21.0%)
	Other bus (Metrobus/Putco)	52 (4.3%)
	Metrorail	200 (16.5%)
	Gautrain	50 (4.1%)
Trip purpose (frequent trip)	Work	762 (63.1%)
	Non-work	446 (36.9%)
	All trips	1208 (100%)

Table 2: Typical attributes and levels tested in SP experiments

Attribute	Levels
Mode constant	Car, Gautrain, Taxi, Bus, BRT, Train
Number of transfers (PT only)	No transfers; 1 transfer
Travel cost	current -30%; current; current +20%
In-vehicle travel time	current -25%; current; current +25%
Walk time to PT	5 mins; 10 mins; 30 mins
Wait time for PT	5 mins; 10 mins; 20 mins
Seat availability	Seat not available on BRT bus Seat is available on BRT bus
Walk quality (BRT questionnaires only)	Good (paved sidewalk & lighting); Poor (no paved sidewalk or lighting)
Feeder mode (BRT, train & taxi questionnaires only)	Walk to BRT; feeder bus to BRT (no transfer); taxi to BRT (transfer)

The SP questions were designed based on a main-effects fractional factorial design, using the common mode choice attributes shown in Table 2. Most attribute levels were calculated as a percentage variation around the value reported by the respondent for their reference trip. In order to keep down respondent burden, only three of four attributes were varied at a time using a block design.

3. MARKET SEGMENTATION

In order to understand the potential BRT market better, the transport passenger market was segmented a priori according to the degree of captivity or choice that people have in selecting the mode to use for a particular trip. The focus on captivity (defined as the condition of having only one travel mode (or a subset of modes, such as public transport) to use) and choice is appropriate for three reasons. Firstly, the number of modal captives (and their characteristics) in the city is of policy interest as it reflects people with limited or no choice, which is usually taken as a bad thing. Secondly, demand forecasting accuracy improves if captivity is explicitly accounted for (Beimborn et al., 2003). Thirdly, system planning might improve: by separating populations into sensitive and non-sensitive groups, more appropriate strategies can be fashioned to serve each group effectively (and maximise ridership), than by combining them into one mixed group about which, on average, less is known.

For this study four market segments were defined:

- <u>Car captives</u>: People with only the car mode available for a specific trip. For this study car captives were further divided into two subgroups:
    - <u>Lifestyle car captives</u>: People whose car captivity is due to personal, life cycle or activity-related factors – for instance, a worker who needs their car at work every day, or a parent whose trip patterns are too complex to undertake with public transport; and
    - <u>Availability car captives</u>: People whose car captivity is due to the current unavailability of alternatives, but who might be willing to switch to public transport in future, should an acceptable option become available.

- Public transport captives: People with one or more public transport options available but no car available for a specific trip at a specific time;

- Choosers: People with both a car and at least one public transport option available for their trip.

The distinction between lifestyle and availability car captives is important as the former is highly unlikely to use public transport, no matter how good the service is – they are presumed insensitive to transport interventions – while availability captives might become choosers if their set of options expands. But the distinction is contingent on the quality of the public transport intervention on offer. For this study captivity was defined relative to a typical BRT service. Thus, if new BRT services are provided in an area that currently has no (perceived) access to public transport, the population of potential users will increase by the number of current *availability captives* but not by *lifestyle captives*.

A set of rules was subsequently developed to categorise each trip into a captivity/choice category. Car captives were defined as current car trips for which the respondent could identify no alternative non-car mode. Within this group, lifestyle captives were those non-trader respondents who failed to choose the BRT option in any of the nine SP games offered to them. Availability captives switched to the BRT in at least one hypothetical SP scenario. Public transport captives were current bus, taxi, train, or Gautrain users who had no car alternative available for their trip (either as driver or passenger). The rest was choosers: current public transport users with a car alternative, or current car users with a public transport alternative available.

A few relevant points about the approach adopted towards market segmentation:

- Captivity is defined on a trip-by-trip basis, and might change for the same person over the course of a day. For instance, a car-owner may have a public transport route available for the work trip in the morning (chooser trip), but no such option for a shopping trip to a mall in the afternoon (car captive).

- Non-motorised captives – people currently walking (or, rarely, biking) or not travelling due to the absence of affordable motorised transport options – were not considered in this study. This class of user warrants a separate in-depth study to understand their constraints and preferences better.

A model was estimated to predict a trip's captivity status given the tripmaker's personal and household factors, modal access, and trip-specific variables. The model was significant, with an R^2-value of 0.447[1]. The model was then applied to the weighted 2014 COJ Household Travel Survey (HTS) data of motorised trips (excluding trips by under-18s) to provide a picture of the estimated distribution of captivity in the COJ in 2014. The overall results are sumamrised in Figure 1 below.

[1] A discussion of the approach to and results of the captivity modelling exercise is outside the scope of this paper.

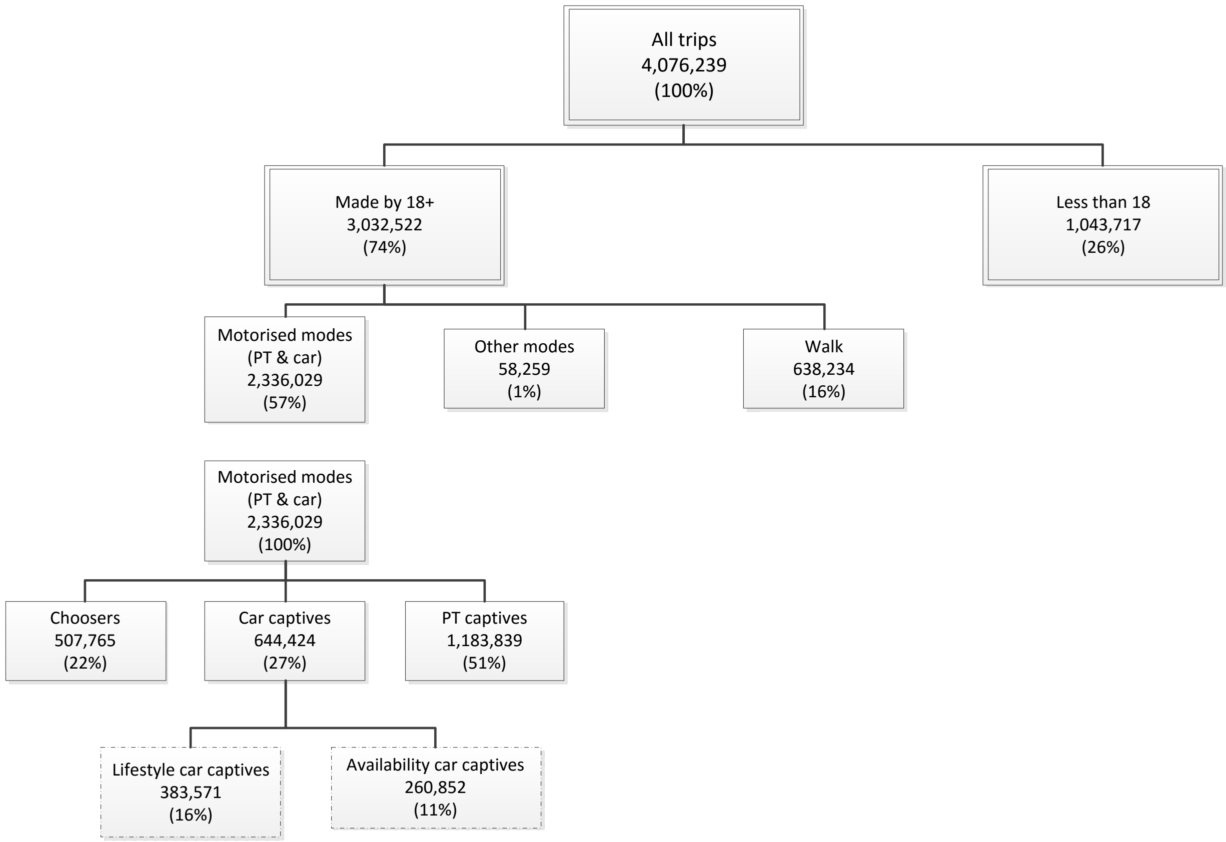

Figure 1: Overall distribution of captivity in COJ (estimated on weighted base year trips reported in HTS)

Of the 2.3 million daily motorised trips in the COJ, about half are captive to public transport – made without the option of a car. Just more than a quarter are classified as car captive trips – so 1 in 4 motorised trips are currently made without the (perceived) alternative of public transport available. The remaining 22% of trips are classified as chooser trips. It follows that, of trips where the car is available (chooser plus car captive trips), just more than half feel they have no alternative but to drive.

However present car captives are not all persistently opposed to using public transport. About 4 out of every 10 car captives are classified as availability captive – these quarter of a million car users would be willing to use good public transport (BRT) options, should such options become available to them.

4. CHOICE MODEL ESTIMATION

The mode choice models estimated from the survey data employed several state of the art approaches, including:

- Estimation of mode choice using combined SP and RP dataset: The responses to the SP questions were used to estimate the coefficients of service variables like travel time and cost, when people are faced with a choice between modes. This tends to capture respondents' trade-offs more robustly than does RP data, as the attributes can be precisely defined with minimal collinearity and measurement error. In addition, the RP data reflecting the actual service attributes currently faced for the reference trip was used to estimate the Alternative Specific Constants (ASCs). As the RP data capture the current market situation better than SP data, the resultant ASCs reflect decision makers' valuation of the relative attractiveness of each mode *as it is experienced in the market*. This practice exploits the particular strengths of each type of data in a consistent choice framework, and for the same individuals[2].

- Segment-specific coefficients: In line with the hypothesis that different market segments value aspects of a public transport service differently, the choice model allowed the estimated coefficients to vary across sub-groups in the sample. In particular, different coefficients were estimated for different captivity groups, namely choosers and captives. Captives refer only to public transport captives, while Choosers include both availability car captives and choosers as defined earlier – thus all respondents who displayed a willingness to choose between car and public transport. Lifestyle car captives' responses were excluded as they made no conscious choice between car and other modes for their last trip, and were not willing to select BRT in any SP game, so their data contains no information on choice[3]. Confidence intervals of estimated coefficients were checked; in cases where they overlapped between two groups, it meant that the coefficients were not statistically different from each other, and a single coefficient was estimated for both groups combined.

- Random coefficients and panel effects with mixed logit model: A mixed logit (ML) model was estimated that allowed some coefficients to be random variables rather than fixed parameters. This has two advantages over the conventional multinomial logit model (MNL), namely (i) it allows for preference heterogeneity in the sample, and (ii) it allows correlations in the errors between repeated observations for the same person, i.e. panel effects stemming from the SP game. The ML model has become a very popular model formulation for the analysis of choice data, especially data from SP experiments, in part due to this ability (Hensher & Green, 2003). The ML model generally outperforms the MNL model in terms of model fit, because of the increased explanatory power of the specification (Hensher, 2001).

[2] The sequential estimation procedure described by Swait et al. (1994) was followed. In the first step the choice model is estimated using only SP data. A second model is then estimated using the RP data, but the utility coefficients are fixed at their SP values while new ASCs are estimated. Because the size of the error in SP and RP data varies, an additional scale parameter has to be estimated that is used to rescale the SP coefficients relative to the ASCs.

[3] This has the dual effect of delivering more significant coefficient estimates in the choice model (as the remaining sample is more homogeneous), and inflating the willingness to choose BRT, but it is not a problem as long as the captives are added back during forecasting.

Table 3: Estimation results – mode choice model from SP & RP data

Type of variable	Variable	Coefficient (t-value): PT captive	Coefficient (t-value): Chooser
Alternative Specific Constants	Bus	**-0.9339 (-3.64)*****	
	BRT (Reference category)	0.0000	
	Gautrain	+19.7326 (0.01)	
	Taxi	**-0.9175 (-6.39)*****	
	Train	+0.1082 (0.45)	
	Car	**+1.7641 (6.53)*****	
Service variables *(Note: scale parameter already multiplied in)*	Travel cost (Rands)	**-0.0697(-20.28)*****	**-0.1667(-25.43)*****
	In-vehicle travel time § (minutes)	**-0.0050(-4.95)*****	
	Walk time at start of trip § (minutes)	**-0.0144 (-8.80)*****	
	Waiting time (minutes)	**-0.0195 (-10.83)*****	**-0.0072 (-3.81)*****
	Seat available on BRT (Yes=1 – only in BRT utility)	0.0264 (0.66)	
	Number of transfers	**-0.0914 (-5.74)*****	
Standard deviation of random parameters	St. dev of In-veh. travel time	**0.0456 (8.29)*****	
	St. dev of Walk time	**0.1130 (10.89)*****	
Scale parameter	Scale parameter	**0.3009 (8.57)*****	
	Number of observations = 866 individuals Log-likelihood = -4077.4 McFadden R^2 = 0.66 Likelihood ratio test: Chi-squared=15665 (p-value= 0.000)		

Notes: Significance levels: ***= >99.9% **=99.9% *=99% ‘’=95% ‘=90%
§ Coefficients estimated as random parameters; value shown is mean value of parameter

The results are given in Table 3. Two parameters were estimated as normally distributed random parameters, namely in-vehicle travel time and walk time. The cost coefficient remains fixed (Sillano and Ortuzar, 2005). Where only one coefficient is reported for both user segments, segment-specific coefficients were not statistically different from each other or could not be estimated.

Looking at the results, the following observations are made:

- The model is highly significant, as indicated by the high R^2-value and likelihood ratio test values. In addition, almost all the coefficients were highly significant, implying that the model captures systematic choice behaviour in the sample with a high degree of confidence.

- Alternative specific constants were estimated with mixed levels of significance. The insignificant ASC for the train mode indicates that passengers perceive no qualitative difference between train and BRT. In the case of Gautrain the failure to estimate an ASC is most likely due to the inadequately small sample of Gautrain users (50), rather than qualitative similarity with BRT. For car, taxi and bus modes strong ASCs were estimated.

- All coefficients for service variables were estimated with high levels of significance (except the seat availability variable), and all have the expected signs. The walk time coefficient (-0.0144) is about three times the in-vehicle time coefficient (-0.005), suggesting that people dislike walking to public transport much more than travelling in a vehicle. This is as expected from literature. The same applies to the waiting time coefficient (-0.0072 to -0.0195), which is between 1.4 and 4 times the value of the in-vehicle travel time. People dislike transferring, as indicated by the significant negative coefficient (-0.0914).

- Some coefficients were found to differ significantly between user groups, suggesting that it is indeed appropriate to segment users before model estimation and forecasting. Differences appear specifically in the cost and waiting time coefficients. Specifically:
    - Passengers who can exercise a choice between BRT and car options have larger (or more negative) cost coefficients, meaning that they have a higher willingness to pay for improvements in their travel experience.
    - PT captives value the time spent waiting for a vehicle more negatively than choosers. This is possibly a result of the more negative experience PT captives have of waiting for public transport as compared to choosers, many of whom currently use the car and do not have the first-hand experience of waiting.

- Standard deviations estimated for the two random variables (in-vehicle travel time and walk time) were significantly different from zero, suggesting that the parameters are indeed random rather than constant, and validating the use of a mixed logit rather than a MNL model.

- The estimated scale parameter is also significant, attesting to the successful combination of SP and RP data in the same model.

5. IMPLICATIONS FOR BRT DESIGN

The estimated utility functions provide useful insight into the structure of preferences within the potential BRT passenger market in SA. We examine three insights: willingness-to-pay, alternative specific constants, and the relative size of terms in the utility functions.

5.1 Willingness-to-pay

Willingness-to-pay (WTP) values reflect the marginal rate at which passengers are willing to trade improvements in one aspect of the service for deterioration in another. The most common WTP measure is the value of travel time savings (VOT), calculated as the ratio between time and cost coefficients, for instance:

$$\text{Value of in-vehicle travel time (IVT)} = \frac{\beta_{IVT}}{\beta_{cost}}$$

Converted into Rands/hour, this measure is usually interpreted as the increase in fare that passengers are willing to bear in exchange for one hour decrease in travel time. In the present case the IVT variable is a random parameter, so the VOT value explicitly varies across the population, and the VOT is the average value for the population.

The calculated WTP values for different markets are shown in Table 4.

Table 4: Mean Willingness to Pay (WTP) values, calculated from estimated model coefficients

Variable	WTP: PT captives	WTP: Choosers & Availability car captives
In-vehicle travel time (R/hour)	R4.30	R5.98
Walk time at start of trip (R/hour)	R12.39	R17.21
Waiting time (R/hour)	R16.78	R8.56
Value of each transfer	R1.31	R1.82

The values of time are relatively low, compared to previous studies in Gauteng. For instance, the GITMP25 model used to evaluate various transport scenarios for Gauteng, as part of the 25-year Integrated Transport Master Plan study, used the values of time shown in Table 5. The COJ values of time are comparable to the values used previously for low-income households, but orders of magnitude lower for medium and high income households. Some of the difference is due to the fact that the COJ values exclude lifestyle car captives who might reasonably have a higher value of time. However, car captives are a small fraction of the overall sample; their exclusion does not explain the entire difference. It is more likely that previous models estimated on stated preference data overstated values of time due to policy bias and realism issues.

Table 5: Values of time used in GITMP25 model (2011 base year, home-based trips) Source: GITMP 25

Variable	Low income Household	Medium income HH	High income HH
In-vehicle travel time (R/hour)	R4.50	R34.50	R56.00
Waiting time (R/hour)	R9.00	R69.00	R111.90
Walk time (R/hour	R11.30	R86.30	R139.90

This finding is very important for the design of new public transport systems, in four ways. Firstly, it suggests that most potential passengers have a very limited willingness to pay for saving travel time, either inside or outside the vehicle. It suggests that people are much more sensitive to price changes than to speed changes, insofar as their daily travel is concerned. This points to the limitations of the BRT design paradigm which is heavily oriented towards raising travel speeds via segregated bus lanes and fully enclosed stations; yet is unable to recover the costs of doing so from the average passenger.

Secondly, the above does not apply to *all* potential passengers: VOT is not a single value but varies across the population (in the above case following a normal distribution). This suggests that niches of users exist with sufficiently high WTP for faster services. There must therefore be a market for differentiated services, such as express or premium services, for which a higher fare can be charged.

The third implication follows from the two to four-fold difference between the value of in-vehicle and out-of-vehicle travel times in the market. Potential passengers attach more importance to shorter walk and wait times than to faster speeds once on-board a vehicle. This finding is universal among public transport users internationally. The implication is that, from the passenger's perspective, having services with reasonable frequencies (with low waiting times), and with enough penetration and network coverage to reduce walk distances, are at least as important as short travel times. Once again, heavily trunk-oriented BRT designs with limited routes, low feeder frequencies, large station spacings, and exclusive lanes are prioritising speed over access and frequency. (It is interesting to note that minibus-taxis tend to get these priorities exactly right, which helps to explain their popularity). Given the relatively low densities BRT currently tends to operate in in SA, it might be more appropriate to spend money on increasing network coverage and frequencies, and improving the waiting experience with adequate shelters, than to invest heavily in a network of segregated busways.

The negative contribution of transfers to the BRT utility is relatively mild, with one transfer equating to the equivalent of less than 10% of present BRT fares. This suggests that, for the average passenger, more transferring would be an acceptable price to pay for having a more integrated public transport system with better coverage, provided the feeders and transfers are carefully designed and managed.

A fourth implication is that ridership forecasts based on inflated VOT values would tend to overpredict passenger numbers for time-saving modes such as BRT. Forecasts fail to recognise that a portion of the market has *no* willingness to pay for BRT, due to lifestyle and preference factors; by lumping car captives with high-value-of-time individuals, the mistaken conclusion is reached that, if only BRT can be fast enough, it will attract even these passengers. This might be one of the reasons why predicted ridership levels have failed to materialise for BRT systems such as Rea Vaya.

5.2 Alternative specific constants

Recall that the ASCs were estimated from RP data and reflect passengers' valuation of the *current* attractiveness of each mode, after controlling for differences in the independent variables (price, travel time etc.). The relative sizes of the constants thus give a sense of how passengers (current and potential) perceive the quality of each mode, *based on actual experiences in the market*. The ASC estimates in Table 3 are relative to the BRT constant which is fixed at zero.

As can be expected, people with a car available rank it as more attractive than BRT (as indicated by the significant positive constant). Apart from Gautrain, Bus Rapid Transit is recognised as a superior option to all other public transport modes. BRT is especially seen as a big improvement on regular bus services (including Putco and Metrobus).

The most important finding is that BRT significantly outperforms minibus-taxi services in the passenger's mind, among passengers who actively made a choice between taxi and BRT for their actual trip. This means that BRT does not simply compete with taxis on price, frequency and travel time, but that passengers take into account other qualitative advantages of the BRT. These might include safety, predictability and convenience (although this study did not examine these factors in detail). It confirms that the COJ's strategy of replacing minibus-taxi operations with BRT services has been successful in delivering a higher service quality to passengers, and that passengers take these improvements into account when making travel decisions.

Passengers who choose between train (Metrorail) and BRT do not, in contrast, take any qualitative features into account (as indicated by the insignificant ASC estimate), suggesting that BRT competes with train largely on price, and that a fraction of passengers with severe affordability constraints will always prefer lower-priced train services.

5.3 Relative size of terms in utility functions

It is finally useful to ask to what extent does the qualitative versus the service variables contribute to passengers' current choices between modes. We focus only on BRT and taxi here, using the estimated utility functions for public transport captives to estimate the average size of each term in the utility function for the actual RP trip that was made. The average values of each service variable (travel time, cost etc.) is used, for respondents who actually had both taxi and BRT options available (amounting to 237 people). The results are shown in Table 6.

Table 6: Results: Average size of terms in utility functions, BRT versus minibus-taxi

	Average value of service variable		Average size of term (β.x)			% of difference
	TAXI	BRT	TAXI	BRT	difference	
Alternative specific constant (ASC)	--	--	-0.918	0.000	0.918	73%
Travel cost (Rands)	R 18.72	R 13.93	-1.304	-0.970	0.334	26%
In-vehicle travel time (minutes)	46.0 min	28.8 min	-0.230	-0.144	0.086	7%
Number of transfers	0.34	0.23	-0.031	-0.021	0.010	1%
Walk time at start of trip (minutes)	7.5 min	10.3 min	-0.109	-0.148	0.039	3%
Waiting time (minutes)	9.1 min	11.5 min	-0.178	-0.224	0.046	4%
			-2.769	-1.508	1.261	100%

For current taxi/BRT choosers in the sample, BRT outperforms taxi (on average) in terms of fare, travel time, and number of transfers, while requiring slightly longer walk and wait times. However, collectively these differences account for only one quarter of the total difference in utility (attractiveness) between the modes. A full 73% of the average difference in utility is caused by the large difference in the ASC values.

Current BRT passengers choose Rea Vaya overwhelmingly not for its competitive fares and travel times, but for its other qualitative features that are captured by its constant. This is both an opportunity and a warning. It means that the qualitative aspects that distinguish Rea Vaya from the taxi mode – perhaps greater safety, comfort, payment convenience, and so forth – are worth much in the passenger's mind, and exert an important influence on the decision to use BRT. It means that BRT authorities would do well do understand these qualitative aspects better, and have to pay very close attention to service quality during the design and – especially – the operation of the service, since service quality is primarily an outcome of how well a service is operated. This is arguably the more difficult part of running a successful public transport service. It also means that, no matter how fast and affordably BRT operates, it will struggle to retain and increase its market share if it does not offer service quality of a high perceived standard.

6. CONCLUSIONS

The paper described an effort to understand passenger preference among current and potential Bus Rapid Transit users in South Africa through two approaches, namely (i) segmenting the market in a way that more clearly distinguishes between users with different preferences, and (ii) estimating an advanced choice model incorporating data on both stated and revealed preferences to obtain quantitative information on trade-offs passengers are willing to make.

The segmentation analysis showed that approximately 1 in 4 current car users see themselves as unlikely to ever switch to a BRT mode (based on current service offerings), and are therefore insensitive to public transport improvements. A further 25% of car users currently face no feasible perceived alternative to the car, but are willing to consider using a future BRT if it is suitable to their needs. There is thus evidence that the potential market for BRT among car users is substantial, as long as it meets the needs of users.

What these needs are varies by market segment. Choice users (with a car alternative available) value speed and short walking times more highly than captive users (without a car alternative), suggesting that the availability of good feeder modes and high frequencies (both on and off trunks) is very important especially in areas with many choice users. However all potential passengers have a very low willingness to pay for such enhancements, suggesting that severe affordability constraints will be a permanent feature of BRT systems in SA. This throws into question the current BRT paradigm as it is implemented locally, which tends to follow an infrastructure-heavy (and costly) approach in order to deliver higher speed and reliability along trunk routes, while many passengers are more in need of better access and higher frequencies inside their neighbourhoods (and are more willing to pay for these). It might be necessary to rethink the way BRT is designed and planned in order to concentrate more on delivering a complete network than higher speed.

The analysis further highlighted the important role that subjective service quality elements play in making the BRT mode attractive. These features contribute more towards explaining current users' use of BRT than time or cost differences with competing modes. This suggests that BRT authorities should understand and improve service quality at all costs if they are to protect and grow BRT's market share into the future.

ACKNOWLEDGMENTS

This work was funded by the City of Johannesburg. The input of colleagues from TPO Consulting, officials from the Transport Department, and Marina Lombard during the execution of the work is gratefully acknowledged.

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