UNDERSTANDING PUBLIC TRANSIT RIDER SATISFACTION USING CLUSTERING AND BAYESIAN REGRESSION METHODS

Joel Huting, Corresponding author
Metro Transit
560 Sixth Avenue North, Minneapolis, MN 55411
Tel: 612-349-7535; Email: joel.huting@metrotransit.org

Kim Eng Ky
Metro Transit
560 Sixth Avenue North, Minneapolis, MN 55411
Tel: 612-349-7535; Email: kimeng.ky@metrotransit.org

Eric Lind
Metro Transit
560 Sixth Avenue North, Minneapolis, MN 55411
Tel: 612-349-7535; Email: eric.lind@metrotransit.org

Rebecca Freese
Metro Transit
560 Sixth Avenue North, Minneapolis, MN 55411
Tel: 612-349-7535; Email: rebecca.freese@metrotransit.org

Joshua Pansch
University of Minnesota
301 19th Avenue South, Minneapolis, MN 55455
Tel: 612-349-7535; Email: pansc009@umn.edu

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ABSTRACT

Public transit rider satisfaction is well-studied in the academic literature and transit industry. Numerous studies have focused on the factors that drive overall satisfaction and thus provide ample insights to transit agencies on investment priorities. However, there is less published research on the difference in satisfaction across transit mode (light rail, commuter rail, bus), bus route-type (express, arterial bus rapid transit, local service), or demographic groups. This study builds the body of research by providing a comprehensive assessment of public transit rider satisfaction among Metro Transit riders in the Minneapolis/St. Paul metropolitan area. Additionally, it proposes a methodology for analyzing surveys that addresses the categorical and interdependent nature of survey data – a process that employs Gower's distance and a partitioning around medoids (PAM) clustering algorithm to segment riders based on attitudes along with a Bayesian logistic regression model to profile the unique identified clusters. Light rail, arterial bus rapid transit, express, and particularly commuter rail riders were much more likely to be satisfied when compared to local bus riders. Satisfaction tended to increase with age, low and high-income riders were more satisfied than middle income riders, people of color tended to have slightly lower satisfaction than white riders, while riders who reported having a disability were somewhat more satisfied. Transit reliant riders tended to be less satisfied, whereas new transit riders (less than two years of riding experience) were more satisfied than more experienced riders. Riders who had experienced various forms of street harassment on transit were less satisfied.

Keywords: Public Transit, Satisfaction, Cluster Analysis, Bayesian logistic model

INTRODUCTION

Customer surveys have been used in public and private industries since the 1960s to understand customer satisfaction with products or services (*1*). Public transit operators historically measured only internal metrics of service quality; however, this changed as transit managers wanted to understand the customer perspective (*2*). Transit operators and researchers began to implement and analyze customer satisfaction surveys to understand priorities for investment to improve service to their customers.

Satisfaction has been defined as the difference between customer expectations and the service level delivered (*1*). High satisfaction is thought to increase loyalty and improve customer retention and thus ridership (*3*). Many transit customer satisfaction surveys have been implemented and analyzed over the years and have generally sought to understand which attributes of transit service contribute the most to overall satisfaction and thus provide transit operators with priorities for investment.

In general, these surveys ask riders to rate various attributes of transit service (e.g. overall satisfaction, total travel time, cleanliness, etc.) on a Likert scale of unacceptable to excellent (*2*). These ratings are then typically converted numerically for analysis. A variety of statistical methods have been used to analyze these surveys. These methods have ranged from bivariate Pearson correlation to various forms of regression analysis, structural equation modeling, path analysis, decision trees, and neural networks (*2*). These methods generally treat riders' reported overall satisfaction as the dependent variable and use the ratings on other variables as independent variables to statistically test the effect of each attribute on overall satisfaction.

Various paradigms for analysis of this nature have also been employed. Importance-Performance analysis (IPA) was first developed by Martilla and James (*4*) and subsequently used in transit customer satisfaction studies by Weinstein (*5*), Shen et al. (*6*), Figler et al. (*7*), and Stradling et al. (*8*). IPA classifies service attributes into four quadrants based on the statistical relationship between the attribute and overall satisfaction (importance) and the mean rating of the attribute (performance). Service attributes in the low-performance/high-importance quadrant are prioritized for investment, while those with high-performance/low-importance are given the lowest priority.

Wu and Cao (*9*) and Cao and Cao (*10*) applied three-factor theory as developed by Deng et al. (*11*) to extend and improve on IPA by addressing potential non-linear and asymmetric relationships between service attributes and overall satisfaction. This method classifies attributes into three groups: Basic factors, which significantly impact overall satisfaction only when performance is low; performance factors, which significantly impact overall satisfaction both when performance is high and low; and exciting factors, which significantly impact overall satisfaction only when performance is high.

There are two potential drawbacks to these commonly used approaches. Most fundamentally, the responses of a single transit customer are likely to be correlated to each other, such that high satisfaction in the overall rating is likely to indicate high satisfaction in individual attributes, and vice versa. Methods such as IPA which utilize importance values derived from correlations between attributes and overall importance, rather than a stated importance as surveyed in the instrument, are susceptible to distortion due to the lack of independence in these variables.

Secondly, the practice of treating ordered categorical rankings (such as those on a Likert scale) as continuous real numbers is convenient for fitting the data into existing statistical frameworks, but artificially constrains opinions to be integers spaced at equal distance. This means, for instance, that a change from an opinion of "Poor" to "Fair," would be constrained to be equal to a change from "Good" to "Excellent" on a Poor-Fair-Good-Excellent scale. Violating this proportionality assumption invalidates the results of the statistical procedures typically used to understand survey data (*12*). Utilizing statistical approaches which can accommodate the inherent correlation of responses within respondents, and the non-numeric character of the Likert scale, would be a significant advance for these reasons, and is thus an aim of this current study.

In terms of research findings, most studies found service quality attributes such as reliability, travel time, or frequency to have the highest impact in predicting overall satisfaction (*5*, *13*, *14*, *15, 16, 17, 18, 19*). Others found these attributes to be of secondary impact, but nevertheless very important (*3*, *8*, *9*, *19*). Shen, et al. (*6*) and Abenoza, et al. (*3*) found availability of information to be the most important attribute, while Eboli and Mazzula (*13*) and Lai and Chen (*21*) found cost to be the most important predictor. Cleanliness of vehicles was found to also be a very important attribute in a number of studies (*6*, *13, 14, 15, 17, 19*).

Recognizing possible heterogeneity of preferences across transit riders, some researchers have explicitly compared satisfaction across different transit modes or bus route types. Cao, et al. compared satisfaction among BRT, Metro, and bus riders in Guangzhou, China and found Metro riders to be the most satisfied, followed by BRT and conventional bus (*22*). Wu and Cao noted differences in investment priorities between express and local bus riders when using three-factor theory in Minneapolis-St. Paul, Minnesota. Tyrinopoulos et al. segmented the transit market by demographic group (e.g. age and sex) and compared satisfaction metrics across segments, noting some differences across gender (*19*), while Andreassen found differences in preferences between high- and low-frequency transit users (*23*).

While many studies have identified the attributes of public transit service that most impact overall satisfaction, few have explicitly attempted to identify how these factors may vary across demographics, mode, or bus route type. To our knowledge, no study has systematically examined all of these factors within a single study. This current research provides a more complete understanding of public transit rider satisfaction heterogeneity and begins to close that gap.

DATA AND METHODS

Every two years, Metro Transit – the primary public transit provider in the Minneapolis-St. Paul, Minnesota metropolitan area – conducts a customer satisfaction survey to better understand its riders. The most current survey was conducted in November 2016. This survey used a combination of paper, online, and in-person intercepts. In order to obtain representative coverage in terms of mode, bus route-type, time-of-day, and day-of-week, paper surveys (with the option to complete online) were randomly assigned to bus and rail trips in these various strata. Representation was monitored throughout the data collection period and strategic, in-person intercepts were used to ensure representation of underrepresented groups when needed.

The survey asked respondents to rate Metro Transit on 20 attributes of transit service using a five-point Likert scale (Excellent, Good, Fair, Poor, Unacceptable). These attributes ranged from reliability of service and total travel time to safety while waiting. The full list of attributes can be found in Appendix A. Riders were also asked to report demographic information and answer a set of questions related to their travel characteristics/preferences and household characteristics. Additionally, two questions were asked to determine if customers had experienced street harassment and if fear for safety had ever prevented them from using transit. There were 33,000 surveys distributed and 8,294 returned; 4,429 bus, 3,296 light rail, and 569 commuter rail riders provided responses (see Apependix C for more detail).

Straight-line respondents (those who chose the same response to every question) were removed from the data, because it is unlikely they carefully considered each question. This yielded a total of 7,454 observations. The data were further prepared for analysis by removing respondents who did not complete at least half of the questions, reducing the data to 6,646 observations. For the remaining respondents, it was noted there were four questions that had sizable numbers of missing values in the responses: handling of complaints and concerns (2,065 missing), accessible for people with disabilities (911 missing), environmental friendliness of the vehicles (835 missing), and transferring is easy (626 missing). These questions ask respondents about particular aspects of transit that are not universal, and many may not have responded if they had not had first-hand experience with the subject of the question. The mode of each of these questions was used to impute the missing values. Any other responses with missing values were dropped. The final dataset for analysis was comprised of 5,588 complete observations.

Cluster Analysis

The analysis was a two-step process that first used a partitioning around medoids (PAM) clustering algorithm to identify unique groups of riders based on their responses to the 20 attitudinal questions and then used a Bayesian logistic regression model to profile the identified groups. This approach addressed the categorical and interdependent nature of the data and enabled identification of unique groups of riders who hold similar attitudes and then provided a description of those groups in terms of demographics, household characteristics, etc.

PAM is a clustering method that partitions data into similar groups, or clusters. PAM differs from k-means clustering in that it uses a data point as the cluster center, or medoid, instead of calculating a cluster average (*24*). This is advantageous when working with categorical data because it does not require squared Euclidean distance for minimization, as k-means clustering does. In this case, Gower's distance was used as the measure of similarity to allow for the handling of ordinal data (*25*). The similarity between two observations i and j is defined as the average score taken over all possible comparisons:

$$S_{ij} = \sum_{k=1}^{v} s_{ijk} / \sum_{k=1}^{v} \delta_{ijk} \quad (1)$$

where s_{ijk} is a similarity score between individuals i and j on characteristic k and is further defined based on the type of data. δ_{ijk} is the number of characteristics where comparisons were possible and ν is the total number of possible comparisons.

The PAM algorithm is as follows:

1. k of the n data points are chosen to be initial medoids of k clusters
2. The remaining n-k data points are assigned to the medoid closest to it, based on the dissimilarity.
3. Each cluster is searched for a new data point that lowers the average dissimilarity most. If a point is found, it is assigned as the new medoid of the cluster. If at least one medoid has changed, go back to step 2, else the algorithm ends.

The Gower's dissimilarity (inverse of similarity) matrix and PAM algorithm implementation were completed using the daisy() and pam() functions in R version 3.3.3 (*26*). The number of unique clusters chosen for the final clustering solution was identified using the silhouette width metric – a measure of the separation of clusters in a clustering algorithm (*27*). Higher silhouette width values indicate a greater degree of separation among clusters and thus a more desirable solution.

Profiling Clusters

To better understand the classification of respondents into clusters, we used responses to the demographic, household, and travel behavior questions in the survey as potential predictor variables. The assigned multivariate cluster value of each respondent was used as the response variable in a logistic regression. The responses to the supplementary questions on the survey were coded as categorical factors to predict the assigned cluster. The influence of each demographic predictor (detailed in table 1) was tested in a Bayesian multiple regression framework (*28*), with a response including the mode of each variable as the reference group.

We used this approach for a number of reasons. First, the desired outcome of the analysis – a probabilistic estimate of the contribution of each predictor to the overall probability of being classified in a particular cluster – is the natural output of the Bayesian framework: a posterior probability distribution. This is in contrast to traditional (frequentist) regression methods of estimating a binary "significance" of each variable according to a criterion test against a null hypothesis of no effect. The ability to judge the importance of variables on their contribution to the overall classification probabilities is preferred. Second, when using multiple predictors, some of which can be expected to have little to no effect, the use of independent, zero-centered, normally distributed prior probabilities can act to prevent overfitting by forcing the data (through the likelihood) to contribute a strong signal to alter the posterior probability (*28*). Instead of adding, dropping, dredging, or model-comparing predictors in and out of the model to avoid over-fitting, all estimates including those centered on the zero are simply reported, which is the naive prior expectation. Finally, the Bayesian framework can be extended simply to the generation of predictive probabilities by updating the model, and these predictions of classification are the ultimate goal of the analysis.

The regression was estimated using the 'stan_glm' function of the package 'rstanarm' (*29*) in R 3.3.3 software. The logit (log-odds) link to the binomial distribution was used, and as noted above, used a normally distributed prior with mean of zero and SD of 1 for each coefficient. Chain convergence, mixing, and posterior predictive fit were examined using the 'shinystan' package. Additionally, correlations in the posterior estimates of coefficients were examined to ensure independence of estimates. Means and 95% credible intervals of estimated coefficients to capture the posterior probability density were observed.

TABLE 1 Predictor Variables

Variable	Type	Mode
Age	Demographic	25-34
Gender	Demographic	Female
Household Income	Demographic	$35,000 to $49,999
Race/Ethnicity	Demographic	White/Caucasian
Disability Status	Demographic	No
Years using transit	Travel Behavior/Preferences	More than 5 years
Main reason use transit	Travel Behavior/Preferences	Saves money on parking
Days per week use transit	Travel Behavior/Preferences	5
Ever taken transit for special events	Travel Behavior/Preferences	Yes
Transport method if transit not available	Travel Behavior/Preferences	Drive alone
Mode Surveyed	Travel Behavior/Preferences	Local bus
Payment type	Travel Behavior/Preferences	Stored value on Go-To card
Primary purpose of trip	Travel Behavior/Preferences	Work
Number of members in household	Household characteristics	3

Number of cars available to household	Household characteristics	2
Experienced harassment	Safety	No
Fear for safety	Safety	No

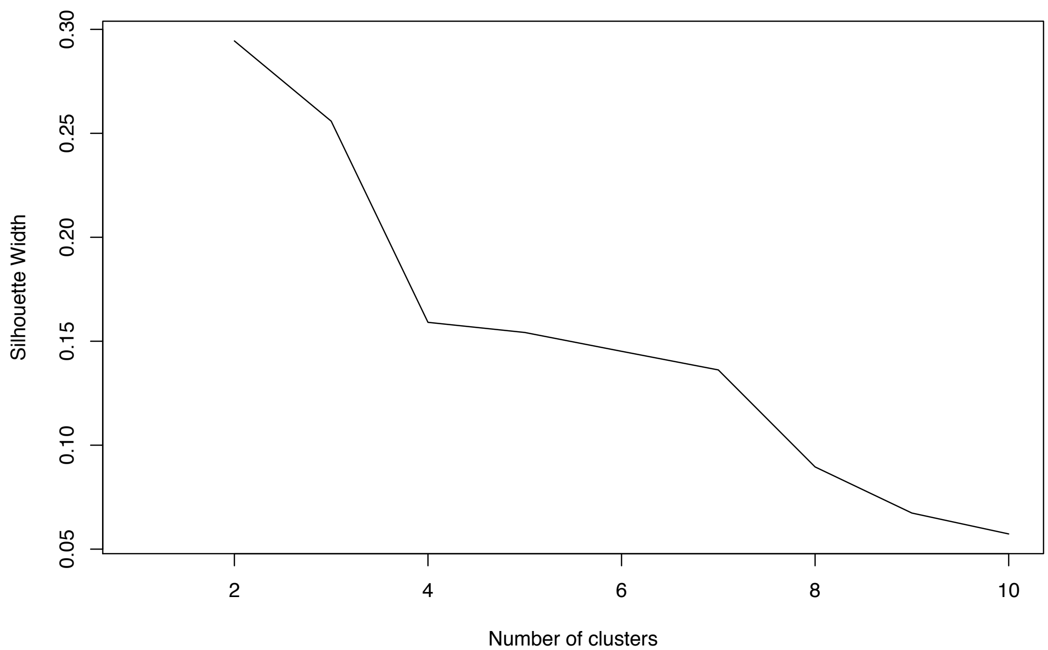

FIGURE 1 Silhouette width metric to choose the number of clusters.

RESULTS

Cluster Analysis

Figure 1 depicts the silhouette width metric for a range of candidate clustering solutions in this study. As clearly indicated in Figure 1, a two-cluster solution was optimal. Accordingly, this was specified in the final model. Thus there are two distinct groups of riders based on their ratings on the 20 attitudinal questions. The next step of the analysis was to profile these unique groups in terms of demographics, household characteristics, and travel behavior characteristics/preferences.

Figure 2 provides a visual depiction of these differences in terms of the overall satisfaction and response to individual attributes of service. It is evident in this figure that ratings are very different across clusters. The first cluster (henceforth referred to as the "Excellent" cluster) tended to rate most attributes of transit service as excellent or good. The second cluster (henceforth referred to as the "Good" cluster), tended to be characterized by attribute ratings of "good" or "fair", with notable proportions of respondents rating attributes as "poor" or "unacceptable". Overall, 1,895 (33.9%) of respondents were in the Excellent cluster and 3,693 (66.1%) were in the Good cluster.

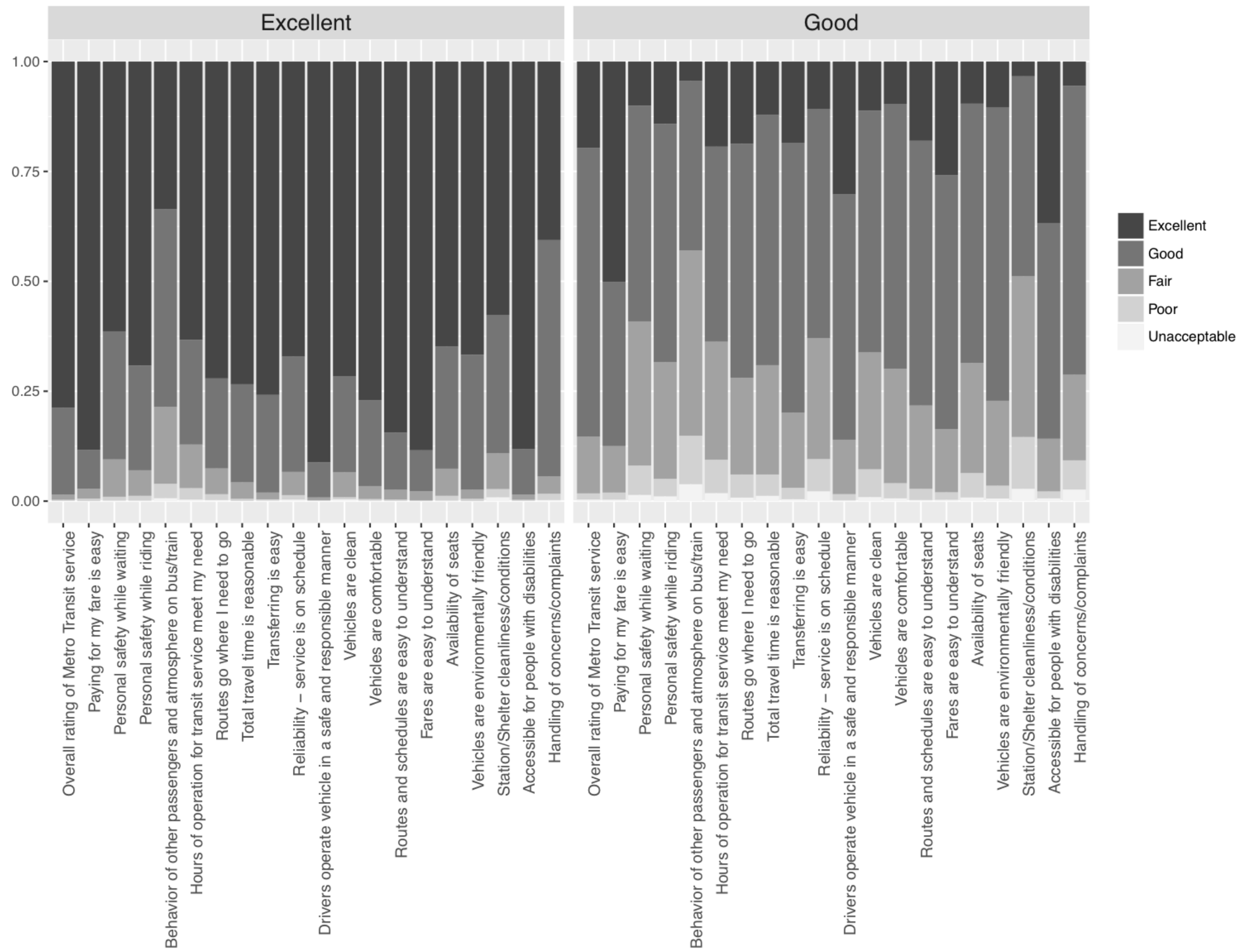

FIGURE 2 Differences in Attribute Ratings Across Clusters (Proportion of responses in each category)

Profiling Clusters: Bayesian Logistic Regression Model

Full model output can be found in Appendix B. The key findings from the model fit are detailed below.

Mode/Route Type

Commuter Rail ("Northstar"), Arterial BRT (A Line), Light Rail (Blue Line and Green Line), and Commuter/Express service riders are more likely to be classified in the "Excellent" group, indicating higher satisfaction. Figure 3 depicts the distribution of the parameter estimates for these mode/route-type variables and the proportion of respondents in each cluster by mode. The point on the distributions represents the median of the posterior distribution; the dark thick line and the lighter thin line represent the 50% credible interval and 95% credible interval, respectively. The estimates are of difference on the log scale from the reference respondent (Local bus). Thus, for example, a Green Line rider is about 5% more likely to be in the Excellent responders group and a Northstar rider is more than 20% more likely than the average local bus passenger to be in the Excellent responders group.

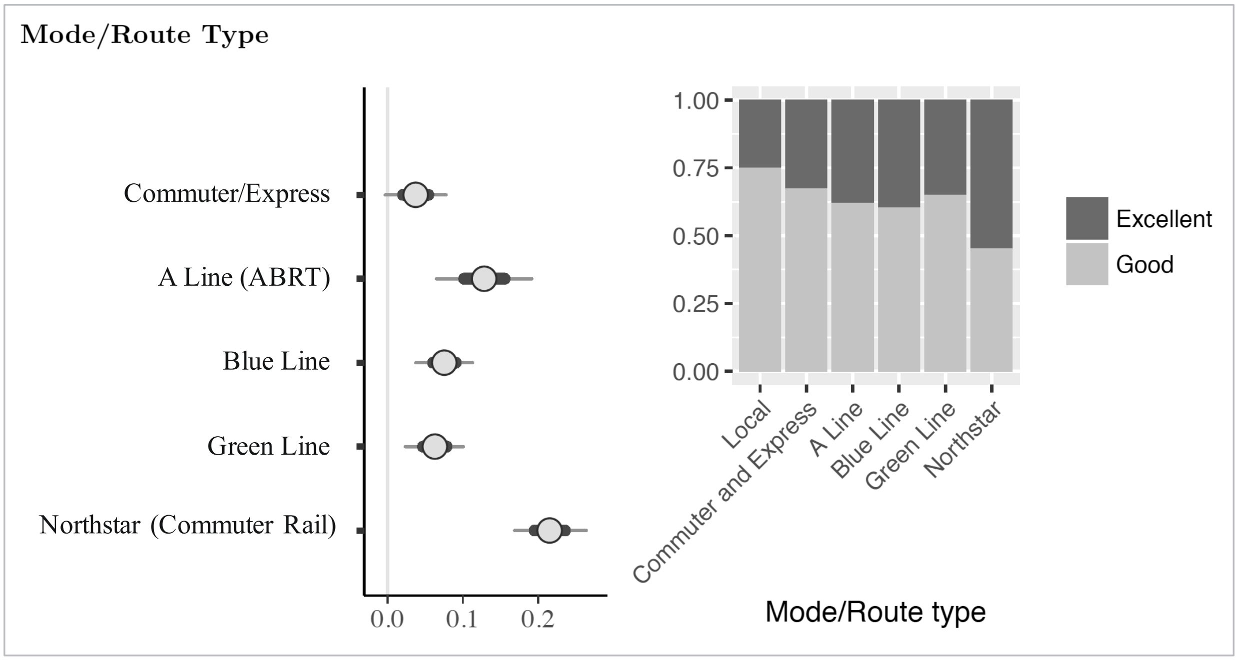

FIGURE 3 Model estimates of mode effect distribution and proportion of respondents in each cluster by mode.

Demographic Variables

Overall, younger riders tended to be less satisfied than older riders. As age increased, the probability of being classified in the Excellent group increased linearly. This effect is shown in figure 4. Compared with white riders, people of color (black/African American, Asian, and Native/American Indian riders) tended to report slightly lower levels of satisfaction. Males were slightly less likely to be satisfied than females. Riders who reported having a disability tended to report higher levels of satisfaction.

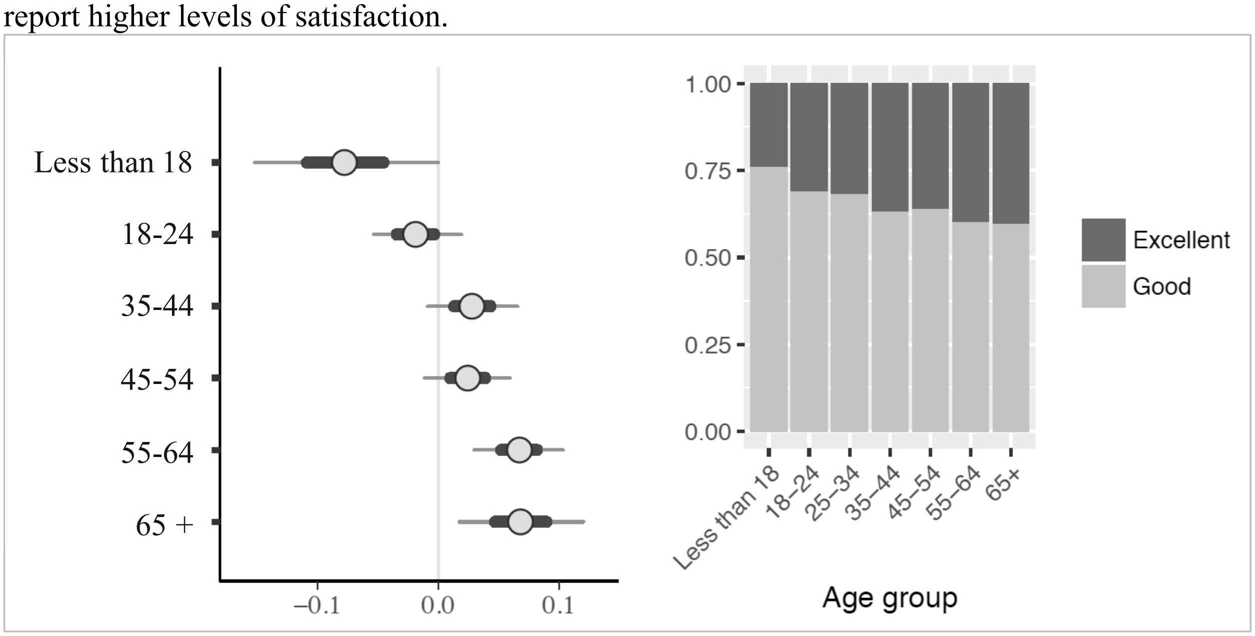

FIGURE 4 Model estimates of age effect and proportion of respondents by cluster by age

Household income

A distinct influence of household income on probable classification was found, although it is not a linear increase or decrease with higher income. Instead, both very low (<$25,000 per annum) and very high (>$75,000) income riders were likely to be classified in the Excellent group. This effect is depicted in figure 5. Importantly, the lowest income categories likely included respondents who were college students. In contrast, middle income riders were more likely to be classified in the lower satisfied, Good group. Particularly, riders with annual household incomes between $25,000 and $75,000 were demonstrated to have lower satisfaction. This "U-shaped" relationship of satisfaction with income could also reflect similar dynamics to the travel behavior variables described below.

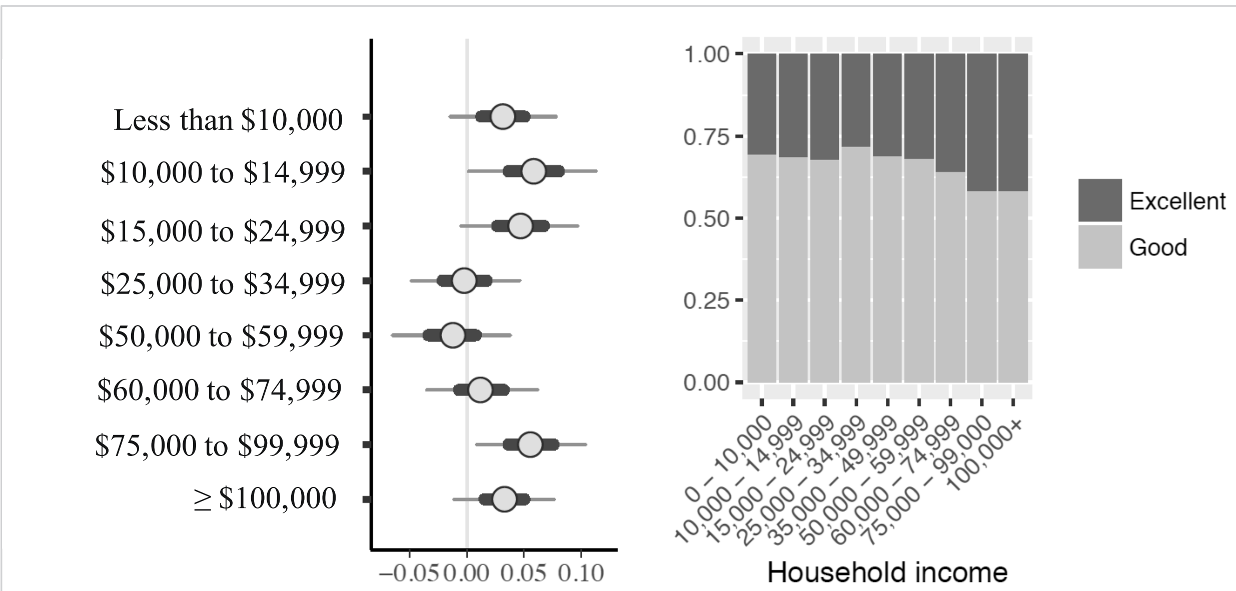

FIGURE 5 Model estimates of income effect and proportion of respondents by cluster by income

Travel Behavior/Preference Variables

Riders who take transit fewer than two days per week or those who take transit every day tend to be more satisfied when compared with riders who take transit four or five days per week. Taken together with the income predictions described above, it appears the single variables of household income and number of trips per week are likely to be capturing distinct experiences with the transit system at the extremes of each variable. High income riders who ride occasionally are likely to rate the service as Excellent, as are low income, seven-day riders. Middle-income weekday commuters, as a group, are less likely to be classified in the Excellent responders category.

Somewhat in contrast to this interpretation, riders who take transit primarily because they don't have access to an automobile or other personal transportation were less likely to be satisfied. Conversely, riders whose primary reasons for using transit were "subsidized by employer", "saves time", or "more predictable travel times" tended to rate transit satisfaction higher. Riders whose primary trip purpose was "special event" or "social/entertainment" tended to report higher satisfaction. Finally, new riders to the transit system (those with less than two years of experience using Metro Transit) were more likely to be classified in the more satisfied, Excellent group.

Household Characteristic Variables

Riders who do not have an available automobile (more transit reliant) tended to be less satisfied. Satisfaction increased slightly for one-car households and was similar for two-, three-, or four-car households. Few differences were found across households of various sizes, although it is noted that households with six or more members reported higher probability of being in the Excellent cluster.

Safety Variables

Metro Transit asked two additional questions on the survey related to safety and security. The agency sought to understand the prevalence of street harassment (unwanted sexual comments, contact, touching, or exposure) as well as the proportion of riders who avoided a transit trip due to fear for safety and security. In both cases, respondents who reported having experienced street harassment or avoided a transit trip out of fear were less likely to be classified in the Excellent cluster, indicating lower satisfaction.

CONCLUSIONS

This study helps fill in the gap in the literature by introducing a novel approach to accessing public transit rider satisfaction across demographics and modes. Public Transit rider satisfaction was systematically analyzed across mode, bus route-type and demographic groups using a clustering alogithm and a Bayesian logistic regression. This novel method addressed concerns associated with the interdependent and categorical nature of Likert-scale survey data. The survey data collected here are typical of data available to many public transit agencies, which could improve their understanding by adoption of this robust method, as opposed to the traditional approaches.

Results from Metro Transit indicate that satisfaction is higher amongst commuter rail, light rail, commuter/express, and arterial bus rapid transit riders when compared to local bus. This finding agrees with Cao, et al. in that arterial bus rapid transit riders are more satisfied than other bus riders (22). Young riders, people of color, and males tended to be less satisfied than older, white, and female riders respectively. Middle income riders tended to be less satisfied than high- or low-income riders. New transit riders were more satisfied than experienced riders, while the most transit-reliant riders tended to be less satisfied. These findings can be used to target interventions, both in terms of improvements to the transit system and communications or marketing efforts.

REFERENCES

1. TCRP, A., 1999. Handbook for Measuring Customer Satisfaction and Service Quality. *TCRP Report*, *47*.
2. de Oña, J. and de Oña, R., 2014. Quality of service in public transport based on customer satisfaction surveys: A review and assessment of methodological approaches. *Transportation Science*, *49*(3), pp.605-622.
3. Abenoza, R. F., Cats, O., & Susilo, Y. O. (2017). Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution. Transportation Research Part A: Policy and Practice, 95, 64-84.
4. Martilla, J. A., & James, J. C. Importance-performance analysis. The journal of 406 marketing, 1977, pp. 77-79.
5. Weinstein, A. Customer satisfaction among transit riders: how customers rank the 408 relative importance of various service attributes. Transportation Research Record: 409 Journal of the Transportation Research Board, 2000, No. 1735, pp. 123-132.
6. Shen, W., Xiao, W., & Wang, X. Passenger satisfaction evaluation model for Urban rail 395 transit: A structural equation modeling based on partial least squares. Transport Policy, 396 2016, pp. 20-31.
7. Figler, S., Sriraj, P., Welch, E., & Yavuz, N. Customer Loyalty and Chicago, Illinois, 411 Transit Authority Buses: Results from 2008 Customer Satisfaction Survey. 412 Transportation Research Record: Journal of the Transportation Research Board, 2011, 413 No. 2216, pp. 148-156.
8. Stradling, S. G., Anable, J., & Carreno, M. Performance, importance and user 415 disgruntlement: A six-step method for measuring satisfaction with travel modes. 416 Transportation Research Part A: Policy and Practice, 2007, Vol. 41, No. 1, pp. 98-106.
9. Wu, X. and Cao, X., 2017. *Using the Three-Factor Method to Identify Improvement Priorities for Express and Local Bus Services in the Twin Cities, Minnesota* (No. 17-02464).
10. Cao, J. and Cao, X., 2017. Comparing importance-performance analysis and three-factor theory in assessing rider satisfaction with transit. *Journal of Transport and Land Use*, *10*(1).
11. Deng, W.J., Kuo, Y.F. and Chen, W.C., 2008. Revised importance–performance analysis: three-factor theory and benchmarking. *The Service Industries Journal*, *28*(1), pp.37-51.
12. Brant, R., 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics*, pp.1171-1178.
13. Eboli, L. and Mazzulla, G., 2007. Service quality attributes affecting customer satisfaction for bus transit. *Journal of public transportation*, *10*(3), p.2.
14. Eboli, L. and Mazzulla, G., 2012. Performance indicators for an objective measure of public transport service quality.
15. Carrel, A., Mishalani, R.G., Sengupta, R. and Walker, J.L., 2016. In pursuit of the happy transit rider: dissecting satisfaction using daily surveys and tracking data. *Journal of Intelligent Transportation Systems*, *20*(4), pp.345-362.

16. Stuart, K., Mednick, M. and Bockman, J., 2000. Structural equation model of customer satisfaction for the New York City subway system. *Transportation Research Record: Journal of the Transportation Research Board*, (1735), pp.133-137.
17. Brons, M., Givoni, M. and Rietveld, P., 2009. Access to railway stations and its potential in increasing rail use. *Transportation Research Part A: Policy and Practice*, *43*(2), pp.136-149.
18. Mouwen, A., 2015. Drivers of customer satisfaction with public transport services. *Transportation Research Part A: Policy and Practice*, *78*, pp.1-20.
19. Tyrinopoulos, Y. and Antoniou, C., 2008. Public transit user satisfaction: Variability and policy implications. *Transport Policy*, *15*(4), pp.260-272.
20. Eboli, L. and Mazzulla, G., 2008. A stated preference experiment for measuring service quality in public transport. *Transportation Planning and Technology*, *31*(5), pp.509-523.
21. Lai, W.T. and Chen, C.F., 2011. Behavioral intentions of public transit passengers—The roles of service quality, perceived value, satisfaction and involvement. *Transport Policy*, *18*(2), pp.318-325.
22. Cao, J., Cao, X., Zhang, C. and Huang, X., 2015. The gaps in satisfaction with transit services among BRT, metro, and bus riders: Evidence from Guangzhou. *Journal of Transport and Land Use*, *9*(3).
23. Andreassen, T., 1995. (Dis) satisfaction with public services: the case of public transportation. *Journal of Services Marketing*, *9*(5), pp.30-41.
24. Kaufman, L. and Rousseeuw, P.J., 1990. Partitioning around medoids (program pam). *Finding groups in data: an introduction to cluster analysis*, pp.68-125.
25. Gower, J.C., 1971. A general coefficient of similarity and some of its properties. *Biometrics*, pp.857-871.
26. R Core Team. 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
27. Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, *20*, pp.53-65.
28. Gelman, A., J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin, editors. 2013. Bayesian data analysis. 3. ed. CRC Press/Chapman & Hall, Boca Raton, Fla.
29. Stan Development Team (2016). rstanarm: Bayesian applied regression modeling via Stan. R package version 2.13.1. http://mc-stan.org/.

APPENDIX A: Attitudinal Survey Questions

Please rate Metro Transit's performance on the following: [Excellent, Good, Fair, Poor, Unacceptable, Don't know]

- Overall rating of Metro Transit service
- Paying for my fare is easy
- Personal safety while waiting
- Personal safety while riding
- Behavior of other passengers and atmosphere on bus
- Hours of operation for transit service meet my needs
- Routes go where I need to go
- Total travel time is reasonable
- Transferring is easy
- Reliability - service is on schedule
- Drivers operate vehicles in a safe and responsible manner
- Vehicles are clean
- Vehicles are comfortable
- Routes and schedules are easy to understand
- Fares are easy to understand
- Availability of seats
- Vehicles are environmentally friendly
- Shelter conditions/cleanliness
- Accessible for people with disabilities
- Handling of concerns/complaints

APPENDIX B

TABLE 2 Full logistic regression model output

Coefficient	Mean	SE Mean	2.50%	97.50%
(Intercept)	0.261	0.001	0.180	0.343
harassedYes	-0.094	0.000	-0.132	-0.055
fearYes	-0.127	0.000	-0.162	-0.091
transit_for_special_eventsNo	-0.013	0.000	-0.041	0.015
days_taken_transit0	0.099	0.000	0.039	0.159
days_taken_transit1	0.072	0.001	-0.015	0.160
days_taken_transit2	0.036	0.000	-0.024	0.097
days_taken_transit3	-0.021	0.000	-0.074	0.033
days_taken_transit4	0.008	0.000	-0.034	0.051
days_taken_transit6	-0.001	0.000	-0.045	0.045
days_taken_transit7	0.034	0.000	-0.011	0.079
paymentCash	0.029	0.000	-0.014	0.072
paymentPass on a Go-To-Card	-0.018	0.000	-0.064	0.031
paymentMetropass	0.005	0.000	-0.035	0.043
paymentU-Pass	0.027	0.000	-0.036	0.087
paymentCollege Pass	-0.020	0.001	-0.119	0.078
paymentStudent Pass	0.014	0.001	-0.068	0.101
paymentOther	-0.023	0.000	-0.084	0.041
purposeCollege/University	-0.023	0.000	-0.085	0.041
purposeSchool (K-12)	-0.060	0.001	-0.158	0.040
purposeSocial or entertainment	0.051	0.000	-0.011	0.112
purposeSporting or special event	0.085	0.001	-0.005	0.178
purposeMedical	-0.052	0.001	-0.154	0.047
purposeShopping or errands	-0.023	0.000	-0.074	0.027
purposeAirport	0.075	0.001	-0.066	0.215
purposeOther	0.041	0.001	-0.027	0.109
modeCommuter and Express	0.047	0.000	-0.002	0.097
modeA Line	0.123	0.001	0.049	0.198
modeBlue Line	0.073	0.000	0.028	0.120
modeGreen Line	0.068	0.000	0.022	0.112
modeNorthstar	0.212	0.000	0.153	0.270
if_trip_not_existWalk	0.011	0.001	-0.053	0.074
if_trip_not_existBike	-0.031	0.001	-0.114	0.055
if_trip_not_existOther transit	0.023	0.000	-0.024	0.068
if_trip_not_existSomeone would drive me	0.012	0.000	-0.043	0.070
if_trip_not_existCarpool	-0.009	0.001	-0.104	0.084
if_trip_not_existUsed car share (HourCar, car2go, etc.)	-0.047	0.001	-0.196	0.092
if_trip_not_existUsed Uber/Lyft	0.001	0.001	-0.065	0.065
if_trip_not_existTake a taxi	0.090	0.001	0.007	0.173
if_trip_not_existWould not have made the trip	0.027	0.000	-0.029	0.081
genderMale	-0.017	0.000	-0.043	0.010
raceBlack/African/African American	-0.015	0.000	-0.056	0.027
raceAsian/Asian American	-0.044	0.000	-0.098	0.011
raceMixed race	-0.020	0.000	-0.078	0.040
raceHispanic/Latino/Mexican	0.002	0.001	-0.068	0.073
raceAmerican Indian/Alaska Native	-0.040	0.001	-0.152	0.071
raceOther	-0.045	0.001	-0.159	0.063
have_disabilitiesYes	0.056	0.000	0.007	0.104
ageLess than 18	-0.072	0.001	-0.161	0.023
age18-24	-0.001	0.000	-0.045	0.043
age35-44	0.029	0.000	-0.014	0.071
age45-54	0.031	0.000	-0.013	0.073
age55-64	0.062	0.000	0.018	0.106
age65+	0.064	0.000	0.001	0.123

hh_incomeLess than $10,000	0.029	0.001	-0.025	0.086
hh_income$10,000 - $14,999	0.059	0.001	-0.006	0.126
hh_income$15,000 â€“ $24,999	0.045	0.000	-0.014	0.106
hh_income$25,000 - $34,999	0.005	0.001	-0.052	0.062
hh_income$50,000 - $59,999	-0.016	0.001	-0.081	0.044
hh_income$60,000 - $74,999	0.011	0.001	-0.046	0.071
hh_income$75,000 - $99,999	0.048	0.001	-0.009	0.106
hh_income$100,000+	0.030	0.001	-0.021	0.083
number_automobiles0	-0.045	0.000	-0.092	0.004
number_automobiles1	-0.028	0.000	-0.067	0.009
number_automobiles3	-0.037	0.000	-0.095	0.021
number_automobiles4+	0.005	0.001	-0.082	0.092
n_household1	-0.004	0.000	-0.051	0.044
n_household2	0.002	0.000	-0.038	0.046
n_household4	-0.001	0.000	-0.051	0.050
n_household5	0.025	0.001	-0.041	0.091
n_household6+	0.069	0.001	-0.006	0.144
reasonsMultiple reasons	0.014	0.000	-0.032	0.059
reasonsMore convenient	0.013	0.001	-0.065	0.091
reasonsSave time	0.083	0.001	0.010	0.160
reasonsSubsidized by employer or other organization	0.043	0.001	-0.045	0.130
reasonsProvide regular exercise	0.068	0.001	-0.118	0.253
reasonsPrefer car-free or car-light lifestyle	0.022	0.000	-0.038	0.083
reasonsEnvironmental	0.018	0.001	-0.075	0.108
reasonsDo not have access to car or other transportation	-0.034	0.001	-0.086	0.017
reasonsSave money on gas or auto expenses	0.052	0.001	-0.011	0.114
reasonsAvoid stress of driving/traffic congestion	0.017	0.000	-0.034	0.069
reasonsPredictable travel time compared to driving	0.071	0.001	-0.064	0.209
reasonsOther	-0.003	0.001	-0.154	0.149
use_transit3 to 5 years	0.014	0.000	-0.020	0.047
use_transit1 to 2 years	0.055	0.000	0.017	0.093
use_transitLess than 1 year	0.099	0.000	0.058	0.141

APPENDIX C

TABLE 3 Survey Instrument Distribution and Transit Ridership

Mode	Surveys Distributed	Surveys Collected	2016 Average Weekday Boardings
Northstar (Commuter Rail)	2,000	569	2,534
Light Rail (Blue Line and Green Line)	12,000	3,292	69,723
Bus (includes A Line, Commuter/Express, and Local buses)	19,000	4,429	199,179