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Managerial Segmentation of Service Offerings in Work Commuting

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ABSTRACT

This study reports an implementation of procedures that multivariate methodology make available to assess the relative importance of attributes of service offerings to work commuters. Adaptive choice conjoint analysis was used to derive the importance weights of attributes in available service offering to a commuter sample. A clustering procedure was then used to define homogeneous sub-groups of the sample and the combination of demographic differences that discriminate clusters. Results of this assessment are used to indicate how a market in work commuting can be segmented on the basis of user indications of the importance of attributes of service offerings.

KEYWORDS: Market segmentation, Urban transportation, Transportation mode choice, Conjoint analysis, Service design

INTRODUCTION

While the U.S. Department of Transportation and Caltrans both have increasing public transit ridership as part of their strategic goals, these goals have been difficult to achieve (Siggerud 2006; U.S. Government Accountability Office 2010; Weiner 2008). Part of the difficulty is that, on one hand, riders and potential riders have diverse needs in public transport services. On the other hand, designers and managers of public transport service offerings often do not have well defined indication of these needs from travelers themselves. Work commuting is a useful starting point to address goals in public transportation usage because of its regularity in timing and importance to the economy. The challenges to riders and managers are clearly increased when the trips are intermodal as a large percentage of work commuting is.

Clearly, public transit exists in a competitive environment where many potential customers have alternatives ranging from driving alone to telecommuting, and transit managers are challenged to find the most effective methods of maintaining and increasing ridership. Variability in the design service offerings to meet needs of users and potential users remains an important capability to increase ridership in work commuting.

Market segmentation has been shown to be an effective method to guide the design of variable transit services that can help transit agencies increase ridership and revenues. We next provide a background on segmentation that can be a design procedure and their applications that can be a basis for segmentation of work commuting usage.

Market Segmentation in Urban Transportation

A typically high level of aggregation in conventional analysis of urban commuting by transit agencies may be obscuring meaningful differences in usage sensitivity to design variables among identifiable sub-groups of work travelers. In many cases, work travelers would be likely to increase their usage for designs that more closely match their needs even under a constraint that the increased revenue from the service differentiation equal or exceed the cost of differentiation.

Segmentation perspectives recognize that markets can be disaggregated on the basis of levels of product or services offerings that the users prefer. Under commonly encountered conditions, willingness to use a mode of work commuting is expected to be sensitive to the closeness of service offerings to user ideal levels of attributes that underlie the offerings. While there has been recognition of the benefits of segmentation in transportation studies, we can find few real applications of efficient methods to accomplish it in the study of public transportation usage in work commuting. There are a number of recognizable reasons for this. Since public transportation offerings are often organized in close geographical proximity, it is more difficult to define and operationally segment these markets. However, Silver (2012) has demonstrated significant differences in preferred service offerings between travel corridors in close proximity in a transit district. At a minimum, market segmentation can provide the transit manager with a better understanding of the user, and promote a better balance between the operational and promotional functions of the transit agency. In terms of generalizability, it is anticipated that although there are regional differences that are reflected in differences in coefficient weights for design variables, there remains a commonality in the existence of multiple user segments that can be designated within feasible design variables across the regional differences.

To summarize the above points, it has been suggested that there is considerably more opportunity to conceptualize, operationalize and implement segmentation in work commuting than has been recognized. Some of this arises from newer methodology that can efficiently measure what is most important to users in attributes of a trip. The background of these observations in public transportation will next be reviewed.

BACKGROUND OF MARKET SEGMENTATION IN MARKET RESEARCH

More than a decade ago, Elmore- Yalch (1998) directed attention to the contributions that market segmentation can offer to the goal of increasing public transportation usage. Wedel (2000) is among the authors who have more recently reviewed the general contributions that market segmentation can make to objectives of both consumers and providers. Our current capabilities in assessment methodology, design and implementation can substantially increase this contribution.

In more recent studies, Hunecke, Haustein et al 2010 analyzed the usefulness of an attitude-based targeting of groups in predicting a transportation usage measure. An expanded version of the Theory of Planned Behavior (e.g. Ajzen 2011) was used to identify distinct attitude-based target groups. Their results shows that the five groups identified by unique combinations of attitudes, norms, and values differed significantly from each other with regard to travel-mode choice, distances traveled, and ecological impact. Wen, Wang and Fu (2012) explored mode choice behavior in market segments, using a survey data collected in Taiwan. They used nested logit models to capture flexible substitution patterns among attributes of the service offerings while simultaneously identifying the number, sizes, and characteristics of market segments. In their results, most high-speed rail travelers were cost-sensitive, and thus strategies that reduce the access costs were suggested to be more effective than those that reduce the travel times.

The above studies exemplify the benefits of segmentation in applications to public transportation. A first task in implementing a segmentation design is in the efficient and reliable assessment of travel judgments of the importance of attributes in available offerings and satisfaction with these attributes. Presently available multivariate methods can contribute to the capabilities to implement these applications. Applications of methodology in the assessment of both the importance of attributes of service offerings and satisfaction with current levels of these attributes and segments of the traveler market will be indicated in the corridor under study.

Adaptive Choice-Based Conjoint Analysis (ACBC)

Conjoint measurement has psychometric origins as a theory to decompose holistic judgments (e.g., ratings or rankings of full profiles of different levels of service attributes) into interval scales for the importance of each component attribute. The objective of conjoint analysis is to determine which combination of a limited number of attributes is most influential in respondent choice. Huber (2005) provides a review of the history and application of conjoint methodology.

Commonly implemented conjoint methodology presents respondents with individual profiles of levels of a set of attributes in a product or service offering. The respondent is asked to rate or rank “liking” or the equivalent for each profile. The variation in attribute levels across evaluated profiles provides a basis to generate overall importance weights for each of the attributes.

ACBC models are designed to reduce the number and complexity of the choice profiles presented to respondents. ACBC uses early judgments of ratings or ranking of full profiles to select the profiles that the respondent is subsequently shown for rating or ranking. This methodology generally reduces the number of profile judgments a respondent is asked to make. In the initial stage of ACBC, “must have” questions directly follow “unacceptable level” questions. Once the respondent has completed the initial stage of screening questions, a transition is made to the second stage of the choice task.

In this stage, the respondent is only shown a series of choice tasks that present attributes that were indicated to be actively processed in the first stage. The screening procedure of ACBC also allows non- linear combinations of attributes in a respondent‟s judgment that more realistically represent processing on attribute levels. The procedures that are implemented here will assess *the importance of service attributes* to work travelers with adaptive choice conjoint analyses. As in most applications, respondents also complete a direct allocation of a fixed budget amount (constant sum) to each of the attributes. Binner Neggers and Hoogerbrugge (2009) provide a detailed application of ACBC in their report of a case study.

Travel Corridor under Study

Electronic survey methodology was used to identify segments of work commuters in a travel corridor of Santa Clara county in the Bay area of Northern California where high technology employers predominate. U.S. census datasets allow demographic profiles of residents in the county in California that will be studied and a comparison of these profiles to profiles for the state of California at the last census. The profiles of the county and state are shown in Table 1.

Table 1 County Demographics

Descriptor	Santa Clara County	State of California
Percent of Residents with Bachelor"s Degree or Higher	40.5	26.6
Median Household Income	$88,525	$61,017
Mean Travel Time to Work (minutes)	26.1	27.7
Persons Per Square Mile	1,303	217

Source: U.S. Census Bureau 2010 (http://www.census.gov/)

As indicated in the table, the county itself has higher educational levels and income and is more densely populated than the state. However, travel time in work commuting in the county does not significantly differ from that of the state. Given the education and income differences, commuters in the county may be able to better discriminate service qualities and more willing to pay more for service that better fulfills their needs. This increases the importance of defining their judgments over a range of influential factors in service offerings. The travel corridor under study primarily services high-tech companies. The boundaries of the travel corridors and the transit route are shown in figure 2. This travel corridor is used by individuals who are largely in professional occupations and have higher than mean educational and income levels than the State of California or even the county of Santa Clara. Sample demographics will be reported in detail in a later section.

METHOD

Respondent Sample

Participants were obtained from a number of major companies in the densest geographical location of high tech companies in the county. In each company that was a source of respondents, a coordinating employee obtained from ten to twenty four other employees with an interest in participating. Participation was done as a public service and a learning experience with modern survey methods. To further incentives for participation, 50 $10 gift cards were distributed to participants through a random drawing from completed questionnaires. A total of 274 respondents completed both the conjoint tasks and questionnaires.

Attribute Set in Profiles of Service Offerings for Work Commuting

While large numbers of relevant attributes have been identified in previous study of public transportation, it appears that four or five have clear predominance in importance. For example, recent study suggests that safety, waiting time and uncertainty in arrival time to be among attributes that predominate in importance (e.g. Iseki and Taylor 2010) in an urban setting. Additionally, there is clear indication in these studies that out-of-vehicle travel time (wait time) is weighted as significantly more important than in-vehicle travel time (Iseki and Taylor 2010; Wardman 2001). A hierarchical decomposition of the results of focus groups of work commuting in public transportation and privately owned vehicles (POVs) in the county extends the lists of factors previously considered but does again indicate the predominance of a relatively small set of factors. These factors were used in the design of the conjoint analysis task and closed end questionnaire. Appendix Figure A1 shows the decomposition in factors for one of these groups.
Figure 1 shows an exemplary screen from the ACBC task that was used.

Figure 1. Exemplary Screen in Full Profile Choice Task

Next could you please rate how well the following profile of features in a public service offering for work commuting meets your personal needs?

<u>Cost</u> 15% above current
<u>Comfort</u> about the same
<u>Uncertainty</u> 15% less than current
<u>Total travel time</u> about the same
<u>Wait time</u> 10% less than current

Which of the following reflects your judgment above how well the offering meets your needs.

- O Does not at all meet my needs.
- o Partially meets my needs.
- o Neutral for all my needs.
- o Mostly meets my needs.
- o Perfectly meets my needs.

The top of this screen shows the levels in a profile of service offerings for work commuting. Since exact statistics for current levels of all attributes are not available, the common method of comparing this profile to the current profile a respondent faces is in percentage comparisons to current levels. The bottom of the screen shows the rating scale that the respondent faces for each screen.

RESULTS

Conjoint Weights of the Attributes in Profiles of Service Offerings

The conjoint derived weights for the importance of attributes and a constant sum allocation to these attributes in the sample are reported in Tables 2 and 3, respectively.

Table 2. Means and Standard Deviations of Conjoint-derived Importance Weights of Attributes

	Mean	Std. Deviation
Importance Cost	23.145	10.5042
Importance Comfort	8.2391	7.4622
Importance Uncertainty	14.1638	9.0747
Importance total travel time	18.675	10.0458
Importance wait time	16.9781	10.0757

Note: "Cost" is trip cost, "Comfort" is crowdedness and seat comfort, "Wait time" is average time between mode connections, "Travel time" is total travel time. "Uncertainty" is the variance in total travel time. N= 274

Table 3. Constant Sum Allocation to Attributes of Service Offerings

	Mean	Std. Deviation
MoneyspentCost	22.83	18.989
MoneyspentComfort	15.72	13.143
MoneyspentUncertainty	19.43	14.410
MoneyspentTotaltraveltime	22.84	15.827
MoneyspentWaittime	19.42	14.745

Note: "Cost" is trip cost, "Comfort" is crowdedness and seat comfort, "Wait time" is average time between mode connections, "Travel time" is total travel time. "Uncertainty" is the variance in total travel time. N= 274

Recall that Conjoint Analysis uses the ratings of profiles of the attributes in a service offering to derive overall importance weights. The benefits of this method have been reviewed earlier. Constant sum allocations ask the respondent to directly assign importance weights to each attribute under the condition that the sum of the weights is a constant, here 100. A significant relationship between the sets of conjoint derived and constant sum importance weights that are measuring the same underlying judgments is anticipated (Louviere and Islam

(2008). This is consistent with previous findings and is an indicator of a stable underlying judgment of importance weights.

Since differences in derived importance weights between POV and public transport work commuters in the sample were small and not statistically significant, results were analyzed for the entire sample. The relationship of the conjoint derived importance weights to the constant sum allocations as an indicator of importance weights was first considered. In measurement properties, weights derived from the conjoint procedure have significantly smaller standard deviations and background studies have extensively demonstrated that conjoint derived weights are meaningful predictors of actual choice (e.g. Huber, 2005).

Canonical correlations between the conjoint derived importance rates and constant sum allocations to attributes indicate that the relationships between the two sets of variables were reducible to two dimensions (canonical variates) that each explain more than 20% of the measured variables. The first pair of canonical variates showed a significant correlation of 0.382 ($p<0.05$).

Clustering of Conjoint Derived Importance Weights for Service Attributes

Following the results of conjoint analysis to estimate part-worths (importance weights) for each of the attributes in terms of which service offerings have been defined, cluster analyses were used to identify traveler segments based on the revealed conjoint weights. Cluster analysis identifies groups (clusters) of individuals or objects that are similar to each other but different from objects in other groups (clusters). Methods of cluster analysis are commonly distinguished as hierarchical and non-hierarchical. Hierarchical clustering groups data that are generally for multiple measure variables by creating a cluster tree or *dendrogram*. The tree is not a single set of clusters, but rather a multilevel hierarchy, where clusters at one level are joined as clusters at the next level.

Nonhierarchical clustering partitions a dataset into a small number of clusters by minimizing the distance between each data point and the center of the cluster while maximizing the distance from other clusters. Instead of using the tree like construction of hierarchical clustering, non-hierarchical procedures use pre-specified starting points (cluster seeds) and a pre-defined number of clusters to generate a cluster solution. In the present application, a two stage design of cluster analyses was used to obtain the benefits that alternative clustering methods can offer (e.g., Chapman and Goldberg 2011). In the first stage, hierarchical clustering (e.g. Ward‟s method, Murtagh, 1983) was used to maximize within cluster homogeneity and indicate the number of clusters to be further investigated. In the second stage nonhierarchical was used to generate maps of the distribution of clusters.

The Ward hierarchical clustering results indicated a three or four cluster solution using the standard methods of the dendrogram pattern and increases in the agglomeration coefficient. Both three and four cluster solutions were investigated in applications of K-means clustering. Results of the four cluster solution were similar to those in the three cluster solution with an additional cluster that was small in number of respondents and offered no addition insight into the distribution of importance weights across attributes.

Mean Kappa coefficients (e.g., Fleiss 2011) also indicated the best fit of a three clusters solution. The robustness of this solution was confirmed by using hold-out sampling to repeatedly define clustering in .66 samples of the total numbers of respondents. In this procedure, different random draws of respondents are used to examine the clustering results and support the stability of the clustering that will be interpreted. Results of the three cluster solution in K means clustering are presented in Table 4.

Table 4. Centroids of a Three Cluster Solution in K-Means Clustering

Cluster	1 Cost/uncertainty	2 Cost predominate	3 Time predominant	F Sig
cost	<u>18.950</u>	<u>32.149</u>	18.981	70.758*
comfort	9.579	6.321	7.431	5.680**
uncertainty in travel time	<u>18.878</u>	7.961	10.112	64.843**
total travel time	16.858	19.736	<u>23.204</u>	7.181**
Wait time	14.942	12.792	<u>34.043</u>	128.608**
n	148	97	39	

(bootstrap 1000 samples, $\alpha = .05$) Since the clusters have been chosen to maximize the differences among cases in different clusters and the observed significance levels are not corrected for this the F tests cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Results in Table 4 indicate that the attribute comfort is lowest in importance across all clusters. The predominant clusters can be discriminated as follows

Cluster 1: Uncertainty in travel time and cost predominate in importance
Cluster 2: Cost as a single attribute predominates in importance in this cluster and is greater in importance than in other clusters.
Cluster 3: Total travel time and wait time predominate in importance in this cluster

Cluster Profiles in Demographics

The demographic profiles across the relationship of cluster memberships to differences in demographic measures were next examined. Cross-tabulation of differences in main effects of demographic categories across clusters is reported in Table 5.

Table 5. Cross Tabulation of Cluster Membership and Demographic Variables

Characteristic	Cluster 1	Cluster 2	Cluster 3
	Cost/uncertainty *(n* =129)	Cost predominant (*n*=91)	Time predominant *(n*=51)
Occupation			
1=professional	16	12	5
2=non professional manager	13	9	13
3=administrative support	15	15	8
4=technical support	24	12	9
5=skilled labor	7	2	4
6=other service	8	9	8
7=other	25	18	25
Test statistic	$\chi^2 = 18.052$	$p<0.10$	
Male/Female			
1=Male	57	52	29
2=Female	72	39	22
Test statistic	χ^2 = /4.471	$p<0.10$	
Marital status			
1=Single	82	63	41
2=Married or living together	47	28	10
Test statistic	$\chi^2 = 5.767$	$p<0.20$	
Education			
1=High school graduate or less	19	9	4
2=Some college	57	41	26
3=College graduate	40	31	17
4=post graduate education	13	10	4
Test statistic	$\chi^2 = 3.573$	$p=0.89$	
Income group			
1=0-25,000	40	24	29
2=25,001-50,000	28	27	8
3=50,001-75000	20	19	7
4=>75,000	41	21	7
Test statistic	$\chi^2 = 19.535$	$p<0.01$	
Mode of commuting			
1=private	78	50	25
2=public	42	38	13
Test statistic	$\chi^2 = 1.692$	$p=0.42$	
Age			
1=<25	64	38	20
2<26-35	49	28	13
3<36-45	16	3	4
4<46-54	8	7	2
5>=55	10	9	0
Test statistic	$\chi^2 = 9.077$	$p=0.33$	

Table 6. Demographic Descriptors of Clusters in Conjoint-derived Importance (CDI) Weights for Attributes of Service Offerings

Dependent variable: k means clustering of conjoint derived importance weights

	Cluster 1 Uncertainty/Cost	Cluster 2 Cost predominate	Cluster 3 Time predominant
		cluster centroids	
CDI Cost	18.950	32.149	18.981
CDI Comfort	9.579	6.321	7.431
CDI Uncertainty in travel time	18.878	7.961	10.112
CDI Total travel time	16.858	19.736	23.204
CDI Wait time	14.942	12.792	34.043
Independent variables: demographic predictors of cluster membership			
Occupation	professional, sales, admin support	tech support, skilled labor, other service	non-professional managers
Marital Status	married	single, not married couple	married
Education	college graduate/ post graduate	some college	college graduate
Income Group	50-75,000	0 – 50	50,000 – 75,000, >75,000
Age Group	35 to >55	<35	36-45

While defining segments of work travels in actionable attributes of service offerings remains an essential prerequisite to designing variation in these attributes that most satisfy the needs of travelers, a challenge in inferring policy from the results is in delivering differences in services to members of distinct clusters that travel in a common corridor.

In delivering service offerings to different segments, route differences that vary in both day and time are design variables meriting consideration. This can differentially serve shopping needs of married commuters and social needs of younger professional commuters. On routes with travelers that approximate the demographics of the first and third clusters in Table 9, increasing frequency of service in critical time periods to reduce total travel time and waiting times, and providing direct displays and mobile accessed information on exact timing of service vehicles can reduce uncertainty and wait time. Travel times at different times of the day that include approximation of random delays and use these in scheduling can be indexed. An additional possibility is in smaller sized but larger number of vehicles that go to locations not on the regular schedule. While these procedures have been implemented independently, matching their delivery in combination to identifiable traveler segments in work commuting has not been previously examined.

SUMMARY AND DISCUSSION

Public transportation has high fixed costs because of the required capital in conveyance and maintenance and labor costs that are at least insensitive to levels of usage. When variable costs are typically much less important than fixed costs, increased ridership from more accurate and efficient matching of design attribute to stated needs of travelers can offset modified design costs. A basic approach to doing this is in segmentation of traveler markets.

Methodology to efficiently segment markets for public transportation offerings has been introduced and exemplified in an application to an urban travel corridor in which high tech companies predominate. A principal objective of this study has been to introduce and apply multivariate methodology to efficiently identify segments of work commuters and their demographic discriminants. A set of attributes in terms of which service offerings could be defined was derived from background studies and results of focus groups of work commuters in the county. Adaptive choice conjoint analysis was used to derive the importance weights of these attributes in available service offering a sample of work commuters in the travel corridor under study. A two-stage clustering procedure was then used to explore the grouping of individual"s subsets into homogeneous sub-groups of the sample that can be the basis for differentiation in service offerings.

In the first stage of the procedure, hierarchical clustering was used to determine the number of clusters and the initial cluster centers. K means non-hierarchical clustering was next used to examine the clustering in derived levels of the attributes. A cost predominant cluster, a time predominant cluster and a hybrid cluster in which both of these attributes were highly weighted is indicated in the three cluster solution. The demographics that discriminate memberships in the clusters were then examined. Cross- tabulation in main effects was not found to significantly discriminate segments and recursive partitioning was used to identify interactions between demographic predictors. Income and education was correlated with professional occupations and were not significant predictors after occupational group and age were entered. In occupation, the time and cost predominant cluster was discriminated from other clusters by younger commuters in professional and administrative support occupations. Discriminant analysis of the non-linear combinations of demographic variables indicated the increased contribution of non-linear combinations of demographics in classifying clusters.

The fact that unmarried people are the most segmented group when it comes to their preferences for service attributes in the results offers a potentially significant insight for long-range transit planning in the U.S. Over the past few decades, the share of unmarried persons of the U.S. population increased dramatically. Since this sub-group of the study sample appears to be a highly segmented market, we face an important challenge as transit planners if we want to increase (and maintain existing) transit ridership. The market segmentation techniques employed in this report suggest the challenges we face and point us towards how to address them successfully. While as noted, it is a challenge to deliver differentiated service offerings in this and other transit markets, companies in a range of other industries that include airlines and department stores have used effective methods to accomplish this.

Implications of these results for delivering design variation to different segments were discussed. The challenge of delivering design variation when segments travel in corridors that are not geographically distinct was noted and directions to accomplish this were reviewed. In this case, segments can be defined in terms of demographics of those who most travel different routes. Combinations of methodologies that have not been previously integrated in transportation studies have been exemplified in the reported application. These methods are accessible to service designers in public transportation or those that consult for designers. Although the results of this application are not readily generalizable because of the non-representative sample, size of the sample and its high tech location, they do serve to indicate a basic implementation of the proposed methodology and its interpretation. It is timely to use available multivariate methodology more widely in disaggregating markets for the use of public transportation. Work commuting is an appropriate sub-group of travels to initially direct attention to because of its regularity and economic importance.

APPENDIX

This appendix lists programs that support the statistical procedures used in the analyses and their supporting documentation.

A basic tutorial on using conjoint and cluster analysis for market segmentation.

http://www.slideshare.net/ragsvasan/a-simple-tutorial-on-conjoint-and-cluster-analysis

Conjoint Analysis in SPSS

http://www-01.ibm.com/support/docview.wss?uid=swg27038407#en

Manuals-- IBM_SPSS_Conjoint.pdf

Conjoint Analysis Sawtooth

http://www.sawtooth.com/index.php/blog/archives/understanding-conjoint-in-15-minutes-by- joseph-curry/

Sawtooth specializes in Conjoint Analysis programs. There are working papers on applications at their site.

Conjoint analysis in JMP (SAS)

Youtube on application in JMP by a leading practitioner. Part I and II

http://www.youtube.com/watch?v=MTlIUp8bujE

Tutorial on two-step cluster analysis in SPSS

http://spss.co.in/video.aspx?id=62

Hierarchical cluster analysis in R

http://www.r-tutor.com/gpu-computing/clustering/hierarchical-cluster-analysis

K means clustering in R

http://www.r-statistics.com/2013/08/k-means-clustering-from-r-in-action/

Cluster analysis in JMP (SAS)

http://www.jmp.com/support/help/Cluster_Analysis.shtml

Recursive partitioning in JMP

Using JMP® Partition to Grow Decision Trees in Base SAS

Recursive partitioning in SPSS (CHAID)

http://pic.dhe.ibm.com/infocenter/spssmodl/v16r0m0/index.jsp?topic=%2Fcom.ibm.spss.modeler.help%2Fclementine%2Fnodes_treebuilding.htm

Recursive partitioning Salford Systems
Owner of the original and most used software for recursive partitioning
http://www.salford-systems.com/

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