An Experiment to Derive Predictive Models of Public Response to Policy Manipulations in Public Bus Transportation

by

J.J. Louviere, R. Meyer,
F.C. Stetzer and L.L. Beavers

December, 1974

Technical Report #35

Center for Urban Transportation Studies
Institute of Urban and Regional Research
University of Iowa

This report was produced as part of a program of Research and Training in Urban Transportation sponsored by the Urban Mass Transportation Administration of the Department of Transportation.

The results and views expressed are the independent products of university research and are not necessarily concurred in by the Urban Mass Transportation Administration of the Department of Transportation.

INTRODUCTION

This report continues work begun at the University of Iowa in 1972 (Institute of Urban and Regional Research) and initially reported in Louviere, Beavers, Norman, and Stetzer (21). This work represents an extension of previous work in modal demand and policy sensitivity begun under U.M.T.A. sponsorship in 1971 (20,21,22,23). This particular report summarizes the methodology and results pertinent to an experiment in predictive modeling of demand for public bus transportation as a function of several policy-sensitive factors. Although the methodology closely parallels that reported in (21) above, important departures will be noted in this document.

BACKGROUND

The current state-of-the-art in travel demand forecasting has been summarized in a recent Highway Research Board Report (12). This paper will not attempt to review the field, as comprehensive discussions are contained in that document. It is sufficient to note that our approach is closely related to the so-called "abstract mode" approaches (14, 18, 25), but is derived from a consideration of theories of human information processing and evaluation developed in psychology (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 15, 16, 26, 27). Those readers familiar with the modal demand conceptualizations derived from economics and other related areas (14, 18, 25) will find the conceptual framework (theory) presented here to be similar. Most of the terms used herein that may appear unfamiliar are defined in (21), should the reader wish to refer to a more detailed discussion of theory and methodology.

Basically, it is assumed that individuals process the same information in a quantitatively similar fashion. Each piece of transportation related information relevant to choice of mode -- be it the fare on the bus, the location of the bus stop, the travel time advantage of one mode over another, etc. -- can be represented by two parameters: its <u>weight</u>, or importance;

and its <u>scale value</u>, or the position of the item along the dimension of judgment. These two parameters interact in a multiplicative fashion and form the basic primitives in algebraic theories of human evaluation.

It should also be understood that although we will use the term "evaluation" throughout this paper, it is considered synonymous with the terms "decision," "judgment," "attitude," "impression," "opinion," "feeling," "preference," etc. Although these terms often have sharp definitional distinctions in the literature (26), the same basic psychological process -- evaluation, or the processing of information -- is inherent in each. Thus, an understanding of the basic process -- the object of inquiry in this report -- simultaneously illumines each of these separately defined processes.

For simplicity we assume that individuals transform the objective transportation environment (i.e., objective reality) into a new, subjective dimension, which is used as sone of the bases for evaluating information. That is, the relationship between the objective and subjective dimensions may be expressed as follows:

$$s_i = f(S_i), \tag{1}$$

where s_i is the ith subjective stimulus value corresponding to the ith objective stimulus S_i.

For example, if the subjective evaluations are transformed in a linear fashion this would mean that subjective evaluations increased (or decreased) one unit for each unit change in the objective stimulus. It is likely, however, that these transformations are not linear (21, 23). This is, one's evaluation of the "goodness" of bus fares might be expected to decrease at an increasing rate. Thus, unit changes in real fares would occasion increasingly greater than unit changes in subjective "badness."

But the individual does not consider the objective factors which influence his evaluations one at a time. Rather, the individual "puts together" a number of factors simultaneously in his evaluations. This simultaneous evaluation process, of course, does not preclude the individual from changing the composition (both number and nature) of the factors which influence his evaluations as the occasion warrants. In fact, we will provide evidence of such changes in this paper. Because the individual can, and apparently does change the criteria of relevance, as well as the importance placed upon them, traditional methods of modeling travel demand cannot possibly provide accurate assessments of real demand. The current methods, because they study individual behavior, can and do identify and describe the subtle changes in human evaluations. Thus, the real problem is to discover how the individuals "put together" the information they use to evaluate transportation alternatives.

Once the objective transportation environment is transformed, the individual weighs or places some importance on each item of information. The items then are combined in some fashion to make an evaluation. If these processes do not occur simultaneously, they occur so rapidly, that they may be treated "as if" they so occurred. There is not yet any proof, for example, that studying the individual items or factors which influence judgments will allow us to predict the manner in which they will act in concert (5, 7, 8, 9, 10); although Louviere and Meyer[1] have shown that if one knows the right model a priori, one can use scale values derived from consideration of items one-at-a-time to predict responses to combinations of these items.

The point is worth elaboration. Consider an experiment in which one desires to scale (measure) the effects of two drugs A and B on a rat. One might first inject several dosage levels of A on one set of rats and several of B on another set; or inject A, observe behavior, let the effects of A dissipate, then inject B and observe behavior. But suppose one wanted to measure the joint effects of administering A and B together? We submit,

---

[1] This paper is under editorial consideration at the time of writing.

knowledge derived from administering A and B separately would not be very useful in predicting the joint effects (A and B) unless one had a prior theory of how A and B combined to result in the observed behavior. "Techniques" and "methods" of scaling attempt to measure the single effects of a set of transportation factors, without consideration of their joint effects and without an *a priori* model to describe the joint effects. It is clear that a considerable amount of error may possibly obtain in such efforts.

The remainder of this paper is devoted to a discussion of an experimental and analytical method for describing the conjoint effects of several simultaneous influences on travel demand in the context of public bus ridership. It also suggests extensions from the realm of practical prediction to that of theory construction -- the former being the main focus of this paper.

METHOD

Five factors which are potentially manipulable in public policy decisions regarding design and implementation of public bus systems are examined. These factors are bus fare (10¢, 25¢, 40¢);headways (15 minutes, 30 minutes, 45 minutes); reliability (4 minutes, 8 minutes, 12 minutes late); parking costs downtown (10¢/hour, 20¢/hour, 30¢/hour); and difference in travel time of bus over car (10 minutes, 15 minutes, 20 minutes). All combinations of these factors would describe 243 different bus systems. The object is to describe the behavior (evaluation response) of individuals with respect to each of the different systems. We want to be able to do this at the level of the single individual so that any systematic errors in aggregation to group data can be detected. One such error, e.g., would be the use of different evaluation strategies by different individuals or subsets thereof.

Working at this level requires repeated measures experimental designs so that intra-subject as well as inter-subject reliability can be assessed. This demands careful attention to experimental controls and procedures, and virtually precludes survey methods at this stage of the research. The large number of possible different bus systems (243) demands some procedure for reduction because such a large number of judgments will be difficult for people to make.

Concommitantly, model-building considerations demand careful attention to statistical estimation possibilities. Because orthogonality of factor design greatly enhances parameter estimation and test of goodness-of-fit possibilities, this property should be retained. Previous findings have indicated that non-linear models would be necessary to describe the response behavior; hence, as much information regarding higher-order factor combinations (3-way, 4-way) as possible should be retained. Fractional factorial designs (17, p. 12) permit one to preserve orthogonality while still examining some interaction terms in a design. The experimental design employed in this research is a 1/3 reduction (81 combinations) of a completely crossed 3^5 factorial design (5 factors at 3 levels = 243 combinations) which permits independent estimation of all main effects and two-way interactions. Appendix One contains the levels of the factors in the 81 combinations.

Except for fractionation of combinations, the experiment closely follows the procedure detailed in (21, 23). The major difference is that each subject judges experimental items that contain five phrases at a time for a total of 81 items. A typical item is shown in Figure 1. The response scale was changed: instead of either end being marked off by "0" or "100", it was marked off by "always take car" and "always take bus," respectively. In this experiment the 150 millimeter line scale was scored to the nearest 5 mm (see Louviere, 19), deriving a 30-category scale. Thus, scores of greater than 15 indicate increasing likelihood of taking a bus, with 22.5 denoting a 50% chance of taking the bus. Thus, this scale permits one to separately define likelihoods of using either mode of travel.

Two experimental sessions were held. The first session consisted of six students solicited at $2.50 per hour from the Iowa Office of Student Employment. The second session consisted of four men and one woman

64

Parking costs average 10¢ per hour.
The trip takes about 10 minutes longer by bus than by car.
The fare is 40¢.
The bus is scheduled to pass the closest stop every 30 minutes.
The bus may be as much as 4 minutes late.

Never take bus /____/ Always take bus

Figure 1. A Sample Experimental Item

solicited from an outlying subdivision at the terminus of one of the bus routes. All of the latter subjects were non-student volunteers. Regardless of session, all subjects evaluated each of the 81 experimental combinations four (4) times. The first set (replication) of evaluations was treated as practice and not analyzed. Subjects were instructed to assume buses and cars were their only travel alternatives; they were asked to evaluate each separate bus system in the context of a trip to school or work. They were told that the ends of the scale, "always . . .," "never . . .," represented absolute certainty of an evaluation. That is, nothing could possibly alter this evaluation. To emphasize the wide range of possibilities not explored in the experiment, subjects were shown combinations of items (bus systems) that were considerably worse and/or better than those they would evaluate. Instruction sheets and descriptions of these better and worse systems were left with the subjects to be referred to as they chose.

Experimental items were placed in "packets" consisting of the 81 items and nine "filler items." Fillers are combinations of items that are more extreme than those in the experiment; they serve to transfer bias away from the items of interest because subjects quickly learn the "best" and "worst" combinations and adjust their responses accordingly. Within a packet (90 combinations) the order of presentation of the items is randomized, as is the order of presentation of the phrases within items. This technique, called "counterbalancing," reduces order of presentation bias. Subjects were run in groups with no discussion permitted amongst themselves. The experiment took about one (1) hour to complete on the average.

RESULTS

Because the experiment is a fraction of a factorial design, in a repeated measures format, Analysis of Variance has a straightforward application. Significant Main Effects denote that the factor(s) involved had a statistically greater effect than a prediction made on the grand mean alone. Significant Interaction Effects indicate that the joint effect of each pair of experimental factors had an effect significantly different from simply adding or subtracting the Main Effects. Thus, significant interactions warn that linear combinations of the main effects are not adequate to account for the response data. Thus, analysis of variance can suggest possible algebraic functional forms which relate experimental factors to response. If one has an a priori model in hand, ANOVA can also serve as a test of goodness-of-fit. These tests, summarized in (7, 8, 9, 10), involve deductions about the partitioning of the interaction variance and tests for the hypothesis that the variance is in those components in which the model says it should be and not in those where it should not be.

Calculation of the "right" error term is a bit more complicated in repeated measure designs: it is the interaction of each effect with replications. Procedures for computing these terms in a very large design such as this preclude all but computer processing. Existing routines (17) do not make provisions for repeated measures designs in the fractional case; hence, some modification is required.[2] The first step in the analysis was to compute the replication effects -- the total sum of squares due to each of the three replications in the analysis. Dividing each sum of squares by its degrees of freedom (1) gives the Mean Square. The ratio of two mean squares is distributed as F (1 and 1 df); hence, the hypothesis of No Replication Effects can be tested. This test is not as powerful as might be desired because there is some chance that in the large number of tests (3 per subject, 11 subjects = 33) required, some alpha or beta errors may arise by chance. Nonetheless, the largest F ratio in the 33 tests did not approach 50% of the critical value; thus, there is considerable likelihood that there are no significant replication effects. The reader is invited to peruse actual data in Appendix Two to determine the apparent randomness of response patterns.

---

[2] Our special thanks to Dr. Duane Meeter of the Department of Statistics at Florida State Univ ersity for his helpful suggestions in this analysis.

Because there are no significant replication effects anticipated, the total within cells variance may be used as the measure of error. Thus, the Mean Square for within cells was used as a pooled error term. The results of this analysis are summarized in Table 1, in which sessions one and two are identified.

In session one, only the fare x parking costs interaction appears systematic. This is borne out by inspection of the Mean Squares for session one (Appendix Three). Only fare and parking costs appear to have predominate main effects, although travel time difference has some effect on two subjects, and frequency of service, an effect on a third. Reliability appears to be systematically discounted, although it is involved in a significant fare x reliability interaction in subject two's data.

In session two, the fare x parking cost interaction is again significant and systematic -- in this session across all subjects. Despite the larger number of apparently signficant interaction effects in the data of Session Two, many of these effects appear psychologically meaningless except for the fare x parking costs effect. For example, subject three exhibits a number of significant effects that are the consequence of a change in strategy in the cells corresponding to 10¢ parking costs, and have no meaningful interpretation. Subject four, on the other hand, appears to have meaningful reliability x parking costs, reliability x travel time difference, and parking costs x travel time difference effects. Graphs (not shown) of these effects suggest convergence to the right -- the typical bi-linear form of a multiplying model (7, 8, 9, 10, 23).

Although it is common for some researchers to "accept the analysis as it comes out of the computer program," a word about "significance" of effects is in order here. Interaction effects, in particular, are difficult to interpret in the absence of a theoretical model. Previous research in this area has consistently uncovered multiplying functions (21, 23), and we have little reason to anticipate other than these in these data. Inspection

Table 1. Summaries of Analyses of Variance, Sessions I and II

Session I							Session II					
Terms	S1	S2	S3	S4	S5	S6	Terms	S1	S2	S3	S4	S5
1	**	**	**	**	**	**	1	**	**	**	**	**
2					**	*	2		**	*	**	
3							3	**		**	**	**
4	**	**	**	**	**	**	4	**	**	**	**	**
5		**			**		5		**	**	**	**
1-2					*		1-2			*		
1-3		**					1-3			**		
1-4	**		**				1-4	**	**	**	**	**
1-5					*		1-5	**				
2-3							2-3					
2-4							2-4			*		
2-5							2-5					
3-4							3-4			**	**	
3-5							3-5			**	*	
4-5							4-5			**	**	

Critical Values

df	= 2,162		4,162	
	3.03	.05	2.40	.05
	4.68	.01	3.39	.01

* = .05; ** = .01

of the experimental cells (81) revealed considerable within cells variance of precisely those points responsible for the observed interactions. Graphically, these appear as crossovers: the subject considered all levels of one variable approximately equal and the lines cross randomly. The data reported in this document show no systematic trends in interaction effects, except for the fare x parking cost effect.

As a first approximation to developing predictive functions, multiple regression is applied to the response data. Care must be exercised in interpreting the coefficients, however, because they are confounded with the physical unit of the independent variables. A better estimate of the magnitude of effect of the factors can be obtained by examining the "t" values because they are dimensionless quantities, dependent entirely on the effect of the variable on the dependent variable. These values are listed in Table 2 for both linear and log-linear regressions. These regressions employ the mean cell response (81) as the dependent variable.

It is clear that there is a substantial difference between the subjects of session one and those of session two: students versus townspeople. The magnitude of the fare and parking cost effects is clear and systematic. Secondary influences are provided by the remaining three factors in the data of session one. Although the influences of these last three factors appear more prominent in the data of session two, we shall show that it is only apparently so. This is because two subjects appear to have adopted entirely different evaluation strategies (subjects two and three), and the remaining three subjects adopted different strategies in the last one-third of the experiment (27 cells where the fare was 40¢). Thus, the interpretation of both ANOVA and regression results is especially difficult and potentially misleading for these subjects. Thus, the results in Table 2 are intended for comparative purposes only.

Table 3 provides a detailed breakdown of the analysis of the first 54 and last 27 cells for the subjects in Session Two. All subjects exhibited

Table 2. T Values for Both Sessions

t Values (log)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
1	-15.71	-11.85	-15.18	-6.37	-11.88	-15.79	-4.39	-4.14	-0.19	-4.24	-5.61
2	0.31	-0.79	-0.01	-2.59	-4.08	-1.70	-0.60	-4.56	-1.27	-1.38	-0.23
3	0.15	-1.82	-0.58	-1.59	-0.86	0.39	-1.49	-0.83	2.06	-3.15	-1.36
4	7.80	7.25	14.96	-9.41	7.41	8.29	8.05	6.08	5.05	10.34	7.09
5	-0.21	-2.60	-0.20	-0.49	-0.71	1.25	-0.23	-4.73	-3.76	-7.39	-1.26

t Values (linear)

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
1	-14.34	-13.76	-15.80	-7.79	-17.58	-18.54	-4.74	-4.87	-1.15	-5.35	-8.09
2	-0.13	-1.18	-0.19	-2.36	-6.91	-2.25	-0.60	-5.49	-1.18	-2.62	0.31
3	-0.35	-2.34	-0.50	-1.93	-1.54	0.54	-3.14	-0.69	1.70	-4.49	-2.46
4	6.68	7.65	12.52	-11.11	11.42	9.49	10.65	6.55	5.74	13.39	9.11
5	-0.40	-3.21	-0.71	-0.28	-2.66	0.56	-0.30	-5.95	-4.45	-10.19	-2.18

differences in the proportion of variance accounted for by the various independent variables and in the "t" values. Had the subjects been following the same evaluation strategy in both sets of cells, the differences would be attributable merely to random chance.

The test for this is the approximation to t.[3] As Table 3 clearly shows, there are considerable differences between the parameters in the two sets of regressions across subjects. The hypothesis that there are no significant differences in strategy between blocks of cells across subjects must therefore be rejected. Ideally, a test on pooled data would have enabled a stronger statement within the group; however, due to different strategies within the first 54 cells, pooling the data would have led to fallacious inferences.

As a group, therefore, the subjects appeared to follow a similar evaluation strategy in the last 27 cells, which is confirmed by the fit of a linear regression ($R^2 > .80$) equation to these data. Fits of regression equations to the first 54 cells resulted in R^2 of .50. Fits of regression equations to all 81 cells produced R^2 of .65. This is in contrast with equations fit to the group data of Session One which resulted in R^2 of .94. Individual regression equations for Session One produced R^2s $> .70$, the best being .87, with the median being .81. The individual subjects in Session Two were much more difficult to fit: range of .44 to .82, with a median of .66.

Table 3 also confirms the improvements in fit in the last 27 cells (R^2). As anticipated, controlling for 40¢ fare reveals a definite change in evaluation strategy. Subject one, e.g., reveals a big increase in weight on parking costs for the last 27 cells, subject two places more emphasis on parking costs and less on travel time in cells 55-81, subject three

---

[3] Snedecor, G.W. and Cochran, W.G. Statistical Methods, Iowa State University Press, Ames, 1968. See esp. p. 437.

Table 3. Regression Parameters for Cells 1-54 and 55-81 Session Two Subjects

Cells	$\underline{S}_1$	$\underline{S}_2$	$\underline{S}_3$	$\underline{S}_4$	$\underline{S}_5$
1-54					
Parameters					
Frequency of Service	-.023*	-.119	-.035	.015	.033
Reliability	-.479	-.060	.234	.056	-.339
Parking Costs	.423	.138	.167	.022	.259
Travel Time	-.135	-.446	-.385	.045	-.249
r^2	.67	.65	.38	.87	.69
55-81					
Parameters					
Frequency of Service	-.044	-.127	-.044	-.032	-.023
Reliability	-.403	-.009	.051	-.393	-.255
Parking Costs	1.089	.374	.422	.376	.937
Travel Time	.107	-.248	-.441	-.422	-.211
r^2	.83	.72	.67	.78	.87

*Indicates a non-significant t at the .05 level for 77 degrees of freedom in a test for parameter differences in cells 1-54 and 55-81.

discounts reliability and emphasizes parking costs for a 40¢ fare, subject four changes her parameters completely, while subject five gives added weight to parking costs.

These relative weights are difficult to interpret because they are functions of not only the statistical relationship with the dependent variable, but also of the scale unit. They, in combination with their "t" values (Table 2), describe the relative contribution to the total variance in the response accounted for by each. Thus, in a purely descriptive and predictive sense they describe the expected effects on patronage response for a unit change in any one or more of the independent variables. Thus, they are not theoretical models of response behavior, they are statistical prediction functions.

The reasons these linear regression functions predict well, as pointed out by Dawes (16), Dawes and Corrigan (15), and Yntema and Torgerson (27) is: 1) that each so-called "independent" factor (and they <u>are</u> in these experiments) is monotonically related to the dependent variable; 2) the relative weights are not affected by error in the dependent variable because error reduces the expected values of all weights by the same constant amount, and hence must also reduce the predicted values by the same amount. This does not affect correlations with <u>true</u> scores, but it does affect correlations with observed scores; 3) error in the measurement of the independent variables (e.g., use of objective instead of subjective values) tends to make optimal functions more linear. Thus, as Dawes and Corrigan conclude (15, pp. 9-10), the linear regression models fit because linear functions approximate conditionally monotone functions, relative weights are unaffected by error in the response measure, and conditionally monotone functions tend to become more linear in the presence of increasing error in the independent variables. Their use as predictive functions, therefore, is clearly appropriate. It is important to note, however, that relative weights and physical scales (cents, minutes) are not the same as true weights and subjective scales. True weights and subjective scales must be obtained by numerical methods (e.g., 13, 24). They are not the subject of inquiry of this document, although their derivation is fundamental to complete understanding of the travel response process.

DISCUSSION AND CONCLUSIONS

This paper has demonstrated that the responses of samples of people (students and citizens) to policy manipulations of the transportation environment can be studied and described in laboratory situations. Consistent with previous results (15, 16, 21, 23, 26), subjects were found to exhibit numerous non-linear relationships in their data, which nonetheless could be described via linear regression. It seems likely that the true functional relationship is multiplicative, as noted earlier (21, 23) and later studies will attempt to confirm this hypothesis. Such relationships are important to establish because they can fundamentally affect our ability to predict to real world situations. While it appears as though linear regression will permit adequate prediction over the ranges observed in the laboratory, systematic discrepancies may lead to wide variance with real world data.

It would also appear that the subjects of Session Two adopted different decision strategies. This is dramatically demonstrated in the data for subject three (Appendix Four). A theoretical model for his data can be easily derived. It is simply "respond 29.0, except where parking costs equal 10¢." By applying this rule we can predict data with an average squared error of 0.654 (with one cell removed -- chance accounts for this single discrepancy). In the remaining cells, his responses varied systematically with fare and travel time differences. Aggregating across such different strategies would clearly produce misleading results. Indeed, these results suggest that procedures, such as those discussed in this paper, will be necessary to disclose such individual differences.

Future work should proceed in several directions. First, there is a need to develop experimental procedures which will permit simultaneous examination of more factors at more levels, while holding the number of judgments required to a minimum. Second, intimately related to the first point is a need for the development and/or extension of procedures for parameter estimation and goodness-of-fit to these situations in which the number of possible experimental points is large, but the number of observed points is small. Third, there is a need to recognize the importance of experimental research in cause-and-effect modeling. If the public and/or its agencies are unwilling to permit researchers to conduct experiments with actual transportation systems, then money should be directed toward psychological experimentation as the next best alternative. Finally, the research results and methods being developed and discussed in this document must be extended to the real world if confidence in future research is to be forthcoming. The extension of this research to real world situations is, at the time of this writing, under proposal, and given favorable reviews will begin in the near future. It is hoped that a discussion of issues, methods, and results will stimulate discussion and research in this area of potential significance for both transportation and psychology.

REFERENCES

1. Anderson, N.H., "Linear Models for Responses Measured on a Continuous Scale." Journal of Mathematical Psychology, 1964, 1, 121-142.

2. Anderson, N.H., "Effects of Choice and Verbal Feedback on Preference Values." Journal of Experimental Psychology, 1969, 79, 77-84.

3. Anderson, N.H., "Functional Measurement and Psychological Judgment." Psychological Review, 1970, 77, 153-170.

4. Anderson, N.H., "Integration Theory and Attitude Change." Psychological Review, 1971, 78, 171-206.

5. Anderson, N.H., "Looking for Configurality in Clinical Judgment." Psychological Bulletin, 1972, 78, 93-102.

6. Anderson, N.H., "Cross-task Validation of Functional Measurement." Perception and Psychophysics, 1972, 12, 389-395.

7. Anderson, N.H., "Information Integration Theory: A Brief Survey." In D.H. Krantz, et. al. (Eds.), Contemporary Developments in Mathematical Psychology, Vol. 2, San Francisco: W.H. Freeman, 1974.

8. Anderson, N.H., "Algebraic Models in Perception." In E.C. Carterette and M.P. Friedman (Eds.), Handbook of Perception, Vol. 2, New York: Academic Press, 1974.

9. Anderson, N.H., "Cognitive Algebra." In L. Berkowitz (Ed.), Advances in Experimental Social Psychology, Vol. 7, New York: Academic Press, 1974.

10. Anderson, N.H. and Alexander, G.R., "Choice Test of the Averaging Hypothesis for Information Integration." Cognitive Psychology, 1971, 2, 313-324.

11. Birnbaum, M.H. and Veit, C.T., "Scale Convergence as a Criterion for Rescaling: Information Integration with Difference, Ratio, and Averaging Tasks." Perception and Psychophysics, 1974, 15, 7-15.

12. Brand, D. and Manheim, M.L. (Eds.), Urban Travel Demand Forecasting, Special Report No. 143, HRB, Washington, 1973.

13. Chandler, J.P., "STEPIT--Finds Local Minima of a Smooth Function of Several Parameters." Behavioral Science, 1969, 14, 81-82.

14. Crow, R.T., Young, K.H. and Cooley, T., "Alternative Demand Functions for 'Abstract' Transportation Modes." Transportation Research, 7, 1973, 335-354.

15. Dawes, R.M. and Corrigan, B., "Linear Models in Decision Making." Psychological Bulletin, In Press, 1974.

16. Dawes, R.M., "A Case Study of Graduate Admissions: Application of Three Principles of Human Decision Making." American Psychologist, 1971, 26, 180-188.

17. Hahn, G.J. and Shapiro, S.C., "A Catalog and Computer Program for the Design and Analysis of Orthogonal Symmetric and Asymmetric Fractional Factorial Experiments." Report 66-C-165, Schenectady, N.Y.: General Electric Corp., 1966.

18. Lancaster, K.J., "A New Approach to Consumer Theory." Journal of Political Economy, 74(1966), 1-32.

19. Louviere, J.J., A Psychophysical-Experimental Approach to Modeling Spatial Behavior. Unpublished Ph.D. Thesis, Dept. of Geography, University of Iowa, June, 1973.

20. Anderson, N.H., "Final Report on a Before and After Transit Innovation Study." Technical Report No. 11, The Institute of Urban and Regional Research, The University of Iowa, January, 1973.

21. Anderson, N.H., Beavers, L.L., Norman, K.L., and Stetzer, F.C. "Theory, Methodology and Findings in Mode Choice Behavior." Working Paper No. 11, Institute of Urban and Regional Research, The University of Iowa, July, 1973.

22. Anderson, N.H. and Horton, F.E., "Behavioral Data in Transit Planning." Transportation, In Press, 1974.

23. Norman, K.L. and Louviere, J.J., "Integration of Attributes in Public Bus Transportation: Two Modeling Approaches." Journal of Applied Psychology, In Press, 1974.

24. Norman, K.L., "A Method of Maximum Likelihood Estimation for Stimulus Integration Theory." Technical Report CHIP 35, Center for Human Information Processing, University of California, San Diego, August, 1973.

25. Quandt, R.E. and Baumol, W.J., "The Abstract Mode Model: Theory and Measurement." Journal of Regional Science, 6, 1966, 13-26.

26. Slovic, P. and Lichtenstein, S. "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment." Organizational Behavior and Human Performance, 1971, 6, 649-744.

27. Yntema, D.B. and Torgerson, W.S., "Man-Computer Cooperation in Decisions Requiring Common Sense." Institute of Radio Engineers: IRE Transactions of the Professional Group on Human Factors in Electronics, 1961, HFE-2(1), 20-26.

APPENDIX ONE

Combination of Factors in Experimental Design

CELL	FARE	HEADWAY	RELIABILITY	PARK COST	TT DIFFERENCE
1	10.	15.	4.	10.	10.
2	10.	15.	4.	20.	15.
3	10.	15.	4.	30.	20.
4	10.	15.	8.	10.	15.
5	10.	15.	8.	20.	20.
6	10.	15.	8.	30.	10.
7	10.	15.	12.	10.	20.
8	10.	15.	12.	20.	10.
9	10.	15.	12.	30.	15.
10	10.	30.	4.	10.	15.
11	10.	30.	4.	20.	20.
12	10.	30.	4.	30.	10.
13	10.	30.	8.	10.	20.
14	10.	30.	8.	20.	10.
15	10.	30.	8.	30.	15.
16	10.	30.	12.	10.	10.
17	10.	30.	12.	20.	15.
18	10.	30.	12.	30.	20.
19	10.	45.	4.	10.	20.
20	10.	45.	4.	20.	10.
21	10.	45.	4.	30.	15.
22	10.	45.	8.	10.	10.
23	10.	45.	8.	20.	15.
24	10.	45.	8.	30.	20.
25	10.	45.	12.	10.	15.
26	10.	45.	12.	20.	20.
27	10.	45.	12.	30.	10.
28	25.	15.	4.	10.	15.
29	25.	15.	4.	20.	20.
30	25.	15.	4.	30.	10.
31	25.	15.	8.	10.	20.
32	25.	15.	8.	20.	10.
33	25.	15.	8.	30.	15.
34	25.	15.	12.	10.	10.
35	25.	15.	12.	20.	15.
36	25.	15.	12.	30.	20.
37	25.	30.	4.	10.	20.
38	25.	30.	4.	20.	10.
39	25.	30.	4.	30.	15.
40	25.	30.	8.	10.	10.
41	25.	30.	8.	20.	15.
42	25.	30.	8.	30.	20.
43	25.	30.	12.	10.	15.
44	25.	30.	12.	20.	20.
45	25.	30.	12.	30.	10.

CELL	FARE	HEADWAY	RELIABILITY	PARK COST	TT DIFFERENCE
46	25.	45.	4.	10.	10.
47	25.	45.	4.	20.	15.
48	25.	45.	4.	30.	20.
49	25.	45.	8.	10.	15.
50	25.	45.	8.	20.	20.
51	25.	45.	8.	30.	10.
52	25.	45.	12.	10.	20.
53	25.	45.	12.	20.	10.
54	25.	45.	12.	30.	15.
55	40.	15.	4.	10.	20.
56	40.	15.	4.	20.	10.
57	40.	15.	4.	30.	15.
58	40.	15.	8.	10.	10.
59	40.	15.	8.	20.	15.
60	40.	15.	8.	30.	20.
61	40.	15.	12.	10.	15.
62	40.	15.	12.	20.	20.
63	40.	15.	12.	30.	10.
64	40.	30.	4.	10.	10.
65	40.	30.	4.	20.	15.
66	40.	30.	4.	30.	20.
67	40.	30.	8.	10.	15.
68	40.	30.	8.	20.	20.
69	40.	30.	8.	30.	10.
70	40.	30.	12.	10.	20.
71	40.	30.	12.	20.	10.
72	40.	30.	12.	30.	15.
73	40.	45.	4.	10.	15.
74	40.	45.	4.	20.	20.
75	40.	45.	4.	30.	10.
76	40.	45.	8.	10.	20.
77	40.	45.	8.	20.	10.
78	40.	45.	8.	30.	15.
79	40.	45.	12.	10.	10.
80	40.	45.	12.	20.	15.
81	40.	45.	12.	30.	20.

APPENDIX TWO

Individual Subject Data

SESSION 1 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 1			SUBJECT 2			SUBJECT 3		
1	15.	16.	20.	22.	21.	25.	21.	12.	14.
2	22.	6.	23.	25.	23.	23.	20.	20.	20.
3	23.	22.	23.	26.	20.	25.	22.	20.	22.
4	11.	21.	23.	25.	22.	14.	14.	15.	13.
5	20.	21.	20.	25.	22.	25.	20.	21.	19.
6	21.	26.	24.	28.	26.	25.	20.	21.	23.
7	20.	19.	22.	7.	12.	24.	15.	12.	9.
8	21.	26.	18.	13.	18.	25.	20.	18.	21.
9	3.	23.	22.	22.	13.	28.	19.	21.	24.
10	12.	19.	20.	16.	26.	22.	10.	10.	10.
11	23.	23.	24.	22.	14.	16.	22.	22.	22.
12	23.	23.	21.	28.	26.	24.	20.	18.	20.
13	13.	20.	13.	25.	24.	22.	14.	10.	8.
14	21.	26.	25.	23.	20.	28.	23.	22.	18.
15	21.	27.	24.	24.	24.	24.	21.	22.	20.
16	14.	21.	9.	11.	19.	26.	15.	7.	20.
17	23.	26.	19.	19.	24.	21.	20.	18.	21.
18	19.	18.	25.	12.	21.	26.	17.	21.	20.
19	15.	22.	10.	18.	26.	18.	15.	15.	7.
20	21.	18.	21.	19.	27.	22.	20.	20.	19.
21	26.	24.	21.	25.	24.	22.	20.	18.	21.
22	22.	24.	12.	22.	23.	26.	16.	17.	16.
23	20.	19.	20.	24.	21.	23.	19.	22.	18.
24	6.	26.	23.	17.	22.	13.	23.	22.	20.
25	15.	23.	12.	10.	12.	20.	15.	15.	15.
26	19.	20.	21.	15.	18.	20.	19.	18.	20.
27	22.	20.	8.	25.	28.	23.	21.	21.	22.
28	7.	8.	10.	18.	13.	10.	3.	4.	6.
29	8.	14.	12.	18.	18.	21.	9.	15.	10.
30	19.	21.	16.	21.	20.	22.	19.	15.	13.
31	5.	8.	5.	14.	17.	21.	3.	6.	6.
32	10.	11.	14.	23.	12.	22.	10.	15.	18.
33	21.	8.	25.	21.	18.	19.	9.	13.	10.
34	6.	7.	8.	18.	15.	13.	4.	4.	2.
35	11.	6.	9.	19.	19.	20.	14.	12.	14.
36	17.	6.	17.	11.	13.	26.	15.	14.	9.
37	10.	7.	11.	14.	12.	18.	4.	7.	4.
38	11.	8.	9.	12.	17.	20.	14.	13.	10.
39	23.	18.	19.	24.	16.	18.	18.	18.	8.
40	6.	7.	8.	18.	9.	14.	1.	5.	4.
41	11.	12.	12.	25.	17.	20.	14.	11.	14.
42	22.	10.	14.	19.	18.	18.	14.	14.	18.
43	8.	7.	23.	12.	18.	12.	4.	4.	5.
44	5.	12.	10.	19.	9.	19.	14.	14.	14.
45	18.	20.	16.	23.	21.	22.	18.	15.	13.

SESSION 1 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 1			SUBJECT 2			SUBJECT 3		
46	7.	8.	9.	23.	6.	15.	5.	9.	5.
47	13.	9.	10.	19.	18.	15.	16.	13.	14.
48	8.	18.	16.	22.	14.	22.	15.	15.	8.
49	8.	8.	8.	16.	15.	12.	5.	3.	4.
50	13.	12.	13.	13.	10.	18.	14.	14.	7.
51	8.	18.	22.	24.	22.	20.	13.	16.	19.
52	6.	9.	7.	12.	13.	20.	3.	7.	2.
53	17.	5.	11.	14.	12.	14.	15.	7.	9.
54	17.	25.	21.	22.	17.	22.	13.	13.	10.
55	6.	6.	11.	4.	4.	17.	5.	5.	2.
56	10.	7.	12.	16.	20.	15.	7.	8.	7.
57	6.	12.	10.	14.	13.	14.	15.	7.	14.
58	9.	11.	10.	9.	11.	7.	6.	3.	4.
59	7.	9.	11.	13.	11.	11.	9.	9.	9.
60	11.	8.	8.	15.	8.	20.	12.	14.	12.
61	5.	7.	9.	12.	9.	5.	5.	3.	4.
62	11.	8.	11.	11.	8.	19.	10.	11.	11.
63	8.	6.	9.	12.	18.	23.	6.	13.	14.
64	7.	5.	10.	11.	9.	11.	2.	6.	2.
65	8.	10.	10.	12.	11.	17.	4.	10.	11.
66	11.	12.	11.	21.	16.	19.	13.	13.	10.
67	4.	7.	8.	14.	9.	12.	5.	8.	3.
68	11.	11.	15.	13.	9.	10.	6.	8.	7.
69	11.	9.	12.	21.	17.	11.	19.	8.	12.
70	7.	10.	12.	10.	10.	10.	5.	4.	3.
71	13.	6.	10.	20.	19.	19.	3.	9.	10.
72	12.	13.	10.	11.	17.	14.	6.	10.	9.
73	8.	8.	6.	8.	8.	14.	6.	8.	2.
74	7.	10.	7.	20.	10.	12.	5.	9.	6.
75	11.	9.	7.	17.	19.	20.	14.	11.	10.
76	4.	8.	8.	9.	9.	7.	5.	6.	5.
77	8.	7.	11.	9.	10.	12.	7.	6.	10.
78	10.	12.	11.	15.	7.	15.	14.	13.	10.
79	12.	5.	9.	10.	9.	12.	4.	4.	4.
80	10.	8.	9.	10.	11.	14.	4.	7.	14.
81	9.	9.	11.	16.	13.	17.	11.	12.	8.

SESSION 1 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 4			SUBJECT 5			SUBJECT 6		
1	10.	14.	16.	17.	16.	18.	15.	13.	14.
2	9.	12.	11.	18.	21.	13.	22.	20.	15.
3	2.	6.	10.	21.	20.	25.	20.	25.	16.
4	11.	14.	12.	20.	21.	12.	14.	18.	19.
5	5.	9.	11.	14.	14.	15.	19.	16.	15.
6	8.	6.	13.	27.	26.	26.	21.	21.	17.
7	9.	13.	12.	19.	11.	6.	15.	14.	14.
8	10.	12.	10.	24.	18.	26.	17.	16.	19.
9	5.	12.	10.	23.	23.	23.	19.	19.	21.
10	6.	12.	14.	14.	10.	16.	14.	12.	14.
11	2.	15.	12.	15.	15.	12.	12.	18.	18.
12	2.	5.	11.	22.	24.	16.	16.	18.	14.
13	6.	9.	10.	14.	14.	11.	11.	13.	8.
14	2.	11.	12.	24.	18.	12.	18.	19.	16.
15	1.	3.	8.	25.	21.	23.	22.	20.	18.
16	7.	10.	12.	11.	14.	9.	10.	15.	13.
17	6.	9.	13.	12.	15.	18.	20.	14.	23.
18	4.	9.	6.	15.	19.	16.	19.	19.	22.
19	10.	15.	15.	4.	11.	11.	6.	14.	13.
20	3.	5.	11.	12.	24.	13.	20.	14.	18.
21	7.	10.	9.	17.	16.	16.	17.	20.	15.
22	2.	15.	16.	17.	9.	11.	15.	15.	11.
23	5.	6.	13.	6.	15.	14.	14.	18.	16.
24	2.	3.	5.	17.	11.	16.	11.	18.	13.
25	6.	12.	15.	7.	4.	13.	11.	16.	10.
26	3.	10.	9.	9.	7.	15.	16.	14.	18.
27	5.	5.	9.	14.	24.	14.	24.	19.	17.
28	9.	11.	12.	10.	11.	7.	14.	5.	6.
29	8.	13.	7.	14.	13.	10.	10.	15.	13.
30	1.	2.	9.	24.	20.	15.	15.	10.	15.
31	7.	9.	15.	3.	10.	6.	9.	10.	9.
32	4.	9.	10.	9.	16.	5.	16.	11.	10.
33	3.	8.	10.	13.	14.	14.	12.	14.	14.
34	9.	12.	8.	5.	19.	5.	6.	10.	7.
35	3.	9.	10.	10.	19.	14.	13.	12.	10.
36	2.	3.	9.	14.	15.	7.	11.	14.	15.
37	11.	10.	8.	9.	9.	11.	12.	6.	9.
38	8.	8.	12.	17.	16.	11.	14.	5.	8.
39	4.	8.	9.	16.	16.	15.	8.	17.	12.
40	5.	6.	13.	12.	4.	6.	12.	8.	4.
41	4.	7.	8.	17.	9.	10.	9.	9.	7.
42	1.	4.	6.	17.	15.	14.	9.	12.	16.
43	9.	11.	12.	3.	15.	11.	9.	9.	9.
44	6.	3.	14.	9.	16.	9.	6.	14.	11.
45	4.	3.	8.	17.	16.	20.	13.	17.	14.

SESSION 1   INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 4			SUBJECT 5			SUBJECT 6		
46	10.	10.	12.	11.	3.	6.	13.	9.	5.
47	7.	8.	15.	13.	10.	12.	10.	12.	9.
48	4.	5.	7.	7.	13.	16.	8.	14.	18.
49	8.	7.	7.	3.	6.	5.	8.	9.	8.
50	8.	10.	16.	3.	10.	10.	10.	14.	12.
51	3.	8.	2.	9.	9.	14.	17.	15.	13.
52	8.	12.	14.	4.	12.	6.	9.	9.	7.
53	4.	5.	11.	3.	13.	8.	7.	6.	3.
54	1.	4.	4.	10.	14.	11.	9.	10.	13.
55	5.	5.	15.	5.	2.	2.	4.	3.	4.
56	3.	5.	12.	2.	3.	3.	6.	7.	7.
57	6.	2.	2.	15.	16.	13.	11.	5.	7.
58	3.	8.	14.	7.	2.	5.	8.	5.	5.
59	1.	5.	14.	7.	8.	7.	9.	5.	8.
60	1.	5.	6.	12.	11.	11.	11.	9.	13.
61	2.	5.	12.	5.	14.	2.	15.	5.	7.
62	3.	5.	8.	7.	3.	3.	11.	6.	6.
63	6.	4.	11.	2.	13.	13.	4.	7.	5.
64	7.	9.	11.	3.	3.	2.	4.	5.	4.
65	4.	6.	9.	7.	2.	2.	14.	7.	11.
66	2.	2.	6.	13.	11.	10.	8.	11.	14.
67	8.	5.	8.	2.	6.	3.	3.	8.	5.
68	3.	5.	5.	5.	4.	5.	9.	7.	5.
69	4.	5.	5.	14.	7.	6.	9.	17.	9.
70	2.	6.	16.	2.	2.	3.	8.	5.	10.
71	7.	4.	7.	3.	5.	3.	6.	12.	5.
72	2.	2.	6.	11.	8.	14.	9.	8.	10.
73	10.	13.	6.	2.	6.	4.	5.	6.	4.
74	6.	2.	9.	5.	3.	2.	7.	9.	8.
75	2.	2.	4.	11.	4.	7.	12.	12.	4.
76	9.	7.	6.	3.	3.	2.	3.	5.	7.
77	5.	4.	5.	2.	3.	3.	4.	4.	5.
78	6.	2.	6.	3.	12.	11.	8.	4.	7.
79	3.	1.	9.	2.	2.	2.	4.	5.	4.
80	6.	4.	5.	2.	3.	2.	4.	10.	6.
81	2.	1.	5.	2.	5.	10.	13.	12.	10.

SESSION 2   INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 1			SUBJECT 2			SUBJECT 3		
1	25.	22.	21.	23.	19.	27.	30.	30.	29.
2	24.	26.	24.	24.	25.	23.	30.	29.	28.
3	28.	28.	30.	25.	21.	21.	30.	30.	29.
4	12.	10.	11.	27.	24.	27.	30.	30.	28.
5	19.	26.	27.	22.	20.	23.	30.	28.	27.
6	27.	23.	30.	26.	24.	27.	30.	30.	30.
7	22.	20.	24.	18.	18.	20.	22.	24.	28.
8	20.	8.	18.	18.	23.	27.	30.	30.	29.
9	19.	27.	26.	23.	26.	28.	28.	29.	29.
10	23.	5.	20.	24.	19.	23.	6.	18.	21.
11	25.	25.	28.	18.	11.	17.	29.	15.	3.
12	28.	30.	27.	26.	22.	28.	30.	30.	30.
13	23.	20.	25.	16.	8.	16.	29.	25.	28.
14	21.	24.	26.	23.	18.	24.	30.	30.	30.
15	28.	29.	29.	24.	20.	26.	30.	30.	30.
16	19.	5.	23.	22.	22.	27.	29.	30.	28.
17	21.	17.	22.	24.	20.	26.	28.	29.	29.
18	28.	21.	23.	19.	17.	22.	29.	29.	29.
19	17.	13.	24.	12.	20.	16.	8.	2.	12.
20	28.	27.	27.	22.	18.	21.	30.	29.	30.
21	27.	28.	27.	24.	26.	24.	29.	29.	29.
22	20.	11.	19.	15.	21.	24.	30.	29.	30.
23	23.	19.	26.	16.	14.	25.	30.	29.	29.
24	24.	22.	23.	16.	20.	21.	30.	30.	28.
25	13.	15.	16.	13.	16.	18.	29.	27.	28.
26	18.	25.	24.	18.	10.	17.	30.	26.	28.
27	25.	28.	30.	20.	20.	26.	29.	29.	30.
28	25.	21.	21.	18.	16.	25.	30.	28.	20.
29	26.	19.	29.	18.	15.	17.	28.	27.	29.
30	20.	27.	27.	24.	24.	29.	30.	30.	30.
31	5.	7.	18.	15.	18.	21.	26.	29.	15.
32	27.	23.	24.	20.	21.	27.	30.	29.	30.
33	23.	26.	27.	23.	20.	28.	28.	30.	29.
34	14.	23.	16.	15.	24.	27.	29.	30.	29.
35	24.	15.	23.	19.	18.	18.	28.	29.	29.
36	19.	23.	21.	21.	18.	16.	27.	29.	29.
37	22.	25.	27.	15.	17.	22.	29.	24.	26.
38	28.	26.	27.	22.	16.	28.	30.	29.	30.
39	28.	27.	26.	20.	22.	21.	29.	29.	29.
40	16.	6.	23.	23.	25.	26.	29.	30.	25.
41	24.	20.	24.	22.	17.	26.	30.	29.	29.
42	23.	25.	19.	21.	18.	19.	29.	28.	27.
43	21.	17.	9.	16.	21.	25.	29.	25.	26.
44	18.	20.	18.	18.	18.	18.	26.	26.	29.
45	22.	24.	26.	24.	21.	26.	30.	30.	30.

SESSION 2 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 1			SUBJECT 2			SUBJECT 3		
46	21.	22.	12.	16.	14.	22.	28.	29.	29.
47	20.	21.	22.	18.	21.	15.	30.	29.	28.
48	26.	22.	23.	16.	19.	20.	29.	28.	28.
49	14.	16.	17.	14.	17.	18.	27.	28.	27.
50	22.	21.	21.	17.	18.	20.	29.	28.	25.
51	27.	26.	29.	8.	19.	24.	30.	30.	30.
52	13.	4.	7.	18.	11.	8.	25.	25.	24.
53	23.	21.	22.	18.	18.	21.	28.	30.	30.
54	23.	26.	27.	22.	18.	28.	29.	30.	30.
55	3.	1.	6.	8.	16.	17.	14.	15.	13.
56	24.	26.	23.	7.	24.	21.	30.	30.	30.
57	28.	29.	27.	24.	23.	25.	30.	30.	28.
58	13.	2.	2.	21.	15.	25.	22.	29.	17.
59	24.	22.	24.	19.	23.	25.	30.	30.	29.
60	25.	27.	26.	18.	20.	24.	30.	29.	29.
61	4.	3.	2.	12.	20.	11.	27.	24.	18.
62	18.	16.	24.	23.	19.	19.	25.	28.	29.
63	22.	19.	26.	24.	19.	29.	29.	29.	29.
64	3.	1.	4.	10.	17.	24.	27.	28.	26.
65	27.	25.	26.	18.	21.	25.	29.	29.	29.
66	27.	25.	29.	21.	21.	19.	29.	29.	29.
67	7.	1.	3.	18.	15.	7.	14.	29.	25.
68	21.	27.	23.	19.	10.	16.	27.	28.	27.
69	24.	23.	23.	19.	22.	21.	30.	30.	30.
70	4.	1.	1.	9.	7.	14.	13.	23.	19.
71	16.	18.	18.	19.	19.	24.	29.	30.	29.
72	23.	23.	27.	17.	21.	28.	29.	28.	29.
73	2.	3.	1.	9.	12.	24.	25.	20.	9.
74	26.	21.	25.	13.	15.	16.	27.	29.	25.
75	26.	27.	23.	16.	13.	27.	30.	29.	30.
76	5.	2.	3.	8.	6.	22.	16.	13.	10.
77	22.	13.	23.	22.	18.	22.	29.	26.	29.
78	26.	24.	22.	15.	19.	21.	29.	29.	29.
79	3.	1.	1.	3.	11.	12.	29.	26.	17.
80	21.	17.	24.	16.	20.	23.	29.	28.	30.
81	21.	24.	24.	20.	18.	19.	29.	28.	27.

SESSION 2 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 4			SUBJECT 5		
1	22.	21.	19.	27.	28.	29.
2	19.	17.	21.	26.	27.	28.
3	9.	19.	19.	28.	28.	29.
4	17.	16.	20.	23.	27.	27.
5	19.	18.	16.	23.	23.	24.
6	23.	24.	22.	28.	29.	28.
7	11.	7.	14.	6.	16.	28.
8	19.	17.	19.	26.	23.	28.
9	18.	21.	21.	27.	27.	26.
10	12.	19.	17.	24.	24.	25.
11	16.	13.	17.	24.	26.	26.
12	24.	24.	25.	29.	28.	28.
13	12.	13.	7.	25.	24.	25.
14	22.	21.	20.	28.	29.	29.
15	21.	22.	20.	28.	27.	28.
16	17.	12.	16.	15.	25.	19.
17	14.	14.	17.	25.	24.	27.
18	19.	15.	19.	26.	29.	27.
19	13.	12.	16.	14.	22.	26.
20	20.	19.	20.	25.	28.	29.
21	19.	20.	20.	28.	28.	29.
22	13.	19.	17.	25.	27.	28.
23	17.	18.	17.	29.	28.	29.
24	16.	16.	16.	28.	27.	27.
25	12.	18.	14.	20.	23.	27.
26	15.	13.	14.	24.	24.	25.
27	28.	18.	20.	21.	27.	29.
28	16.	15.	14.	27.	23.	21.
29	15.	14.	16.	24.	27.	27.
30	24.	25.	26.	27.	26.	26.
31	9.	13.	10.	6.	18.	24.
32	19.	17.	20.	27.	27.	27.
33	21.	22.	21.	27.	26.	28.
34	10.	17.	17.	13.	13.	25.
35	15.	16.	17.	18.	23.	24.
36	18.	16.	19.	21.	23.	25.
37	10.	11.	7.	24.	15.	26.
38	17.	19.	22.	29.	26.	29.
39	18.	22.	20.	29.	25.	29.
40	15.	17.	19.	25.	24.	23.
41	16.	16.	17.	27.	26.	27.
42	16.	16.	19.	25.	26.	27.
43	11.	12.	14.	11.	11.	26.
44	14.	15.	14.	22.	26.	25.
45	28.	22.	23.	27.	28.	27.

SESSION 2 INDIVIDUAL DATA FOR THREE REPLICATIONS

CELL	SUBJECT 4			SUBJECT 5		
46	17.	16.	15.	23.	26.	24.
47	16.	14.	18.	25.	25.	26.
48	18.	18.	16.	26.	25.	28.
49	13.	13.	14.	21.	23.	25.
50	16.	16.	17.	20.	21.	27.
51	20.	18.	17.	27.	28.	27.
52	7.	9.	9.	10.	21.	26.
53	19.	15.	16.	24.	29.	26.
54	18.	15.	15.	23.	27.	28.
55	6.	5.	7.	15.	5.	4.
56	19.	19.	19.	26.	20.	22.
57	21.	20.	22.	26.	21.	25.
58	18.	18.	11.	10.	6.	2.
59	17.	19.	14.	24.	24.	24.
60	17.	18.	18.	22.	23.	25.
61	7.	10.	5.	9.	8.	7.
62	17.	15.	14.	11.	14.	21.
63	18.	18.	19.	24.	26.	27.
64	20.	12.	19.	15.	5.	4.
65	17.	18.	16.	27.	20.	25.
66	17.	17.	18.	20.	27.	24.
67	11.	18.	13.	7.	7.	3.
68	14.	14.	14.	18.	12.	23.
69	18.	19.	20.	26.	26.	27.
70	9.	3.	4.	5.	7.	6.
71	13.	18.	16.	19.	20.	18.
72	18.	18.	20.	24.	25.	26.
73	13.	16.	17.	7.	4.	5.
74	14.	9.	19.	27.	24.	15.
75	21.	21.	16.	26.	27.	26.
76	8.	10.	4.	3.	3.	2.
77	17.	18.	19.	26.	19.	25.
78	16.	18.	18.	23.	25.	25.
79	8.	8.	10.	5.	8.	3.
80	13.	11.	14.	13.	17.	19.
81	15.	17.	15.	24.	24.	27.

APPENDIX THREE

Mean Squares

Session I

Source	df	1	2	3	4	5	6
Fare	2	2414.82	1465.38	2241.19	199.35	2148.59	1663.49
Headway	2	26.54	20.44	1.80	24.09	348.39	24.23
Reliab.	2	4.48	44.17	8.03	20.20	17.20	1.82
P. Cost	2	492.35	453.40	1424.33	397.38	940.01	428.45
TT. Diff.	2	5.92	83.60	5.09	2.33	65.34	2.83
Fare x Headway	4	3.85	6.33	6.60	8.25	38.62	16.28
Fare x Reliab.	4	7.42	58.10	2.98	3.80	26.97	3.99
Fare x P. Cost	4	123.50	17.89	43.61	7.52	21.16	13.75
Fare x TT. Diff.	4	16.64	19.81	4.61	6.44	42.72	16.93
Headway x Reliab.	4	7.91	14.58	1.68	11.26	4.54	7.68
Headway x P. Cost	4	8.01	14.71	9.29	2.43	11.06	4.40
Headway x TT.Diff.	4	22.95	2.85	3.46	9.31	12.23	6.41
Reliab. x P. Cost	4	17.67	13.34	3.04	5.60	4.73	5.96
Reliab. x TT. Diff.	4	11.35	3.98	1.86	3.46	3.07	12.22
P. Cost x TT.Diff.	4	19.26	27.81	8.55	5.80	2.18	10.42
Residual	192	14.79	15.20	6.62	11.07	11.44	7.66

Mean Squares

Session II

Source	df	1	2	3	4	5
Fare	2	740.71	198.00	87.15	131.78	1663.06
Headway	2	20.84	254.58	24.62	33.39	5.60
Reliab.	2	295.17	6.58	75.16	100.90	148.12
P. Cost	2	3729.80	354.73	643.60	828.70	2044.50
TT. Diff.	2	2.94	353.05	344.43	481.31	11.30
Fare x Headway	4	6.04	17.16	26.60	2.91	9.25
Fare x Reliab.	4	7.45	1.74	74.62	6.36	9.78
Fare x P. Cost	4	535.45	64.16	87.05	16.74	469.91
Fare x TT. Diff.	4	59.25	15.42	13.15	5.36	2.19
Headway x Reliab.	4	13.24	18.39	13.37	4.43	8.79
Headway x P. Cost	4	11.98	10.48	25.35	7.21	0.84
Headway x TT. Diff.	4	23.27	21.42	15.18	8.50	12.66
Reliab. x P. Cost	4	21.08	26.50	38.82	18.57	16.79
Reliab. x TT. Diff.	4	5.04	3.69	33.63	15.65	17.18
P. Cost x TT. Diff.	4	16.25	9.47	91.85	27.95	7.10
Residual	192	14.04	15.12	9.82	4.99	11.49

APPENDIX FOUR

S3

Model — respond 29.0, except when parking costs = 10¢

Cells 1-27			Cells 28-54		Cells 55-81	
O	$(O-P)^2$	P	O	$(O-P)^2$	O	$(O-P)^2$
29.0	0	29.0	28.0	1.00	30.0	1.00
29.7	.49	29.0	30.0	1.00	29.3	.09
28.3	.49	29.0	29.7	.49	29.7	.49
30.0	1.00	29.0	29.0	0	29.3	.09
29.7	.49	29.0	28.6	.16	28.0	1.00
28.7	.09	29.0	28.3	.49	29.0	0
15.7	176.89	29.0	29.7	.49	29.0	0
30.0	1.00	29.0	29.0	0	29.0	0
30.0	1.00	29.0	29.3	.09	27.3	2.89
30.0	1.00	29.0	28.0	1.00	30.0	1.00
28.7	.09	29.0	27.0	4.00	29.3	.09
29.0	0	29.0	30.0	1.00	28.7	.09
29.7	.49	29.0	29.0	0	27.0	4.00
29.0	0	29.0	28.3	.49	29.7	.49
29.3	.09	29.0	27.3	2.89	28.0	1.00
29.3	.09	29.0	30.0	1.00	29.0	0
28.0	1.00	29.0	29.3	.09	29.0	0
29.3	.09	29.0	29.7	.49	28.0	1.00

Σ(columns) 7.41   14.68   13.23

Σ(3 columns) 35.32

Σ/54   0.654