DYNAMIC TRAVEL BEHAVIOR ANALYSES BASED ON STOCHASTIC DECISION-MAKING STYLES

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Abstract

Over the past half-century, the progress of travel behavior research and travel demand forecasting has been spear headed and continuously propelled by the micro-economic theories, specifically utility maximization. There is no denial that the travel demand models today are sophisticated and in most cases capable of forecasting the main stream of travel behavior in urban areas. However, a quick scan of those models or travel behavior analyses reveals great discrepancies between what is expected and the actual capabilities of the models. These discrepancies go beyond the statistical errors between actual travel behavior and travel demand forecasts, based on theoretical assumptions.

The authors of this paper approach the travel behavior analysis differently. They posed and attempted to answer the following questions:

- Are we applying the appropriate assumptions to the right people for their travel behavior?
- Are the assumptions we use to reflect the actual decision-making processes for the travelers correct?

The proposed approach suggests that we stand back and look at a few levels up along the decision-making process. The conceptual framework of this approach includes:

- A “travel behavior survey” that collects data on decision-making styles,
- Stochastic processes to capture the linkage between decision making styles and traveler’s characteristics, and
- Dynamic assignments of travel choice models according to identified decision-making styles.

It is clear that great challenges lie ahead for the approach proposed here. The lack of development of less researched decision-making styles create great challenges. However, they also provide opportunities for transportation professionals to explore along multiple paths of investigation. The conceptual framework and initial attempts presented here may serve as a stimulus for further explorations. Reasonable representations for different types of decision-making styles will help transportation professionals to understand the fundamentals of travel behaviors. The better understanding of the travel behavior and demand will further help in developing more efficient transportation systems.

1. Introduction

Over the past half-century, travel behavior analysis has made quantum leaps from non-existence, in the 1950s, to the sophisticated models of 21st century. The progress from the first generation, of correlation or simple regression analyses, to the commonly accepted and widely applied logit models has been spear headed and continuously propelled by the micro-economic theories, specifically utility maximization.

The abilities of travel demand forecast models have dramatically improved aided by the sophisticated mathematical functions, massive data collection efforts, and ever-growing computation power. The ever-growing popularity of travel demand models inevitably raises great expectations from transportation professionals, politicians, and general public. However, a quick scan of the current status of those models and travel behavior analyses reveals great discrepancies between what is expected and what, actually, the models are capable of producing. These discrepancies go beyond the statistical errors seen between actual travel behavior and the forecasted travel demand based on theoretical assumptions (Mierzejewski 1996).

While the advancement along those lines, mentioned above, progresses, the authors take a slightly different approach. We would like to pose the following questions:

- Are we applying the appropriate assumptions to the right people for their travel behavior?
- Are the assumptions we used reflecting the actual decision-making processes for the travelers?

To reflect these fragmented decision-making styles, it is not necessary to abandon utility maximization function all together, but to determine to what extend each decision-making style can be observed in actual travel behaviors. The first critical link of this approach is to conduct a “travel decision-making style survey”. Based on the decision-making styles reflected in the survey, we have developed a series of choice models based on principles other than utility maximization. The underlining logic and validity of the proposed models are also tested in this approach. Simulation, another useful tool proposed, is used to verify the predictive capability of the proposed framework.

2. The Incapability of Current Framework: Problem Statement

One of the natural response from transportation modelers, to meet the expectations and improve the analyses, is to develop more sophisticated modeling forms, ranging from simple logit, probit, to nested logit, mixed logit, and to Bayesian Procedures, etc. The travel behavior model evolved from simple regressions based aggregate, revealed preference (RP) data to more sophisticated and elegant mathematical functions based on disaggregate, stated preference (SP) data (McFadden and Reid, 1974. Rice et al., 1981). As a particular example, the logit family of models progressed from binary logit model (BLM) to multinomial logit model (MNL) or conditional logit model (CLM), and to the nested logit model and the mixed logit model. As early as 1972, Watson utilized the binary logit model in the intercity travel mode choice. The multinomial logit model was primarily used to model the multiple choices. Ben-Akiva (1973) derived the nested logit model that is designed to capture correlations among alternatives. Now mixed logit is being considered the most promising discrete choice model that is intuitive, practical, and powerful. It also combines the flexibility of probit (and more) with the tractability of logit.

At the same time, a large number of transportation professionals have devoted their effort to identify and evaluate major utility factors besides time and cost to improve the predictability of the utility functions. Hensher et, al (1975) used an early example to incorporate comfort and convenience in a travel mode choice model. Algers et al. (1974) included comfort and convenience in a study on the value of travel time. Later, one of the authors of this paper (Liu, Pendayla, and Polzin, 1998) proposed a conceptual framework that includes travel time, monetary cost, comfort/convenience, and safety/security in the travel choice models. In a recent choice model, Ben-Akiva et al. (2002) have integrated latent variables to model attitudes and perceptions and their influence on choices.

As summarized by McFadden (2000), the majority of travel behavior research is based on the utility maximization theory. This theory assumes that travelers seek to maximize innate, stable preference, which means the travelers make rational decisions with complete information. In reality, is that true? The answer to this question is actually fairly straightforward and has been partially answered. Past studies and our own travel experiences showed that most of travelers don’t have complete information and some of the travelers make irrational decisions assuming that human rationality is bounded (Simon, 1990).

Fuzzy Logic (FL) and Neural Network Analysis (NNA) are among the techniques that have been used to replace or supplement utility maximization functions. Equipped with the capability of handling large scale, high dimensional data, neural network analysis has recently been tackled by travel behavior analysts (Shmueli et al, 1996 and Hensher and Ton, 2000). After comparing the neural network analysis and nested logit model in terms of the predictive potential capability, Hensher and Ton (2000) found that neural network analysis has the appeal in matching the market share of individuals but lack predictive power in matching the overall market share. It is also worth noting that richer data is almost necessity for unveiling the power of neural network analysis (Shmueli et al, 1996).

Fuzzy logic is another decision-making mechanism in the battery of travel choice approaches. Fuzzy logic theory assumes that decision makers utilize a few simple rules that associate their vague perceptions of the various attributes to their preference to the available alternatives. Combined with concepts from approximate reasoning and fuzzy control, the fuzzy decision-making method was put into use in the route choice model (Lotan and Koutsopoulos, 1993). Lately Vythoulkas and Koutsopoulos (2003) extended the framework to modeling discrete choice behavior in terms of incorporating rule weights. While the fuzzy decision-making model may be robust, the current modeling process is fairly burdensome. The difficulty of defining the approximate criteria for calibration may also prevent its wide applications in travel behavior analysis.

Overall, the development of travel behavior analyses based on principles other than those proposed in microeconomic theory have been fairly slow and have not produced better results than utility maximization functions.

3. Decision-making Styles: The Conceptual Framework

Our proposed approach suggests stand back and look at a few levels up during the decision-making process. That is, utility maximization may not be the uniformly adopted decision-making style by all the travelers. Even though, it is fairly safe to state that a certain portion of travelers do make their decisions based on the maximum amount of information available to them and make rational choices most of the time. On the other hand, a certain portion of travelers may make decisions based on selective information or may only evaluate parameters that are important to them at the particular times, or they may simply follow the act of those who are respected or deemed wise. Therefore, it is possible that certain portion of travelers will follow the utility maximization principle in making decision choices while others do not.

The behavioral theory here is that different mode choice results has more to do with the way that travelers habitually approach decision-making problems and use information that merely maximize their “happiness”. A key segment of this approach proposes “a travel behavior survey” that collects data on decision-making styles. Sproles (1986) stated, “A consumer decision-making style is defined as a mental orientation characterizing a consumer’s approach to making choices.” There are different decision-making style classifications in different fields. For instance, in intercultural relations, the commonly used classification of decision-making styles are; avoidance, complacency, hyper vigilance, and vigilance (Brew, Hesketh, and Taylor; 2001). In psychology, the decision-making styles can be classified as rational, a-rational, and irrational (Clark, et al., 2002). Based on either deductive logic or inductive logic, the rational decision makers chose among the options. A-rational decision makers chose and act based on what has been rewarded (reinforced) or punished (negative) in the past. By irrational decisions we mean decision-making is linked to strong emotions and can be labeled to verge on the arbitrary.

These classifications are simply a means of drawing distinctions, which may loosely follow the styles commonly recognized in decision-making processes. However, we clearly do not mean to suggest that all people can be, once and for all, assigned to one of these mutually exclusive boxes. The above categories can be easily substituted or supplemented by different decision-making styles. The key aspects of this approach is to develop a dynamic model, which assigns each traveling entity, in certain region, to one of the decision-making styles and each decision-making style will be defined by different travel choice functions.

As described in Figure 1, travelers (i) defined by their social economic characteristics (X) may be stratified into a number of decision-making style categories (k) via a decision-making style model. The decision-making style model is defined by

$$D = f(X;\alpha) + \eta \qquad [1]$$

Where:

D: Decision-making style for individuals

X: Social economic characteristics of travelers

α: Parameters to be estimated

η: Random distribution term

Each decision-making style category may be governed by a separate set of decision-making rules. In this framework, we have proposed three ruling sets (k=3), which correspond to the decision-making styles we have defined in the survey. When faced with a number of travel choices (j), such as modes, routes, or service alternatives, defined by system attributes (S), the travelers apply their particular decision rules to their final selection (Y). Being consistent with the decision-making style categories presented in the survey, the decision-making functions are reflected in the following three models:

- Composite Evaluation Choice Model (CECM),
- Single Factor Choice Model (SFCM), and
- Herd Mentality Choice Model (HMCM),

Among the three models presented above, the composite evaluation choice model (CECM) is fairly consistent with the random utility maximization theory, where the utility function can be defined by

$$U = V(X, S; \beta) + \varepsilon \qquad [2]$$

Where:

V: The systematic utility,

S: System characteristics

β: Parameters to be estimated

ε: Random distribution term

As a result, the probability of choices can be defined by the following function:

$$P_{(Y_c)} = \frac{e^{V_p}}{\sum e^{Vp}} \qquad [3]$$

Where:

$P_{(Y_c)}$: The choice probabilities from CECM

Apparent to all travel behavior analysts, the rest of choice making is no different from the conventional utility maximization model once the traveler is assigned to the doctrine of Composite Evaluation Choice Model.

On the other hand, the Single Factor Choice Model (SFCM) represents a series of lexicographic choices made by the potential travelers (Widlert, 1998). Contrasting to the usual lexicographic answer of most SP surveys, the interviewees or potential travelers of such system consciously made their travel choices based a single factor, which may be travel time, monetary cost, safety/security, reliability, or comfort/convenience. To define the particular relationship between the selected factor and eventual choices made, we have developed the following function

$$P_{(Y_s)} = f(S\ ;\gamma\ ) + \delta \qquad [4]$$

Where:

$P_{(Y_s)}$: The choice probabilities from SFCM

γ: Parameters to be estimated

δ: Random distribution term

Last, but not least, the Herd Mentality Choice Model (HMCM) is a complete departure from the concurrent decision-making approaches. A further probe into the herd mentality choice style actually demands a time-dimension into the choice function. That is the current (t) decision-making style is actually based on a certain observation or social learning process (Rotter, 1982) from the past (t-1). To predict the future (t+1) travel choices for those individuals who are governed by HMCM, we have formulated the following function:

$$P_{(Y_h,t+1)} = f(P_{(Y_s,t)}, P_{(Y_c,t)}, P_{(Y_h,t)};\theta) + \upsilon \qquad [5]$$

Where:

θ: Parameters to be estimated

ν: Random distribution term

The equations (3), (4), and (5) can be generalized as

$$P_{(Y)} = P(Y \mid D\ , X, S; \beta, \gamma, \theta) \qquad [6]$$

Therefore, the individual's choice probability for alternatives can be generalized as:

$$P(Y \mid X, S; \alpha, \beta, \gamma, \theta) = \int_D P(Y \mid D, X, S; \beta, \gamma, \theta) f(D \mid S; \alpha) dD \qquad [7]$$

One of the most important motivations for developing the models and functions of each decision-making style is to test a few essential hypotheses, which may provide answers to the questions we have posed in the beginning of this paper. The hypotheses will be elaborated and tested in the following sections. However, they can be simply presented as the following,

1. Various decision-making styles derive statistically different travel alternatives.
2. Utility maximization models based homogenous cluster sample of composite evaluation decision-making style have better fit than that based on a total sample that is "tinted" by other styles.
3. Forecast models based on distinguished choice logics accorded to each decision-making style produce more accurate projection results.

To test the hypotheses stated above, we have generated discrete choice models based on data collected in the "travel decision-making style survey", which will be described in detail in Section 4. A simulation model is necessary to test the third hypotheses, which may also serve as an application to the calibrated discrete choice model, in replicating the three proposed decision-making styles. However, limited by the length of the paper, the simulation model is not included here.

4. Travel Decision-making Style Survey: The Data Collection

The authors designed a survey in response to the proposed framework, composed of four sections, a total of 19 questions, as included in Appendix 1. The first bundle of questions is the socio-economic status of the respondents, such as gender, age, occupation, and income. The second group of questions is about the current or revealed intercity travel practices, such as origin and destination of a particular trip; time, cost, safety, reliability, and comfort attributes of such trip.

The third category of questions is related decision-making style, which is divided into three categories: herd mentality, single factor dominated decision, and composite evaluations. The definition of "herd mentality" is that the traveler will make his or her travel choices by simply following the act of those who are observed, respected, or deemed wise. The single factor categories are further divided into: travel time, monetary cost, reliability, convenience, safety, and others. The composite evaluation process is consistent with the utility maximization approach.

The last section covers the questions of stated choice among travel alternatives defined by various travel time, monetary cost, safety, and reliability attributes. The combined Revealed Preference (RP) and Stated Preference (SP) data not only provides the necessary observation for each mode or service choice model calibrations but also are used to validate the consistency of stated decision-making styles and actual choices they have made.

The purpose of the survey is to collect data to test the theoretical framework proposed above, i.e. to investigate possible relationship between traveler's decision-making style and their preference for different modes or services. The survey candidates were recruited at train stations, work places, and various campus locations around Newark, New Jersey, USA. The survey was conducted via a combination of personal interviews, post mailings, and Internet. Limited by the time and financial resources of this research, the focus of this survey was not on system sampling or clustering techniques. For that reason, the experimental nature of the data cannot preclude its use even though a high quality data is fundamental for the construction of a good model. The experimental nature here means that the sample size and the complete randomness of sampling are not ensured (Ortuzar, 1998).

We have collected a total of 333 questionnaires. After eliminating outliners and invalid cases, the survey yielded 309 valid respondents. Among which 39% were female. The age of those individuals were clustered around two largest groups, 20-30 year old (46%) and 31-45 year old (33%). Almost all of them have valid driver's licenses. The two largest occupational categories of this sample are professional (49%) and student (26%). The household income levels of this group are similar to the overall distribution of income in this region. The largest groups are concentrated in the middle range: 26% from \$25K to \$50K, 27% from \$50K to \$75K, and 27% from \$75K to \$150K.

Not surprisingly, the composite evaluation process is not the predominant mode of decision-making style, which is consistent with the general hypothesis of this research. However, the magnitude of non-composite evaluation decision-making styles is still shocking. Only 41% of the overall sample claimed that they used composite evaluation approach in choosing their travel choices. About 56% of the total surveyed used single factor choice approaches, be it time, cost, safety, convenience, safety reliability or other factors. The other main decision-making style specified in the survey is herd mentality, which is about 3% of those surveyed. Among the 309 valid responses, only one person has chosen “other” than those mentioned above, which is not significant enough to be considered as a separate decision making style. Therefore, the total decision-making style in this survey are confined to the following three categories:

- Herd Mentality
- Single Factor
- Composite evaluation

When comparing the social economic factors, such as gender, age, household income, and occupation between the total sample and the composite evaluation cluster, we have observed very similar distributions, as depicted in Figure 2. The identical distribution of social economic variables between both groups confirms the common pool of sampling sources. That is the difference in decision-making style is not caused by different survey samples but a genuine heterogeneous style among the homogenous population. Meanwhile, significant decision-making styles were observed between various social economic stratifications. As demonstrated in Figure 3, the composite evaluation approach is more prevalent among male and middle income groups while the herd mentality decision-making style has a relatively larger presence among females, home makers and unemployed, and the low and high ends of income groups. Among the single factor decision making style group, the most predominate factors are cost (46%) and time (38%). Comfort and convenience factor played a vital role among 11% of this group. Reliability, safety, and others are among the lower spectrum between one and two percent, as demonstrated in Figure 4.

5. Model Calibration: Hypotheses Testing

To accomplish the objectives of this research, we have set up a series of hypotheses, which will be tested via the survey data we have collected using certain statistic analysis procedures. Travelers of different decision-making styles may attached different weighs to each attributes or completely ignore certain attributes in some cases. In this survey, four attributes, travel time, monetary cost, safety, and reliability, were included in the stated preference section. The composite evaluation decision style balance all four attributes and make travel choices by maximizing utility, defined by the combination of those attributes. The single factor dominated decision-making style take into account only one of the factors among travel time, monetary cost, safety, convenience or reliability. The herd mentality decision style simply follow the act of those who are observed, respected, or deemed wise, regardless any of those factors.

Hypothesis I.

Null-hypothesis (H_0):

Travel alternatives selected via different decision-making styles are identical.

Alternative Hypothesis (H_1):

Travel alternatives selected via different decision-making styles are different and the difference is statistically significant.

The basic approach, to test this hypothesis, is to use the Two Sample Mean Difference Test (TSMDT). To examine if the means of two samples, $\bar{x}_1$ and $\bar{x}_2$, are different, the following equation is used:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2(1/n_1 + 1/n_2)}} \qquad [8]$$

Where:

$\bar{x}_1, \bar{x}_2$: Sample means

n_1, n_2: Sample sizes

s^2: The pooled sample standard deviation *s* is given by
$s^2 = [((n_1-1)s_1^2 + (n_2-1)s_2^2)/(n_1+n_2-2)]$

Applying the TSMDT, we focused on cluster among the travelers participating in the survey. One cluster, called Time Dominated (TD), considers travel time as the only criteria in determining their travel choices. Another cluster, named Cost Dominated (CD), takes only the travel cost into account in selecting travel alternatives. The last cluster is composed of the entire group of travelers who claim themselves conducting Composite Evaluations (CE) in their travel decision-making process. As depicted in Appendix 1, question No. 19, the SP survey, has 12 different pair-wise alternatives, which incorporated travel time, monetary cost, safety and reliability. Those factors are the major attributes utilized individually by those in the single factor decision-making style and simultaneously by the composite evaluation decisions making style. Among which, 9 pairs represent different travel time between the alternatives and base scenario and 10 pairs different costs.

Ideally, the TD group should consistently chose the alternatives that have less travel time while composite evaluation group would balance all four attributes. Analyzing the mean selections that are consistent with their corresponding decision-making style via TSMDT, we are able to test the difference between TD and CE groups and prove whether such differences are statistically significant. A similar approach is also applied to the comparison of CD and CE groups.

As demonstrated in Table 1, the decision-making style consistent choices made by the TD and CE groups are 7.6 and 6.6, respectively, for time dominated pair-wise alternatives. The TSMDT procedure via SAS program generated t-statistics of 3.207 for

TD vs. CE clusters. Such t-statistic may be converted to a P-value of 0.0016, which indicate that the null hypothesis may be rejected at the 95% confidence interval. Similarly, we have performed another TSMDT on CD vs. CE clusters. With a p-value of 0.0218, we confirmed that the difference among travel choices derived from different decision-making styles are significant at 95% confidence interval. Therefore, we should reject the Null Hypothesis I and accept its Alternative Hypothesis: travel alternatives selected via different decision-making styles are different and the difference is statistically significant.

The implications of such rejection of the null hypothesis is important that we are able to segregate the single factor dominated decision-making style from the composite evaluation process, i.e., when compared with the composite evaluation decision style, single factor dominated decision style is often treated as one of the special cases of the latter. The reason is that when travel choices are made based on a single factor, travel behavior analysis often assume that the coefficients or weighing of other factors as zero. Little attention has been paid to the impact of such quantitative change of coefficient on the choice result. A critical examination of such quantitative change in coefficient implies some fundamental changes in travel choice processes. That is such indication actually precludes the application of utility maximization theory to be applied to single factor choice clusters. In other words, the utility maximization assumes that the coefficient of each factor is not equal to zero. The rejection of the null hypothesis I warrants our further test of hypothesis II.

Hypothesis II.

Null-hypothesis (H_0):

Models derived without stratified decision-making styles are equally fitted as those derived from identified decision-making style samples, such as composite evaluation decision-making style.

Alternative Hypothesis (H_1):

Models derived from Composite Evaluation cluster samples are better fitted than those of total sample clusters.

To test this hypothesis, we have calibrated two discrete choice logit models using SP data collected in our "Decision-making Style Survey". The first model utilized all the records from the entire sample, that is all the decision-making styles, including herd mentality choice style, single factor choice style, as well as composite evaluation style, are all treated as if they are based on utility maximization principle. The second model used only those records that are classified as in the composite evaluation style, which is more or less consistent with the utility maximization theory.

We have incorporated travel time, monetary cost, safety, and reliability in both models as the system indicators and income as one of the social economic indicators of travelers. As depicted in Table 2, the coefficients generated from both models (composite evaluation cluster and total sample) for system attributes all have the correct signs. That is, time and cost are often treated as disutility and associated with negative signs while safety and reliability as utility and associated with positive signs. Measured by the p-value, all of the variables included in those two models are significant at 95% confidence level. Among those, time, cost, and safety are significant even at much higher confidence levels, namely 99.99% since all their p-values are smaller than 0.0001.

After confirming the validity of both models, we would like to compare their goodness-of-fit. In the context of a logit model, typically the overall goodness-of-fit is measured by the adjusted likelihood ratio index (LRI), ρ**,** or McFadden's LRI. However, the situation here is different: one type of model is applied to two samples, in which one sample is part of another sample. Consequently the two models may not be compared using McFadden's LRI or log likelihood. Rather, another goodness-of-fit statistic, Percent Correctly Predicted (PCP), may be utilized.

As pointed out by experienced econometrists (Train, 2002), the PCP is calculated as the percentage of sampled decision-makers for which the highest predicted probability alternative is the same as the actually chosen alternative. Usually it is valid to say that the model with the higher percent correctly predicted explains the data better. The assumption incorporated here is that the decision maker is predicted to choose the alternative for which the model gives the highest probability. PCP is the most appropriate criteria that can be applied in this situation.

Comparing the PCP values, included in the last line of Table 1, we conclude that the model derived, based on the composite evaluation cluster sample, is better than that of the total sample. The implication of this conclusion naturally leads to our rejection of null hypothesis II and accept the alternative hypothesis, that is models derived from Composite Evaluation cluster samples are better fitted than those of total sample clusters. As all modelers agree that better fitted models will produce better or more accurate forecasts. To carry this hypothesis testing result further, we suggest that different model structures based on particular decision-making styles should be applied accordingly to produce better projection results.

7. Summary and Further Research

The study manuscript presents a simple but refreshing conceptual framework in examining and improving the validities of travel behavior models. We also tested the hypothesis by conducting a travel behavior survey and calibrating forecast models based on data collected. However, the initial result of the analysis is encouraging. However, it is, by all means, not perfect or conclusive. As for summary, we would rather call it an "opening remark."

To continue the exploration along the decision-making style path, we see a number of potential research areas:

1. More decision-making style surveys will provide the fundamental sources to reveal the linkage between decision-making styles, social economic status, system parameters, and travel behavior.

2. More advanced modeling functions or causal relationships should be developed based on surveys, advanced mathematical formulations, and theoretical advances of travel behavior analysis. It is critical to broaden the travel behavior paradigm so more causal relationship or broader and in-depth explanations may be discovered via diversified travel behaviors observed.

3. Simulation is a useful tool brought by the major advances in computer power and database capacities. When no elegant mathematic functions or statistical relationships are readily available, transportation modelers tend to seek help from simulation models (Train, 2002). A Monte Carlo simulation model is under construction within the scope of this research. Different decision-making styles were generated based on a stochastic process, which is regulated by the hypothesized decision-making styles from the survey. Once an individual traveler is assigned to a certain decision-making style category, the corresponding choice logic will be applied to his or her travel behaviors within the transportation network.

It is clear that great challenges lie ahead for the approach proposed here. The lack of development for a-rational and irrational decision-making styles create great challenges but also opportunities for transportation professionals to explore along multiple paths. The conceptual framework and our initial attempts, presented here, may serve as a stimulus for further exploration. We firmly believe that reasonable representations for different types of decision-making styles will help transportation professionals to understand the fundamentals of travel behaviors. The better understanding of the travel behavior and demand will further help us in developing more efficient transportation systems.

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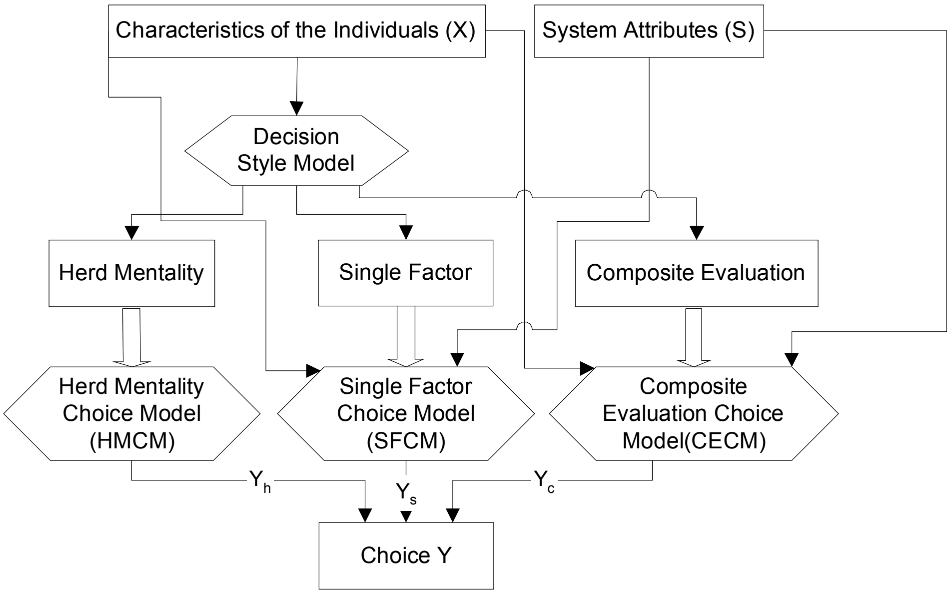

Figure 1. Travel Choice Processes Based on Decision-making Styles

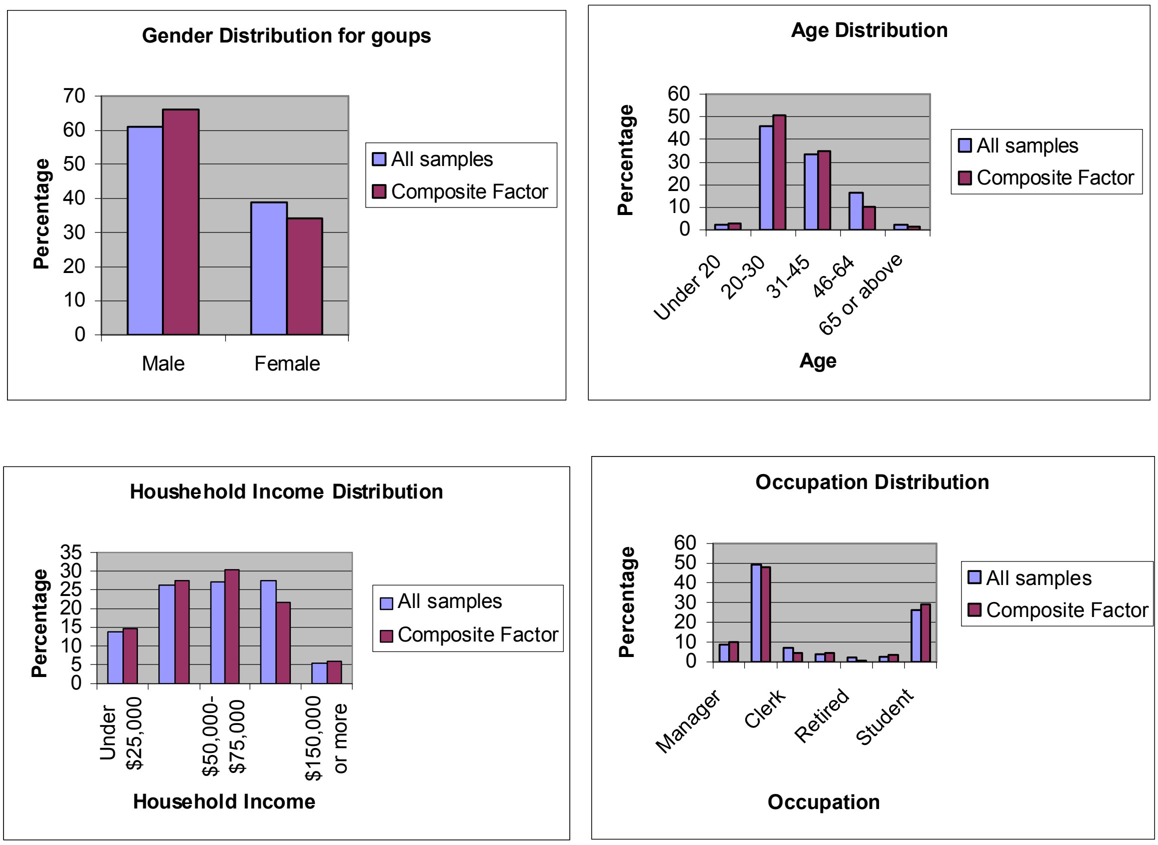

Figure 2. Identical Distributions of “CE” Cluster and “All” Sample

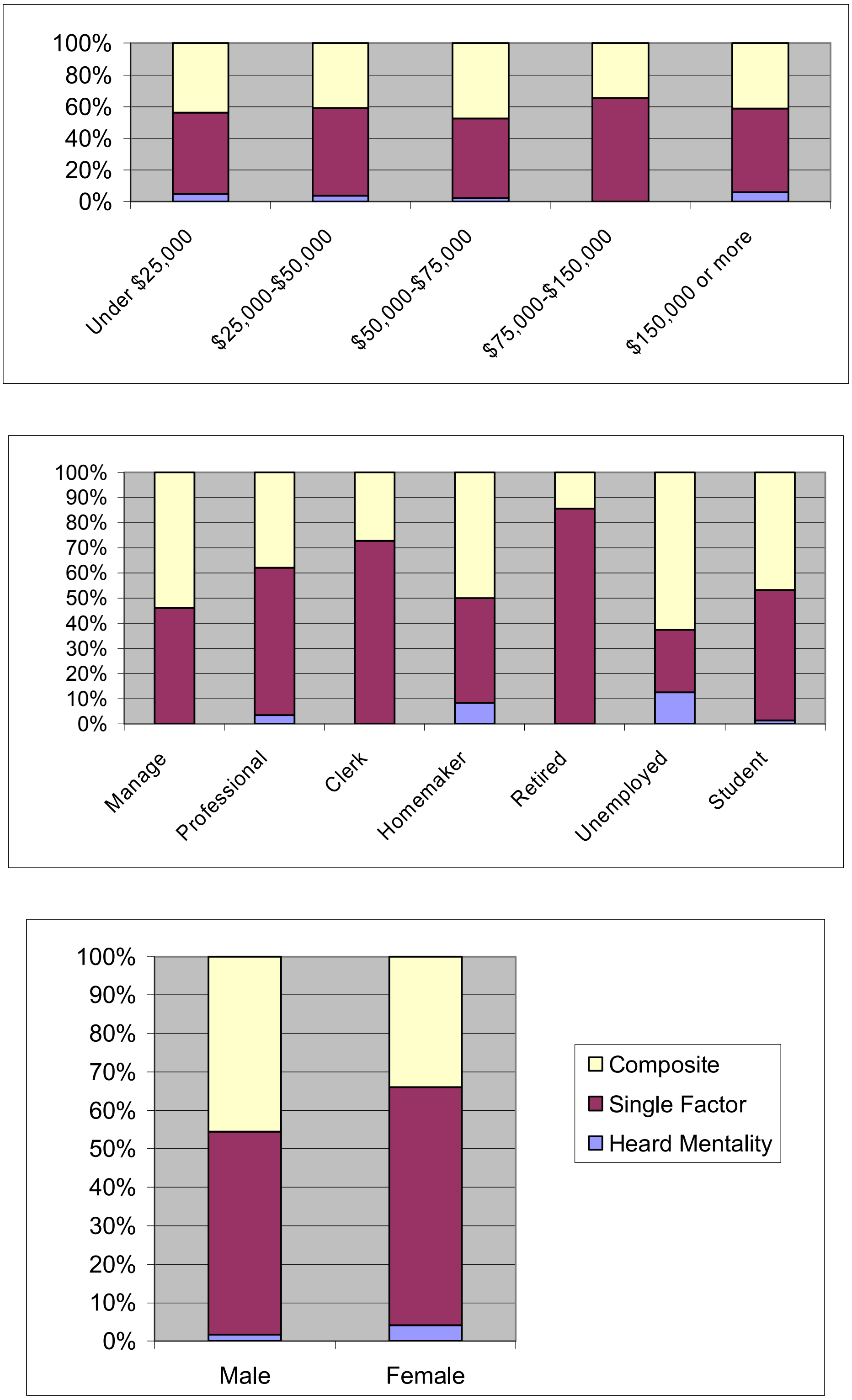

Figure 3. Decision-making Style Distribution Among SE Variables

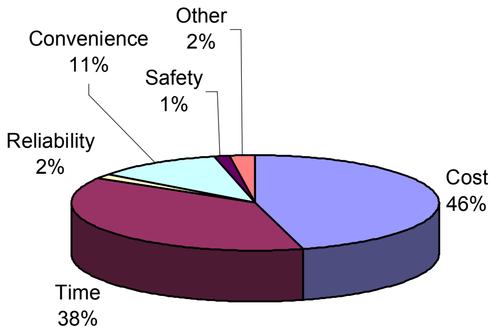

Figure 4. Attribute Distribution Among Single Factor Decision-making Style

Table 1. Two Sample Portion Test (TSMDT) Results

Parameter/Tests	TD vs. CE	CD vs. CE
Selection of Single Factor Cluster	7.6	4.7
(Standard Error)	(0.28)	(0.27)
Selection of Composite Evaluation Cluster	6.6	4.0
(Standard Error)	(0.19)	(0.18)
T-statistics	3.207	2.311
P-value	0.0016	0.0218

Table 2. Comparison of Model's Goodness-of-Fit

	Composite			All		
Parameter	Estimate	Error	P-value	Estimate	Error	P-value
Low income (<$25K)	-0.4528	0.1502	0.0026	-0.5914	0.0984	<0.0001
Low middle income ($25-50K)	-0.3948	0.1132	0.0005	-0.3733	0.0730	<0.0001
Middle income ($50-75K)	-0.2185	0.1102	0.0475	-0.2726	0.0760	0.0003
High income (>$75K)	-0.3468	0.1316	0.0084	-0.2813	0.0793	0.0004
Time	-0.0216	0.0025	<0.0001	-0.0192	0.0016	<0.0001
Cost	-0.0334	0.0043	<0.0001	-0.0285	0.0027	<0.0001
Safety	0.6291	0.0979	<0.0001	0.5316	0.0620	<0.0001
Reliability	6.8911	2.996	0.0214	3.9079	1.9166	0.0415
Time value ($/Hour)	38			40		
PCP	68%			66%		