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Investigating Behavioral Differences in Heterogeneous Decision Rule Segments: An Empirical Analysis

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Abstract

Conventional and contemporary models of travel choice make the restrictive assumption of homogeneity in decision rules. Recent literature has shown empirical evidence for potential heterogeneity in decision rules with regard to utility maximization and regret minimization. Notwithstanding these advances in modeling decision rules, behavioral understanding in the differences in these alternative decision rule segments has not been sufficiently understood. Moreover, the factors which influence the choice of these decision rules have not received significant attention. This study proposes a framework which considers decision makers to have both utility maximizing and regret minimizing tendencies. The variation in these tendencies across decision makers renders the framework heterogeneous. A heterogeneous decision rule model is developed assuming the decision rule adopted to be a latent construct. The study characterizes the regret minimizing and utility maximizing segments based on average values of the segmental attributes. The empirical findings show evidence to confirm that utility maximizers tend to be predominantly captive to personal vehicle usage while regret minimizers might be non-captive to any particular mode. The nature and extent of influence of factors affecting the choice of decision rule is also examined.

Choice of travel mode is one of the most important decisions for urban commuters. When choosing their travel mode, most decision makers face a set of alternatives. Comparing these alternatives, the decision maker makes his or her choice of travel mode. This choice is made by considering a variety of factors including the attributes of the alternatives, trip characteristics, personal and household characteristics, etc. Every rational decision maker is assumed to adopt certain heuristics to process the information regarding these influential factors in order to arrive at his or her choice. This set of heuristics is called decision rule(s).

Decision rules can be broadly categorized as: fully compensatory, non-compensatory, and semi-compensatory in nature (*1*). A fully compensatory decision rule is one where the poor performance of an alternative on one attribute can be completely compensated by good performance on an equally important attribute (*2*). In a non-compensatory rule, poor performance on one attribute cannot be overcome by an improvement in another, regardless of the magnitude of improvement. In semi-compensatory decision rules, this type of compensation is partially possible.

The classic example of a fully compensatory decision rule is that of random utility maximization (RUM). Owing to the ease of its operationalization and its simplicity in representing choice behavior, the utility maximization framework has been in use for quite a long time. Especially with regard to travel-related decisions, utility maximization is the most popular decision rule assumption. However, the utility maximization framework fails to acknowledge the risk-averse nature of travel-related decision making. Recognition of this drawback has led analysts to focus on alternative decision rule frameworks. Random regret minimization (RRM) is one such decision rule, which has received greater attention in the recent past (*2–6*).

The regret theory is based on a decision maker's experiences with an alternative due to poor performance on an attribute. This regret, although it could be compensated to a certain extent by good performance of an

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equally important attribute, cannot be nullified completely. This forces the individual to settle for a trade-off between these attributes in making the choice. Decision makers who adopt semi-compensatory decision rules might potentially regret choosing a particular alternative if they eventually come to know that the performance of another alternative was better on an attribute to which they are very sensitive. Therefore, a regret minimizing decision maker attempts to minimize the potential for regret in his or her chosen alternative.

The propensity to minimize potential regret is founded on the natural human tendency of risk aversion. Risk aversion is the reluctance of a person to accept an alternative with an unreliable performance on one or more attributes as compared with another alternative which is more reliable but perhaps has a slightly poorer performance on those attributes. Decision makers tend to become risk averse when faced with situations of high uncertainty (*3*). Regret minimizing frameworks thus, in some sense, account for the risk-averse nature of a decision maker (*3*, *7*). On the contrary, fully compensatory decision rules are conventionally operationalized in a manner that does not account for the risk-averse nature of decision makers. In fact, they present decision makers as risk neutral; for example, the linearly additive linear-in-parameters utility structure in a RUM framework does not account for the decision maker's risk aversion to certain factors. Further, decision makers may associate similar characteristics with respect to different alternatives (e.g., crowding in bus and train) making them correlated. However, a multinomial logit model in a RUM framework assumes independence among irrelevant alternatives (IIA). McFadden (1976) and Ben-Akiva (1977) independently developed a choice set generation model, called the "Dogit" model, which considers decision makers to be either captive to a particular alternative or completely free to choose from a set of alternatives (*8*, *9*). This relaxes the restriction of IIA. Some of the other models which relax the restriction of IIA include the generalized extreme value (GEV) family of models. The most popular among the GEV family is the nested logit model (*10*) which involves nesting of similar alternatives within a nest. The probability of an alternative within a nest is affected by alternatives in other nests and hence IIA does not hold well in these models.

Conventional models assume that all the decision makers adopt the same decision rule, which may not be true. For example, a risk-neutral decision maker is more likely to adopt utility maximization than a risk-averse decision maker. Similarly, a risk-averse decision maker might be more of a regret minimizer than a utility maximizer. The current study is motivated by this potential heterogeneity with regard to decision rules. It is important to relax the decision rule homogeneity assumption since it could constrain the sensitivities to various factors influencing choice. Such restrictive assumptions might lead to incorrect understanding of behaviors. Decision rule heterogeneity might help to capture differential sensitivity to these factors. Understanding of the factors which influence the adoption of these decision rules is also limited (*11*) and hence merits further investigation. Such an exercise might help analysts to identify segments which are potential regret minimizers or utility maximizers. In light of the above discussion, the following objectives have been identified for the study:

- To propose a framework which allows decision makers to be heterogeneous with respect to the decision rule adopted.
- Benchmark the proposed decision rule framework against homogeneous decision rule frameworks like RUM and RRM.
- Capture and analyze the differential sensitivities in the utility maximizing and regret minimizing tendencies of a decision maker.
- Identify the factors influencing the latent decision rule adopted by the decision maker.

The scope of the study is limited to choice travel mode for commuting to work based on household interview survey data collected in Chennai city. The data was found to be representative of the worker population in Chennai. This study contributes to research on mode choice by comparing alternate behavioral frameworks representing distinct decision rules adopted by individuals. It establishes that decision makers tend to adopt different decision rules. Further, it attempts to segment decision makers based on the decision rules adopted and to compare their behavior with regard to travel mode choice. In addition, the study also captures the factors influencing the latent decision rule adopted by decision makers.

Literature Review

Heterogeneity in choice behavior refers to differences in various segments in the population with respect to the elements of decision making: decision maker; alternatives; attributes related to the decision maker and alternatives; and decision rule. In travel behavior analysis, considerable research has been carried out in capturing heterogeneity with regard to: (a) consideration/availability of alternatives in the choice set (*12*, *13*); (b) perceptions of service levels offered by these alternatives and sensitivity to the various attributes of the alternatives which influence their choice (*14*, *15*); and (c) both systematic and unobserved components of attributes related to the decision maker (*16*). However, heterogeneity with regard to the decision rules adopted by decision makers, especially in the context of travel choice, is very sparsely investigated and hence merits investigation. The following discussion highlights the research contributions with regard to decision rules, especially utility maximization and regret minimization, as well as critically evaluating them.

One of the important properties of the utility maximization decision rule is its fully compensatory nature. It is founded on very strong theoretical backgrounds of consumer behavior and random utility theory. Its extensive usage in representing decision making concepts has made it very popular among behavioral analysts. However, one of its key limitations is its inability to represent the risk-averse behavior of decision makers. In this regard, one of the decision rules which has recently gained attention in the literature is regret minimization. It seems to be a promising alternative to utility maximization in terms of its logical intuitiveness, statistical testability, mathematical tractability, and implementability. In addition, regret minimization, through binary comparisons of alternatives, in a subtle sense attempts to capture the risk-averse nature of the decision makers.

Regret theory was originally proposed and independently developed by Loomes and Sugden (*7*) and Bell (*17*) as an alternative theory of rational choice under uncertainty. The theory is based on the fact that an individual has the ability to anticipate feelings of regret and of satisfaction and the model proposed takes these factors into consideration. Founded on regret theory, Chorus et al. (*3*) proposed the random regret minimization approach and emphasized the key differences between RUM and RRM. Chorus (*2*) also presented various theoretical properties of the RRM framework and compared them with the properties of RUM. Following this, a series of regret minimization models were developed to model various dimensions of travel, like mode choice, recreation site choice, revealed shopping choice, stated route choice, etc. (*3*, *6*, *18*, *19*). Some of these experiments also attempted to quantify and compare the willingness-to-pay measures in the RRM and RUM framework using empirical data (*18*, *19*). While some of the empirical results provide evidence for the superior performance of RRM models in relation to RUM models, there is also evidence to argue otherwise. Chorus et al. (*18*) proposed an attribute-dependent decision rule framework in which each influential attribute was categorized as regret based or utility based (*18*). Note that the hybrid framework still considers the decision rule to be homogeneous across decision makers.

Most of the literature on RRM attempts to understand the behavioral implications of theoretical properties of the RRM framework, explores the possibilities of application of RRM framework to various travel choice dimensions, or attempts to benchmark the empirical performance of RRM against the conventional RUM framework. However, very few attempts have been made to model heterogeneity in decision rules in the context of travel-related decisions, especially choice of travel mode. Srinivasan et al. (*11*) and Hess et al. (*20*) are the studies (to the best of the authors' knowledge) which have attempted to capture the potential heterogeneity in decision rules, namely RUM and RRM (or random disutility minimization [RDM]) frameworks. Although these studies establish the improvement in statistical consistency and predictive ability of the heterogeneous decision rule model, they fail to compare the behavioral differences in the two decision rule segments.

The factors influencing the choice of decision rule are not well understood and hence not much can be derived about them from the literature. While Hess et al. (*20*) used a constants-only binary logit model to explain the choice of decision rule, Srinivasan et al. (*11*) explain it using socio-economic factors. So, other than socio-economic characteristics, not much is known from previous studies in particular with regard to risk tolerance levels or expectations of service attributes which influence the choice of decision rule.

Methodology

Formulation and Estimation Details

Random Utility Maximization. The utility of alternative j as perceived by decision maker i is given by

$$U_j = V_j + \varepsilon_j \, , \, j = 1, 2, 3, \ldots K \tag{1}$$

if the systematic component is V_j and the unobserved component is ε_j. The decision maker chooses the alternative with the greatest utility. The error terms are assumed to be identically and independently Gumbel distributed with mean 0. The resulting probability expression is a multinomial logit model (MNL) as in Equation 2.

$$P_j^{util} = \frac{\exp\left(V_j\right)}{\sum_{k=1}^{K} \exp\left(V_k\right)} \, , \, j = 1, 2, \ldots K \tag{2}$$

Random Regret Minimization. The RRM has a non-linear regret expression with a binary comparison of attributes as in Equation 3. The error term in RRM is also assumed to be Gumbel distributed and hence the MNL probability expression is used. The deterministic component of the potential regret that an individual experiences in choosing alternative j with respect to an attribute m is given by

$$R_{jm} = \sum_{k=1}^{K} \ln\left[1 + \exp\left(\beta_{km}X_{km} - \beta_{jm}X_{jm}\right)\right] \quad (3)$$

and so the regret experienced on j with respect to all attributes is given by

$$R_j = \sum_{\substack{k=1 \\ k \neq j}}^{K} \sum_{m=1}^{M} \ln\left[1 + \exp\left(\beta_{km}X_{km} - \beta_{jm}X_{jm}\right)\right] \quad (4)$$

where:

R_j is the deterministic component of regret experienced on choosing jth alternative,

M is the set of attributes influencing the alternatives, and

K is the total number of alternatives.

Regret minimization is operationalized using a systematic "regret" component involving binary comparison of attributes. Hence, regret minimization involves performing binary operations on attributes. However, the subjective factors were measured on a Likert scale of 1 to 5. Since the objective function for regret minimization involves binary operations, ordinal values cannot be used in these models. Hence, these ordinal ratings need to be converted into a continuous measure on which binary operations are possible. This was done using ordered probit models. The model represents the ordinal indicator of subjective factor as a continuous latent measure making it consistent with a hybrid choice modeling approach. However, for simplicity of estimation and with the focus on the decision rule process, the ordinal factor was estimated independently, making it a sequential likelihood estimation process. These continuous latent measures of perception rating could be used in the regret minimization framework in Equation 4. In an ordered choice model,

$$y_j^* = \theta_j S_j + \omega_j , \quad (5)$$

the latent "preference" variable y_j^* is not observed. The observed component of y_j^* is S_j. The ordered probit model is based on normally distributed error term ω_j assumptions.

$$\begin{aligned} S_j &= 0 \; if \; y_j^* \leq \phi_0 , \\ &= 1 \; if \; \phi_0 \leq y_j^* \leq \phi_1 , \\ &= 2 \; if \; \phi_1 \leq y_j^* \leq \phi_2 , \\ &= 3 \; if \; \phi_2 \leq y_j^* \leq \phi_3 , \\ &\dots \\ &= L \; if \; y_j^* \geq \phi_{L-1} \end{aligned} \quad (6)$$

The probability that S_j takes a value l is given by

$$P(S_j = l) = P(y_j^* \; is \; in \; the \; l^{th} \; range) \quad (7)$$

The final probability structure of an RRM–MNL is as follows:

$$P_j^{reg} = \frac{\exp(-R_j)}{\sum_{k=1}^{K} \exp(-R_k)} , \; j = 1, 2, \dots K \quad (8)$$

Heterogeneous Decision Rule (HDR). As already discussed, it is intuitive to consider that decision makers are heterogeneous with regard to the decision rules they adopt. The current study assumes decision makers choose between regret minimization and utility maximization. However, the decision rule adopted by any decision maker is unknown and hence considered to be latent in the proposed framework. The probability that an individual adopts one of these decision rules is assumed to have a binary logit model structure. Further, the conditional probability that the alternative j is chosen, given the decision maker follows a particular decision rule, is assumed to have an MNL structure. Consequently, the overall probability that an individual i chooses an alternative j is given by

$$P_j = p(util) \; P_j^{util} + p(reg) \; P_j^{reg} \quad (9)$$

where: $p(util)$ is the marginal probability that individual i is a utility maximizer,

P_j^{util} is the conditional probability that alternative j is chosen given that individual i is a utility maximizer,

$p(reg)$ is the marginal probability that individual i is a regret minimizer,

P_j^{reg} is the conditional probability that alternative j is chosen given that individual i is a regret minimizer.

Since the framework assumes the decision rule to be latent, decision makers are probabilistically assigned between utility maximization and regret minimization. These probabilities are $p(util)$ and $p(reg)$ respectively. This latent decision rule is dependent on a continuous random variable, rv_j, representing the propensity to adopt a decision rule. If the value of this random variable exceeds a threshold, the decision maker is assumed to adopt regret minimization, and utility maximization otherwise. A set of factors is assumed to influence the continuous propensity to choose the decision rule.

$$W_j^{util} = \sum_m \alpha_m Z_m \quad (10)$$

$$p(util) = \frac{\exp\left(W_j^{util}\right)}{1 + \exp\left(W_j^{util}\right)} \quad (11)$$

$$p(reg) = 1 - p(util) \quad (12)$$

Table 1. Descriptive Statistics of Sample Data

Average household income: Rs 15,527			
Gender: Male: 84% Female: 16%		Average age: 36.9	
Respondents with:			
Only two-wheeler	Only car	Both two-wheeler and car	No vehicle
61%	2%	15%	22%
Bicycle ownership: 56%		Driving knowledge: 78%	
Work duration (hours/work day)			
<= 8	8–10		>= 10
35%	43%		22%
Work days/week			
3	4	5	6
1%	1%	31%	67%
Respondents with:			
Flexible time schedule: 49%		Employed spouse: 27%	
Travel mode chosen at least twice in the last 3 months			
Two-wheeler	Car	Bus	Train
69%	21%	64%	51%
Autorickshaw	Shared autorickshaw	Company bus	
52%	8%	28%	
Travel mode share			
Two-wheeler 42.0%	Car 6.0%	Bus 20.5%	
Train 16.6%	Autorickshaw 2.2%	Shared autorickshaw 1.4%	
Company bus 5.6%	NMT 5.7%		

where:

W_j^{util} = Utility associated with the choice of RUM as the decision rule

Z_m = Set of individual and contextual factors which influence the choice of decision rule

α_m = Corresponding coefficients of Z_m

Maximum likelihood estimation technique is used to obtain the coefficients in the three models. The likelihood expression of all three models is as follows ($\delta_k = 1$, if alternative j is chosen and $= 0$, if not):

$$L(\beta) = \prod_{i}^{nobs} \prod_{k}^{K} \left(P_k^{\delta_k}\right) \tag{13}$$

Data Description

This section describes the empirical data on work travel mode choice obtained from a sample of 872 workers in Chennai city, India (*11*). Data was collected using face-to-face interviews conducted at randomly sampled households. Table 1 highlights the descriptive statistics of the sample data collected.

The data was found to be reasonably representative of the worker population in Chennai city. In this regard, average household size for the sample and the population were 4.37 and 4.51 respectively. The average age of a worker was 36.9 years for the sample and around 38 for the city. The average household income of the sample (Rs 15,527) was also consistent with the population (Rs 14,500) (*21*).

The alternative modes of travel to work include: motorized two-wheeler, private car, bus, train, intermediate public transport (IPT) (here: autorickshaw, shared autorickshaw, and company bus), and non-motorized transport (NMT) (walk and bicycle). The shares for the modes are shown in Table 1. Two-wheeler has by far the largest share, probably due to its maneuverability and flexibility in trip scheduling. The relatively smaller share of 6% in private car could be due to low car ownership rates and greater travel cost of this mode. A larger proportion of workers chose to travel by bus (20%) than by train (17%). Longer commuting distances and increased physical strain could explain the low share of NMT (5.7%).

Lack of door-to-door services and limited fleet size might have inhibited the usage of shared autorickshaw (1.4%). The choice to travel by company bus (5.6%) is affected by (lack of) service availability depending on the employer organization, and its operation in limited corridors. Usage of autorickshaw (2.2%) may be hindered by operators' lack of compliance with a regulatory fare structure.

Respondents were asked to rate subjective factors of the alternative travel modes—like comfort, safety, reliability, stress, cost, flexibility in departure time, and multiple destinations—on a Likert scale of 1 to 5, where 1 indicates poor and 5 indicates excellent performance. From these ratings, it was found that decision makers perceive the travel cost of personal vehicles and IPT to be high. These ratings also indicate that users give high priority to reliability and comfort in public transit. These ratings may also reflect the risk-averse behavior of decision makers.

The models which are developed account for unavailability of alternatives in the choice set. Certain heuristics were considered to define unavailability of alternatives in the choice set. The utilities of the following alternatives are set to negative infinity so that the probability of choosing the alternative is 0 if

- **Two-wheeler/car:** the household does not own a two-wheeler or car.
- **Bus/train:** distance from home to nearest bus stop or railway station is more than 2 km.
- **NMT:** distance of commute is more than 2.5 km.
- **Company bus/shared autorickshaw:** the person has not chosen it for the last 3 months at least twice.

Results and Discussion

Statistical Evidence for Decision Rule Heterogeneity

Three different models were developed: pure RUM, pure RRM, and HDR consisting of a utility maximizing segment and a regret minimizing segment. The models were developed using a data set of 872 valid observations. The pure RUM model had a likelihood of −870.89, the pure RRM model had a likelihood of −871.13, and the HDR model had a likelihood of −738.05. Since the two homogeneous decision rule models are special cases of HDR, chi-squared likelihood ratio test could be used to compare the goodness-of-fit measures of both pure RUM (21 coefficients) and pure RRM (21 coefficients) models separately with the HDR model (54 coefficients). The results of likelihood ratio tests show that both pure RUM (test statistic of 265.68 against a critical value of 47.40) and pure RRM (test statistic of 266.16 against a critical value of 47.40) perform worse than the HDR model. Hence the test, at 95% confidence level, confirms that the assumption of decision rule homogeneity needs to be relaxed.

Model Validation

The pure RUM, pure RRM, and HDR models are validated using a holdout data set of 30%. The model validation results in Table 2 show that the predicted and actual likelihood ratio index (ρ^2values) are reasonably close to each other (within 10% to 15%). This could be considered as a valid representation of heterogeneity in decision rules. In particular, the relative difference in likelihood ratio indices was the lowest in the case of HDR, which indicates its better predictive ability. The above results confirm that there could be segments in the population which are heterogeneous in the decision rules adopted.

Analyzing Behavioral Differences between Utility Maximizing and Regret Minimizing Segments

Table 2 presents the coefficients for the variables discussed above for all three model structures. The following inferences are made with regard to these models.

Level-of-Service Factors—Travel Time and Travel Cost. The two level-of-service factors that were included in the model specification are travel time and travel cost. The sensitivity to travel time in both the utility maximizing and regret minimizing segments in the HDR model was consistent with that in the pure RUM and pure RRM models. The sensitivity to travel cost in all the modes was found to be significant in the pure RUM model. This sensitivity was highest for travel cost of train, followed by bus, shared autorickshaw, autorickshaw, car, and two-wheeler. The same hierarchy was observed in the pure RRM model except that the decision makers were found to be insensitive to autorickshaw travel cost. On the contrary, the utility maximizing segment in HDR was found to be most sensitive to travel cost in shared autorickshaw, followed by train and bus. The segment was insensitive to travel cost in two-wheeler, car, and autorickshaw. However, the regret minimizing segment of HDR was most sensitive to travel cost in train, followed by bus, shared autorickshaw, car, and two-wheeler. The segment was insensitive to travel cost in autorickshaw. Hence, unlike the utility maximizing segment of HDR, the regret minimizing segment of HDR was consistent in its hierarchy of travel cost sensitivities with the pure RRM model. These findings with respect to travel cost sensitivities exhibit a clear hierarchy from public transport to personal vehicle. This ordering is consistent with increasing privacy, comfort levels, and accessibility provided by the alternative modes. The intermediate range of sensitivity to IPT travel cost is a reflection of (a) the role of IPT modes in urban transport in Chennai city and (b) the service levels IPT offers compared with personal and public transport modes. The high sensitivity to travel cost in train may be due to lower accessibility of trains, and longer waiting times—both while purchasing tickets for travel as well for the service arrival—and difficulty in reaching railway stations.

The HDR model is able to show the differences in travel cost sensitivities in the segments classified based on a decision rule; for example, the regret minimizing segment was sensitive to travel cost in two-wheeler and car while the utility maximizing segment was insensitive to it. However, both the segments were sensitive to travel cost in shared autorickshaw, bus, and train. This is contrary to the findings in the pure RUM and pure RRM model, where sensitivities to travel cost in all the modes were significant.

Subjective Factors. The subjective factors that were included in the model are continuous estimates of perceptional ratings for comfort, safety, reliability, and accessibility of different modes. In order to allow comparison across sensitivities to these different subjective factors, the continuous ratings were normalized by their

Table 2. Comparison of Alternative Decision Rule Models

Variable description	Pure RUM		Pure RRM		HDR-RUM		HDR-RRM	
Alternate specific constant	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Car	1.24	2.10	0.51	2.07	6.34	0.79	0.75	2.78
Bus	−1.95	−0.71	−0.99	−1.47	10.85	2.48	5.19	0.34
Train	−1.30	−0.42	−0.17	−0.18	9.09	1.82	−1.88	−0.95
Autorickshaw	−3.69	−0.59	−1.87	−1.76	8.92	0.91	−6.32	−1.13
Shared autorickshaw	−3.14	−0.54	0.19	0.13	20.29	2.11	−5.17	−1.98
Company bus	−8.59	−1.76	−1.36	−1.35	9.52	1.37	−11.16	−2.18
NMT	5.75	3.19	4.36	2.33	11.41	3.00	7.21	2.06
Level of service factors								
Travel time (generic)	−0.02	−2.48	−0.01	−2.80	−0.03	−2.76	−0.01	−1.54
Travel cost (two-wheeler)	−0.18	−2.24	−0.06	−2.32	0.15	0.68	−0.14	−3.28
Travel cost (car)	−0.28	−2.96	−0.09	−3.72	−1.33	−0.83	−0.14	−4.01
Travel cost (bus)	−1.28	−5.96	−0.32	−6.04	−0.87	−2.92	−0.84	−1.43
Travel cost (train)	−2.07	−4.46	−0.47	−4.87	−1.02	−2.19	−1.71	−3.57
Travel cost (autorickshaw)	−0.32	−1.30	0.16	0.46	−0.01	−0.01	0.13	0.86
Travel cost (share autorickshaw)	−0.95	−1.83	−0.24	−2.60	−2.22	−1.69	−0.20	−1.67
Subjective factors								
Comfort of personal vehicle	0.58	4.39	0.25	3.38	0.86	3.27	0.52	3.75
Safety of bus (bus)	0.50	4.48	0.49	4.47	0.16	1.15	−0.14	0.00
Reliability of train or IPT	0.40	2.68	0.09	2.45	0.01	0.06	0.36	2.76
Accessibility of train (train)	0.78	2.40	0.24	1.86	1.07	2.63	−0.03	−0.17
Trip-related factors								
Distance to workplace (train)	0.08	3.65	0.02	3.42	0.09	3.06	0.00	−0.11
Distance to workplace (company bus)	0.21	8.23	0.09	3.81	0.20	6.30	−0.15	−0.07
Work-related travel (all modes except personal vehicle)	−0.66	−3.55	−0.19	−3.50	−0.33	−1.00	−0.19	−1.54
Binary logit decision rule model								
Constant					−1.01	−1.41		
Education level – school					−1.23	−1.69		
Young age (<40)					1.50	2.75		
Joint trip					−1.99	−2.09		
High congestion rating					−1.93	−3.61		
Road condition rating is bad					−1.49	−2.59		
Bus frequency					1.97	4.19		
Log-likelihood summary	Pure RUM		Pure RRM		Latent HDR model			
Log-likelihood (0)	−1528.84		−1528.84		−1528.84			
Log-likelihood (convergence)	−870.89		−871.13		−738.05			
Likelihood ratio index (ρ^2)	0.43		0.43		0.52			
No. of observations	872		872		872			
Model validation								
Hold-out validation data set (30%)	−290.89 (0.38)		−291.59 (0.38)		−230.55 (0.51)			
Calibration model coefficients applied on validation data set	−313.32 (0.33)		−315.01 (0.33)		−252.61 (0.46)			
Relative difference (%) in Likelihood ratio index (ρ^2) values	12.5%		13.1%		9.2%			

respective standard deviations. The subjective factors which were found to be significant in the models are: the effect of comfort in personal vehicles, safety in bus, reliability of train and IPT, and accessibility of train. All the coefficients were positive, indicating that increase in perceptive rating for these subjective factors leads to increase in utility and decrease in regret for the corresponding alternatives. A similar trend was also observed in the HDR model. The pure RUM model showed a higher sensitivity to accessibility in train, followed by equal sensitivity to all other factors. However, pure RRM showed a higher sensitivity for safety in bus followed by almost comparable sensitivity on all other factors. The utility maximizing segment in HDR was insensitive to reliability in train and safety in bus, however, the remaining sensitivities were consistent with those of a pure RUM model. Similarly, the regret minimizing segment were insensitive to bus safety and to reliability in train in their choices of bus and train respectively.

Trip-Related Factors. Performing work-related trips to places other than workplace and distance to the workplace from home were the trip-related factors that were significant in influencing the mode choice behavior of the decision makers. With regard to work-related trips, all the models showed a negative coefficient. This is indicative of the fact that the decision makers who perform work-related trips outside the workplace have limited travel alternatives other than personal vehicle. This effect was absent in the utility maximizing segment but evident in the regret minimizing segment of the HDR model.

The effect of distance to the workplace from home is intuitive in nature. The likelihood of choosing train and company bus increased in comparison to other modes as distance increased. This effect was observed in all the models. Further, the intensity of this effect was greater in the case of company bus than train. This could be because the establishments (like IT companies) which provide transport facilities for their employees are located on the outskirts of the city. In the case of train, the decision maker might choose this mode only if the distance to the workplace is beyond a minimum threshold distance and hence the usage of train might be associated with longer commuting distances. However, this effect of work distance was absent in the regret minimizing segment of the HDR model. This was also confirmed by the elasticity values in the respective segments with respect to work distance (not shown here) .

Factors Influencing the Choice of Decision Rule

The choice of the latent decision rule between utility maximization and regret minimization was modeled assuming the probability structure of a binary logit model. The following factors were found to be significant in the model. In this model, the positive coefficient indicates that, with an increase in the value of these factors, the probability that an individual considers utility maximization as a decision rule increases. Graduates and postgraduates are less likely to be regret minimizers than those commuters who are not graduates. Similarly, younger commuters tend to be utility maximizers more than regret minimizers. Decision makers who travel to work with other household members are less likely to adopt utility maximization as their decision rule. Commuting as a pair or as a group imposes more constraints on travel, like departure time, mode usage, etc., and hence this causes some impedances to the commuters in their travel choice. However, most commuters who travel with their family members tend to anticipate this impedance and try to minimize the regret associated with it. Decision makers who feel that congestion is high or road conditions are poor are more likely to be regret minimizers. Such ratings for these factors itself is reflective of higher expectations and comparison with higher levels of service which is characteristic of regret minimizing behavior. With the increase in the number of workers among members in the household, the probability of the decision maker being a utility maximizer increases. With a decrease in frequency of buses (number of services per hour), the decision maker tends to be a utility maximizer rather than a regret minimizer.

Segmental Analysis

In this section, the characteristics of these two segments (or classes) in the HDR model are compared. These segments are compared in terms of their individual/household characteristics and trip-related attributes. This comparison is done based on the values of the attributes computed based on the segmental analysis exercise proposed by Bhat (*22*). The average value of any given attribute in the segment D is computed using the following expression,

$$\overline{A_D} = \frac{\sum_{i}^{N} p_D^i \cdot A^i}{\sum_{i}^{N} p_D^i} \tag{14}$$

where:

A^i is the value of the socio-economic attribute for individual i,

p_D^i is the segment membership probability of individual I, and

$\overline{A_D}$ is the segmental average of an attribute.

The segment-wise average values of these attributes characterize these segments and could aid in differentiating the tendencies of these segments. The average of various attributes computed for both these segments is shown in Table 3. In addition to attributes, the mode shares in each of these segments are computed using the same expression as in Table 3. While differences were observed for some of the attributes in these segments, differences in certain other attributes were negligible. However, these attributes with differential in mean values could be used to understand and characterize these segments.

In the RUM segment, the share of two-wheeler was highest (55%), followed by car (12%) and train (9%). This was followed by NMT (8%), bus (7%), company bus (5%), autorickshaw (3%), and shared autorickshaw (1%). In the RRM segment, bus had the highest share (37%), followed by train (26%). This was followed by two-wheeler (19%), company bus (8%), NMT (4%), autorickshaw, and shared autorickshaw (3% and 2% each). The lowest share was for car (1%). The RUM segment had the highest share for personal vehicles (two-

Table 3. Average Values of Attributes in Each Segment

Variables	HDR – RUM	HDR – RRM
Low income	0.31	0.37
Medium income	0.49	0.49
High income	0.20	0.16
Male	0.79	0.81
Distance	10.15	13.3
Young	0.47	0.51
Middle age	0.43	0.36
Old age	0.10	0.13
Captive by vehicle ownership	0.15	0.31
Captive by driving knowledge	0.08	0.16
Semi-captive	0.22	0.26
Choice segment	0.55	0.27
Solo trip	0.85	0.97
Joint trip	0.15	0.03
Short distance (<= 7 km)	0.45	0.34
Medium distance (7–13 km)	0.20	0.18
Long distance (>= 13 km)	0.35	0.48
Bus frequency	1.64	12.12
No. of transfers	0.08	0.18
Employed spouse	0.24	0.20
Flexibility in time	0.46	0.43
Mode shares		
Two-wheeler	55%	19%
Car	12%	1%
Bus	7%	37%
Train	9%	26%
Autorickshaw	3%	3%
Shared autorickshaw	1%	2%
Company bus	5%	8%
NMT	8%	4%

wheeler and car) and the lowest share for IPT modes (autorickshaw, shared autorickshaw, and company bus). Public transport had relatively lower shares than personal vehicles. The RRM segment, on the other hand, had the highest shares for public transport. It also showed a considerable preference for two-wheeler but very little preference for car. The segment showed relatively greater shares for company bus (8%) but very low shares for autorickshaw, shared autorickshaw (2% each), and NMT (4%). The relatively very high shares for two-wheeler and car in the RUM segment suggest that the segment is mostly captive to the personal vehicle (67% shares of personal vehicle). On the contrary, the RRM segment has very high public transport shares (63%) as well as high two-wheeler shares (19%) and relatively greater company bus shares (8%). This means that the segment is not captive to any particular mode. Based on the above observations, it is considered intuitive to characterize the RUM segment as a group which is captive to personal vehicle usage and the RRM segment to be a non-captive group.

The proportion of commuters who have restricted or no access to personal vehicles (either due to lack of driving knowledge or vehicle ownership) is very high (23% in RUM segment versus 47% in RRM segment) in the non-captive group (RRM segment) when compared with the personal vehicle captive group (RUM segment). Further, the proportion of commuters who have full access to personal vehicles is also very high in the RUM segment when compared with the RRM segment (58% in RUM segment and 22% in RRM segment). This implies that the RUM segment is mostly captive to personal vehicle usage. The captivity of personal vehicle in the RUM segment could also be motivated by the greater proportion of joint trips in the segment (15% in segment1 versus 3% in segment 2). This is because, owing to its greater flexibility, the personal vehicle is very useful in making joint trips when compared with other modes. Commuters with flexible work time are more likely to be in the personal vehicle captive group than in the non-captive group. This could also have led to the higher personal vehicle shares in the personal vehicle captive group than in the non-captive group.

The proportion of long-distance trips in the non-captive group is significantly greater (48%) than in the personal vehicle captive group (35%). This could be the reason for higher train and company bus shares in the non-captive group (37% and 8%) than the personal vehicle captive group (9% and 4%). The percentage of short and medium distance trips is considerable in the non-captive group (34% short distance, 18% medium distance) but less than in the personal vehicle captive group (45% short distance, 20% medium distance). This might be the reason for greater share of two-wheelers when compared with the other modes in the non-captive group.

The relatively higher shares of bus in the non-captive group (37% versus 5% in the personal vehicle captive group) are possibly due to them recording very high bus frequency (12.12 services/hr against 1.64 service/hr).

Summary and Conclusions

This empirical study attempts to capture potential heterogeneity in decision rules adopted by decision makers with respect to random utility maximization and random regret minimization. The specific objectives of the study were to (a) propose a framework which relaxes the restriction of decision rule homogeneity; (b) compare its performance with RUM and RRM frameworks; (c) capture the behavioral differences between the utility maximizing segments and regret minimizing segments in the population; and (d) identify the factors influencing the choice of the latent decision rule. In order to achieve these objectives, empirical models were developed using the data collected from working commuters through household interview survey in Chennai city. MNL models were used to model the probabilities in pure RUM and pure RRM models while a latent class model was developed for representing decision rule heterogeneity. Model specification included variables related to level-of-service factors, subjective factors, and trip-related factors. The following findings from the study are noteworthy.

The proposed HDR model performed statistically better than the homogeneous decision rule models, the pure RUM and pure RRM models. This could be considered as primary evidence for decision rule heterogeneity in work travel mode choice. The effects observed in homogenous decision rule frameworks might be normalized effects and reflect the sensitivity in one of the decision rule sub-segments.

On performing the segmental analysis of the two segments, RUM and RRM, the following differences are observed. It was observed that the RUM segment displayed a stronger "inertia, captivity or loyalty" to the personal vehicle compared with the RRM segment. The personal vehicle shares were very high in the RUM segment. No particular mode type had an advantage over all other modes, although public transport modes had the highest shares for the RRM group. The RRM segment had a relatively larger proportion of long-distance trips while the RUM segment had more short and medium trips. The segmental analysis thus supports the model results regarding critical differences between the RUM and RRM segments.

In two-stage simultaneous models, modelers are often faced with the dilemma of specification of suitable variables at the appropriate stage, decision rule process, selection of the chosen mode or both, in the context of heterogeneous decision rule models. Existing models show evidence of heterogeneity due to socio-demographics at the mode level. Tthis may be misleading, however, as such models assume homogeneous decision rules, and thus heterogeneity at a decision rule level may be wrongly reflected as heterogeneity at the mode level.

Some variables were tested at both levels and found to be significant only at the latent decision rule level (e.g. age, education level, bus frequency, etc.). However, in other cases, some variables were included only at the decision rule level and not at the choice level to avoid collinearity, confounding, and error correlations across the two levels (e.g. distance to workplace, joint trip, reliability in train, safety in bus etc.). In such cases, inclusion of variables at both levels led to unstable or counter-intuitive estimates. Since very few studies have explored heterogeneity in decision rules, no explicit attempt has been made to segregate the effect of attributes at both stages. Hence, classification of these attributes and their specification requires more scientific analysis and further investigation.

To the authors' knowledge, data regarding decision rules adopted by users in travel surveys is very sparse, particularly with regard to revealed preference data, mainly because of focus on the alternative travel modes chosen rather than the decision process. However, researchers in marketing, psychometrics, and behavioral economics have attempted to study decision rules in other contexts using stated preference and conjoint experiments. Although a number of decision rules have been modeled in the context of travel behavior for different choice dimensions, almost all these studies have been based on the assumption of homogeneous decision rule.

It is a challenge to frame questions to study the decision process and attribute trade-offs with regard to revealed preference data as it involves providing a number of scenarios to elicit such preferences. There is a possibility of framing and selectivity bias with regard to such data, particularly as the choice process may be latent or partially formed or not well articulated by the decision maker. For these reasons, the reliability, robustness, and validity of such data and instruments to capture decision rules and choice processes directly need to be ensured.

In the absence of such data, and the fact that the choice process is latent, the latent and hybrid choice approaches offer a useful methodological construct to infer the decision making rules. However, the corroboration and validation of these insights with direct measurement remains an important and immediate next step for the generalization and practical use of the models.

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Author Contributions

Both authors contributed to all aspects of the paper.

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