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Random Regret Minimization Approach to Commuting Mode Choice in São Paulo, Brazil

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Abstract

The random regret minimization (RRM) approach has been widely used in transport literature, but its application in the Global South is still marginal. In this paper we discuss individual commuting mode choice in the city of São Paulo (Brazil) from the perspective of the RRM modeling approach and its variants found in the literature. We estimated several multinomial logit models (random utility maximization [RUM], classical RRM, μRRM, and hybrid formulations of RUM-RRM models) and explored regret scale and decision rule heterogeneities using latent class models with specific μ parameters. The results showed that the RRM approach outperformed its RUM counterpart in relation to model fit and suggested that it better captured the mode choice behavior of individuals in the analyzed context. We also found that accounting for heterogeneity in scale and decision rules improved the results of the models, and the specific μ parameters indicated that individuals displayed different regret behavior for travel time and travel cost attributes.

Keywords

planning and analysis, traveler behavior and values, behavior analysis, behavioral process, decision analysis and processes, mode choices

The analysis of individual travel behavior is an important aspect in transportation policy to overcome the challenges in understanding the decision-making process that guides people when choosing different forms of mobility. Discrete choice models have been widely used in analyses of transport mode choice, considering the well-known random utility maximization (RUM) approach (*1*), which assumes that people choose the alternative that has maximum utility as a function of their sociodemographic characteristics and the level of service (LOS) of alternatives represented by their attributes.

Conversely, the random regret minimization (RRM) approach is based on the premise that people account for the regret generated by the binary comparison of alternatives on their attributes (*2*, *3*). Based on regret theory (*4*), the RRM approach has been widely used in transport literature. The classical formulation of the RRM model (*3*) was extended by van Cranenburgh et al. to the μRRM model, allowing for flexibility in the attribute level of the regret function (*5*).

According to literature, the RRM has been applied in various contexts, however its use in the Global South is still limited, especially in Latin America in the context of travel mode choice (*6*). Therefore, in this study we assess individual commuting mode choice in the city of São Paulo, Brazil, using the RRM approach. We estimate a multinomial logit (MNL) classical RRM (CRRM) model and variants of MNL μRRM models comprising hybrid formulations including a simultaneous utility maximization and regret minimization (*7*). We also explore how different decision rules can be used by the population in the decision-making process (*8*, *9*) by estimating latent class (LC) models considering the RUM and RRM paradigms.

We additionally analyze heterogeneity in the travel time and travel cost attributes with regard to the intensity of regret imposed by individuals using specific μ parameters. These analyses are conducted in reference to

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van Cranenburgh et al., who emphasized the need for additional research to comprehend the effects of diverse forms of heterogeneity in the RRM approach (*5*). This study specifically focuses on the heterogeneity associated with decision rules and the scale of regret. It additionally acknowledges that empirical applications of the random modified utility (RMU)—hybrid RUM-μRRM models—remain relatively limited in the existing literature. Finally, we present a correct formulation for the elasticities of the μRRM model first addressed by Belgiawan et al. (*10*).

This paper is divided into five sections. Following this introduction, Section 2 discusses the RRM approach, its properties, and different sources of heterogeneity and applications found in the literature. In Section 3, the dataset used in the paper and the proposed models are detailed, and Section 4 discusses the results. Finally, Section 5 draws the main conclusions of the research and suggests directions for future studies.

Literature Review

The RUM approach accounts for the utility, U_{iq}, for individuals q in the population Q, and alternatives i within the choice set available to the individual, $A(q)$, being characterized by a deterministic and a stochastic component (V_{iq} and ε_{iq}, respectively). The V_{iq} component is defined by the level of the k^{th} attribute of the alternative available to the individual (x_{iqk}) weighted by its respective parameter, β_{ik}, as shown in Equation 1. Assuming that the error terms are independent and identically distributed (IID) and follow an extreme value (EV) Type I distribution, the probability of an alternative being chosen is calculated by the well-known MNL model shown in Equation 2 (*11*).

$$U_{iq} = \sum_{k=1}^{K} \beta_k x_{iqk} + \varepsilon_{iq} \forall i, q \tag{1}$$

$$P_{iq} = \frac{e^{V_{iq}}}{\sum_{A_j \in A(q)} e^{V_{jq}}} \forall i, q \tag{2}$$

Whereas the RUM approach has gained widespread exposure in both literature and practical applications, alternative formulations have been proposed that offer new perspectives on travel behavior, including approaches grounded in RRM methodology and decision field theory (*12*, *13*). The fundamentals of discrete choice models estimated on the basis of regret theory were firstly addressed by Chorus et al. (*2*) and Chorus (*3*), in which individuals make binary comparisons between attributes to minimize the resulting regret when the attribute of the chosen alternative outperforms the attribute of the alternative not chosen. The formulation of the regret function in its continuous form proposed by Chorus (*3*) is shown in Equation 3.

$$R_{iq}^{CRRM} = \sum_{A_j \in A(q), j \neq i} \sum_{k \in K} ln\left(1 + exp\left[\beta_k \cdot (x_{jqk} - x_{iqk})\right]\right) \forall i, q \tag{3}$$

where

R_{iq}^{CRRM} is deterministic part of regret defined as the sum of differences between the considered and the competitive alternatives;

β_k is the parameter related to attribute k; and

x_{ik} and x_{jk} are levels of attribute k of alternatives i and j, respectively.

Assuming that the regret is defined by stochastic terms that follow an IID EV Type I distribution, the MNL models are also employed to estimate choice probabilities as shown in Equation 4.

$$P_{iq} = \frac{e^{(-R_{iq})}}{\sum_{A_j \in A(q)} e^{(-R_{jq})}} \tag{4}$$

RRM models are sensitive to choice set composition and to the compensatory effect (*14–16*). The first refers to the property of independence of irrelevant alternatives in RUM MNL models, which does not apply to RRM models because the probability of an alternative relies on the comparison of its attributes with the other available alternatives (*16*). The second property, the semicompensatory effect, results from the convexity of the regret function, such that improving the performance of an alternative that already has good performance results in smaller reductions of regret, whereas deteriorating the performance of an alternative results in substantial increases in regret (*16*).

In relation to the performance of data used, Wong et al. discuss the advantages and drawbacks of revealed preference (RP) data in RRM models, highlighting that the absence of variability in the attribute levels and the lack of knowledge of the real set of alternatives considered by the individual may limit their applications (*17*). Those authors show that most of the empirical studies have used data from stated preference (SP) surveys, although models with RP data resulted in better performance.

The research by van Cranenburgh et al. (*5*) extended the CRRM model proposed by Chorus (*3*) to the μRRM model comprising the scale of regret parameter (smoothing parameter) as shown in Equation 5. Assuming IID error terms following EV Type I distribution, the probability of the μRRM model is equivalent to Equation 4. van Cranenburgh et al. showed that the CRRM is a special case of μRRM model when $\mu = 1$, and the pure-RRM (P-RRM) model is obtained when $\mu \rightarrow 0$ (*5*). They also discussed how the underlying behavior is similar to the RUM when $\mu>5$, when individuals give equal importance to losses and gains.

$$R_{iq}^{\mu RRM} = \sum_{A_j \in A(q), j \neq i} \sum_{k \in K} \mu \cdot ln\left(1 + exp\left[\beta_k/\mu \cdot (x_{jqk} - x_{iqk})\right]\right) + \varepsilon_{iq} \forall i, q \quad (5)$$

Modeling Heterogeneity Preferences in the RRM Approach

So far, the issue of heterogeneity in transport literature has been explored by mixed MNL (MMNL) and LC models (*18*, *19*). The MMNL has become one of the most important tools in analyzing taste or unobserved heterogeneity when the analyst assumes that the taste related to an attribute follows a continuous distribution, or in the case of LC models by segmenting the population in homogeneous groups of different behavior through a discrete distribution.

In addition to the unobserved heterogeneity in preferences, some authors argue that the decision process can be heterogeneous in the population (*8*); the LC framework has been mostly used to explain such different paradigms of individual choice. Other studies have also observed this type of heterogeneity; for instance, Hess and Chorus compared various LC models incorporating both RUM and RRM classes, demonstrating improved model fit when heterogeneous decision rules are considered (*20*). Hess and Stathopoulos explored the connection between the character traits of individuals and these decision paradigms (*9*).

Another type of heterogeneity is represented by the RMU model proposed by Hensher et al., who state that individuals may minimize the regret for some attributes and maximize the utility for others, thus mixing the RRM and RUM approaches simultaneously in the same model (*21*). Such approach was explored by Leong and Hensher with mode and route choice data in Australia (*22*). More recently, Luan et al. used the CRRM and the generalized random regret minimization (GRRM) models to analyze the impact of the COVID-19 pandemic on travel mode choices and tested different δ parameters of the GRRM model (*23*).

Another source of heterogeneity comprising the μRRM model (*5*) was explored by Wong et al., who estimated this model with both generic and specific scale parameters, though without finding significant results as they did not present better fits compared with the RUM model, nor with significant μ parameters (*17*). To the best of our knowledge, no research reported in the literature so far has considered the decision rule and regret behavior in different attributes simultaneously.

Applications

Several applications of the RRM approach have been described in transport and travel behavior literature, for instance, in relation to road safety (*24*), freight transport (*25–27*), traffic allocation and route decision (*28–31*), demand for recreational activities (*32*), traffic calming schemes (*33*), and passenger mode choice (*34*). Among those comprising RP data, there are applications on parking site decisions (*3*) and route choices (*35*). For additional information, we refer interested readers to the literature reviews conducted by Chorus et al. (*36*) and Jing et al. (*6*). In the Global South context, empirical evidence appears mostly in Asian countries on topics of travel mode choice (*37*, *38*), tourism (*39*), and environmental concerns (*40*). Recently, Isler et al. analyzed the effects of stimulus perception in long distance rail mode choice using RRM models and SP data and found that RRM performs better in fewer cases (*41*). Mauad and Isler compared different modeling approaches to analyze destination choices in the city of São Paulo, Brazil (*42*).

Some studies have also extended the capabilities of the RRM models, for instance, incorporating psychophysical mapping into RRM models to account for perceptions of the attributes using Weber's law (*43*); accounting for cognitive effort to compare alternatives (*44*); and analyzing the bias from measurement error (*45*) and from omitted variables (*46*). Dekker showed potential applications of value of travel time measures for transport appraisal in the context of the RRM approach (*47*).

Applications using the μRRM model have also increased. Belgiawan et al. compared RUM, CRRM, μRRM, P-RRM, and Relative Advantage Maximization (RAM) models across eight datasets (mode choice, location choice, parking choice, carpooling, and car-sharing contexts) (*10*). Sharma et al. estimated MNL RUM and RRM (CRRM and μRRM) models to analyze park-and-ride lot choices in Australia (*48*). However, neither Belgiawan et al. (*10*) nor Sharma et al. (*48*) delved into the scale heterogeneity within the μRRM model, and the hybrid formulations of RUM-μRRM models discussed in this paper have not been previously documented in the literature.

Data and Model Specification

Data

The data used in this research were obtained from the RP "Origin and Destination Household Survey" (OD 2017) conducted in the metropolitan region of São Paulo (MRSP) by the Companhia do Metropolitano de São

Paulo (49). The MRSP is composed by the city of São Paulo, which serves as the capital of the homonymous state, and 38 other municipalities over an urban area of 7,947 km^2 with approximately 21.2 million inhabitants. The data collected in the survey refer to urban trips on a typical weekday previous to the interview and contain sociodemographic characteristics of the household and the individuals, and information about all their trips (origin, destination, departure time, and transport mode). The survey was applied to a stratified random sample of 32,000 households and approximately 100,000 individuals, representing around 42 million trips on a typical day in the MRSP.

The dataset was filtered for modeling purposes by selecting the observations of individuals traveling to work with both origin and destination exclusively in the city of São Paulo owing to the lack of information to estimate LOS attributes outside this area. Observations referring to individuals younger than 16 years, households with income equal to zero, and missing values in any of the sociodemographic attributes were removed from the dataset. In this research we considered only motorized modes of transport: car, bus, and rail comprising the subway and urban rail systems. Moreover, we selected only households owning at least one automobile to avoid cases in which the individual would have only two available alternatives (17).

The attributes of the i^{th} alternatives were travel time (TT_i) and travel cost (TC_i), whereas the considered sociodemographic attributes were age (*AGE*), sex (*SEX*) with male as the reference category, number of individual daily trips (*TRIPS*), number of household members (*HOUSE*), overall household income (*INCOME*) converted to a logarithmic scale, number of trips that started in the morning peak between 7 and 9 a.m. (*PEAK*), and level of education in three categories: up to 7 years (*EDO*), between 8 and 10 years (*ED*1), and more than 10 years (*ED*2) of education. The category *EDO* was set as the base category.

Given that the information reported in the survey refers only to the chosen modes, we inferred that all the alternatives were available to each individual, and we modeled the LOS attributes as recommended by Koppelman and Bhat, including the alternative actually chosen, to avoid biased measures from multiple sources that consider different rules for mode access, and maximum access distance to terminals (50).

Travel time by car and access and egress distances to estimate travel costs were collected from the TomTom application programming interface (API) (51). The monetary costs by car were calculated from the formulation proposed by Gomide and Morato, which is composed of a fixed cost added to a variable cost as a function of the total traveled distance, as shown in Equation 6 (52); these values were updated to 2017 by an inflation rate index (53).

$$CO_{car} = 2,88 + \left(2,31 \cdot \frac{d}{7000}\right) \quad (6)$$

where CO_{car} is total cost of car trips in Brazilian currency (R$), and d is total trip distance in meters.

Travel times by bus and rail were obtained from OpenTripPlanner, an open-source multimodal routing API coded in Java that uses information from GTFS (general feed information specification) files to calculate transit routes (54). In this study, the GTFS file from 2017 was provided by SPTrans, the company that manages the bus fleet in the city of São Paulo (55). Trips that could not be traced were subsequently removed from the final dataset.

In São Paulo, a unique fare of R$3.80 was charged at the time of the survey for trips made exclusively by bus, with temporal integration when a smart card was used in the system. The costs of rail trips were estimated for two groups: *i*) individuals who opted for the rail alternative as reported in the survey, the cost was estimated by considering the trip chain described in the survey, which varied between R$3.80 for trips made solely by rail or integrated with an individual/private transport mode, and R$6.80 for trips involving rail/bus integration; and *ii*) for unavailable trip chains in the survey, we considered an access rule in which the cost was set to R$3.80 for those individuals living 1,500 m or less from nearby train stations, and R$6.80 for individuals with an origin that was more than 1,500 m from the closest train station. The final dataset comprised 8,962 observations; the descriptive statistics are shown in Table 1.

Table 1. Descriptive Statistics of the Attributes

Attribute	Unit	Mean	Minimum	Maximum	SD
TT_{bus}	min	65.45	4.03	281.87	33.88
TT_{rail}	min	93.29	14.61	438.65	46.49
TT_{car}	min	26.40	1.25	122.22	15.57
CO_{car}	R$	6.63	3.06	36.55	2.92
CO_{rail}	R$	6.03	3.80	6.80	1.31
CO_{bus}	R$	3.80	3.80	3.80	0
AGE	years	42.92	16.00	89.00	13.80
SEX	%	45	-	-	-
HOUSE	na	3.14	1.00	12.00	1.30
TRIPS	na	2.91	1.00	17.00	1.36
ln(INC)	na	8.78	5.70	11.51	0.66
ED1	%	5	-	-	-
ED2	%	91	-	-	-

Note: TTi = travel time; *CO* = total cost; *ln(INC)* = logarithm of INCOME; *ED* = education level; SD = standard deviation.

Model Specification

RUM, CRRM, and μRRM MNL Models. We estimated RUM, CRRM, and μRRM models based on Equations 1, 3, and Equation 5 assuming IID EV Type I errors. The specifications started with only the LOS attributes of the alternatives and evolved to include the sociodemographic attributes. Heterogeneity in μRRM can be introduced by considering scale parameters per attribute (μ_m) and different decision rules in the attributes (likewise in the RMU). In this paper, we estimated one model with generic scale attributes and another with specific scale attributes for travel time and travel cost. We then estimated MNL classical random modified utility (CRMU) and μRMU models with generic and specific scale parameters for the attributes processed by the RRM approach, and fixed scale parameters of the attributes processed by the RUM approach equal to 1 ($\mu = 1$). The P-RRM model was not considered as it assumes that individuals are entirely in the domain of regret behavior (with strong loss aversion). The P-RRM as a specific case within the μRRM model helps identifying whether individuals adopt such behavior.The expression for the μRMU model is represented by Equation 7, with the q subscripts omitted for simplicity.

$$R_i^{\mu RMU} = \sum_{A_i \in A} \sum_{k \in K} \mu_k \cdot ln\left(1 + \ exp\left[\frac{\beta_k}{\mu_k} \cdot \left(x_{jk} - x_{ik}\right)\right]\right) + \sum \beta_k x_{ik} + \ \varepsilon_i \tag{7}$$

The final models were estimated with specific and generic parameters related to travel times and costs, respectively. Moreover, AGE and level of education (ED_1 and ED_2) had generic parameters for the bus and rail alternatives, and the other attributes were set with specific parameters for bus and rail, with car as the base alternative. The specifications of the deterministic part of the choice components under RUM and RRM approaches for all alternatives can be found in Appendix A.

Latent Class Models. The LC model was specified as proposed by Hess et al. (*8*). Let $P(y_i|\beta_{RUM}x)$ and $P(y_i|\beta_{RRM}x)$ be the respective MNL choice probabilities of the RUM and RRM models by an individual q according to Equations 2 and 4 considering IID EV Type I errors. In addition, let π_m, Equation 8, be the class allocation probability of the individual making a choice by means of one of the two approaches, where $\sum_{m=1}^{2} \pi_m = 1$ and $0 \leqslant \pi_m \leqslant 1 \ \forall m$.

$$\pi_m \ = \ \frac{e^{(\delta \ + \ \theta_k z_k)}}{1 + \ e^{(\delta \ + \ \theta_k z_k)}} \forall \ A_i \in A(q) \tag{8}$$

where z_k is level of the k^{th} attribute, and θ_k are parameters associated with the z_k sociodemographic attributes.

Therefore, the choice probability conditional to the class allocation model can be calculated by Equation 9,

$$P(y_i|RUM, RRM, \boldsymbol{\theta}) = \ \pi_{RUM} P(y_i \ |RUM) + \ \pi_{RRM} P(y_i \ |CRRM, \mu RRM) \tag{9}$$

Several specifications were tested for the LC and MNL models within the RUM and RRM. The comparison involved the likelihood ratio test (*56*), and the Akaike likelihood ratio index (ALRI) test proposed by Ben-Akiva and Swait for nonnested models was employed to assess and contrast the RUM and RRM models (*57*). The parameters related to the LOS attributes in the LC were specified as in the final MNL models. We tested the sociodemographic attributes in the choice model, in the allocation model, and in both components simultaneously. The best result was found with the sociodemographic attributes in the allocation model, therefore, it is the only model presented in this paper. All models were estimated by likelihood maximization in Apollo (*58*, *59*) implemented in R package (*60*).

Elasticities

Elasticities are important measures for policy-making and widely applied in both transport literature and practice. These measures are already known for the RUM case and are simple to calculate. The elasticities for the RRM approach were firstly addressed by Hensher et al. for the CRRM (*21*), and recently discussed by Belgiawan et al. in the μRRM context (*10*). Readers are referred to the papers mentioned for detailed elasticity formulations in both the RUM and CRRM models. However, an error was detected in the initial derivation of μRRM elasticities in Belgiawan et al., leading to inaccurate equations (*10*). Therefore, we present a corrected derivation for the elasticity and marginal rate of substitution (MRS) of the μRRM model in Appendix B. We additionally highlight distinctions between our formulas and those in Equation 10 by conducting a comparative analysis using two open datasets employed in the study of Belgiawan et al. (*10*). We anticipate that this correction will assist future studies in accurately calculating measures when utilizing the μRRM model. The precise formula for computing μRRM elasticity is presented in Equation 10.

$$E_{iqX_{kiq}}^{\mu RRM} = \left(-\frac{\partial R_{iq}^{\mu RRM}}{\partial X_{iq}} + \sum_{\substack{i \in J \\ j \neq i \\ j=1}}^{J} P_{jq} \cdot \frac{\partial R_{jq}^{\mu RRM}}{\partial X_{iq}} \right) \cdot X_{kiq}$$

$$= \left(\left(- \sum_{\substack{i \in J \\ j \neq i \\ j=1}}^{J} \frac{-\beta_k}{\exp\left[-\beta_k/\mu_k \cdot \left(X_{kjq} - X_{kiq}\right)\right] + 1} \right) + \left[\sum_{\substack{i \in J \\ j \neq i \\ j=1}}^{J} P_{iq} \frac{-\beta_k}{\exp\left[-\beta_k/\mu_k \cdot \left(X_{kjq} - X_{kiq}\right)\right] + 1} + \sum_{\substack{i \in J \\ j \neq i \\ j=1}}^{J} P_{jq} \frac{\beta_k}{\exp\left[\beta_k/\mu_k \cdot \left(X_{kjq} - X_{kiq}\right)\right] + 1} \right] \right) X_{kiq} \quad (10)$$

The aggregate direct point elasticities used to compare both approaches were calculated according to Equation 11 (*61*).

$$E_{iqX_{iq}}^{W_q} = \sum_{q=1}^{Q_s} E_{kiqX_{iq}} \frac{w_q P_{iq}}{\sum_{q=1}^{Q_s} w_q P_{iq}} \quad (11)$$

where $E_{iqX_{iq}}^{W_q}$ and $E_{kiqX_{iq}}$ are aggregate and disaggregate direct point elasticities of attribute X_{iq} of alternative i available to individual q; and w_q is sample weight for individual q within sample Q_s from population Q. We weighted each observation based on an individual weight reported in the OD 2017 survey that accounts for sociodemographic characteristics such as age, gender, and income and its representation in the MRSP population (*49*).

Results

Goodness-of-Fit

The goodness-of-fit measures of the estimated models are shown in Table 2 and their respective log-likelihoods are summarized in Figure 1. LC models that allow for flexibility in decision rules with only LOS attributes provide better results in relation to log-likelihood. In these cases, the MNL CRRM model fit better than the MNL RUM with a log-likelihood difference of 58.92, similar to Wong et al.'s research that highlighted that RRM models estimated with RP data provide better results than RRM models with SP data (*17*).

The μRRM models provided better results compared with the MNL RUM and CRRM models, with log-likelihood differences of 81.6 and 22.68, respectively. Moreover, the log-likelihood differences among the $2\mu RRM$ model and the MNL RUM and CRRM models were 110.36 and 51.45, respectively. It was also noted that allowing for flexibility in the μ parameter improved the model fit, with 28.77 log-likelihood difference at a

Table 2. Goodness-of-Fit of the Estimated Models

LOS	$LL_{initial}$	LL_{final}	ρ^2	ρ^2_{ajust}	AIC	BIC	Parameters
RUM	−9845.76	−7,586.90	0.2294	0.2288	15,185.80	15,228.40	6
CRRM		−7,527.98	0.2354	0.2348	15,067.95	15,110.55	6
μRRM		−7,505.30	0.2377	0.2370	15,024.59	15,074.30	7
2 μRRM		−7,476.53	0.2406	0.2398	14,969.06	15,025.87	8
LC CRRM		−7,400.54	0.2484	0.2472	14,823.07	14,901.18	11
LC μRRM		−7,383.66	0.2501	0.2488	14,791.31	14,876.52	12
LC 2 μRRM		−7,337.09	0.2548	0.2535	14,700.17	14,792.48	13
LOS + SOCIO	−9845.76						
RUM		−6,807.66	0.3086	0.3067	13,651.32	13,779.13	18
CRMU		−6,768.71	0.3125	0.3107	13,573.42	13,701.23	18
μRMU		−6,750.88	0.3143	0.3124	13,539.76	13,674.68	19
2 μRMU		−6,736.49	0.3158	0.3138	13,512.98	13,654.99	20
LC CRRM		−6,622.83	0.3273	0.3254	13,283.67	13,418.58	19
LC μRRM		−6,638.01	0.3258	0.3238	13,316.02	13,458.04	20
LC 2 μRRM		−6,616.07	0.3280	0.3259	13,274.15	13,423.26	21

Note: LOS = level of service; AIC = Akaike information criterion; BIC = Bayesian information criterion; SOCIO = sociodemographic; RUM = random utility maximization; CRRM = classical random regret minimization; RMU = random modified utility; LC = latent class.

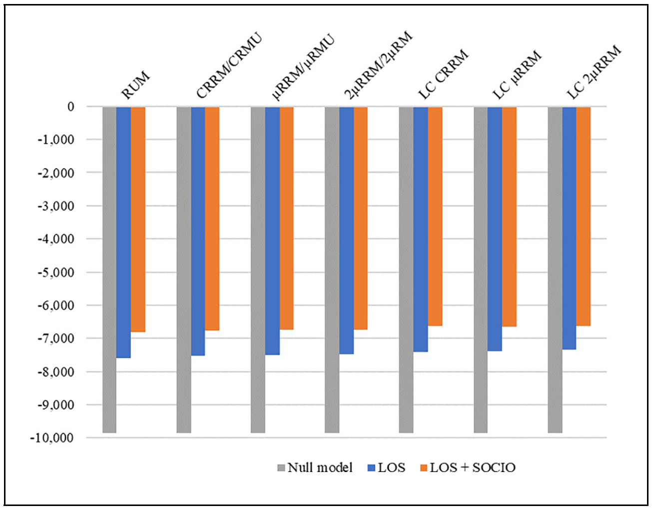

Figure 1. Log-likelihood of models with LOS attributes and sociodemographic attributes (LOS + SOCIO).
Note: LOS = level of service; SOCIO = sociodemographic; RUM = random utility maximization; CRRM = classical random regret minimization; RMU = random modified utility; LC = latent class.

cost of one parameter compared with the μRRM model. The statistical differences tested by the likelihood ratio and the ALRI tests were significant comparing the RUM and RRM models and between the RRM models. It is noteworthy that these differences exceeded the typical magnitudes found in the literature. This suggests that the approach employed in this study holds the potential to effectively model travel behavior, particularly in the context of cities that share similarities with São Paulo.

The *LC* 2μ*RRM* model (LOS) that allowed heterogeneity in decision rules and in the scale parameter provided a 63.45 log-likelihood difference compared with the *LC CRRM* model at a cost of two additional parameters, and a 46.57 log-likelihood difference at a cost of one additional parameter when compared with the *LC* μ*RRM* model.

The results of the models with sociodemographic attributes are also shown in Table 2. It is worth noting that the inclusion of these variables significantly enhanced the results compared with models containing only LOS variables. Moreover, models estimated using the RRM approach demonstrated a superior fit compared with the RUM models, whereas the μ*RMU* models outperformed the corresponding CRMU models.

Allowing for different scale parameters also increased the performance of estimations, given that the log-likelihood of the 2μ*RMU* model differed by 14.39 in its log-likelihood compared with the μ*RMU* model, albeit the difference was lower compared with the models without sociodemographic variables. The differences in the number of parameters between the LC and the MNL models were significantly small; the 191.59 log-likelihood difference was the largest between the $RUM_{(LOS\ +\ SOCIO)}$ and the *LC* 2μ*RRM* models at a cost of three parameters. However, the *LC* μ*RRM* model underperformed compared with the LC CRRM and the LC 2μ*RRM* model. Figure 1 highlights the improvements resulting from the inclusion of sociodemographic variables compared with models containing solely LOS variables.

Parameters

The parameters of the models with only LOS attributes are given in Table 3, and the estimates of the models with sociodemographic variables (LOS + SOCIO) are shown in Table 4. All the MNL and LC estimations had LOS parameters with the expected signs and were significant at a 95% confidence level. According to the data in Table 3, the MNL RRM models resulted in similar parameters, whereas the LC models provided higher values for some of them, similar to those related to the travel costs (*TCs*) of the RUM class in the *LC* μ*RRM* and *LC* 2μ*RRM* models, and the travel time by car (TT_{car}) of the RUM class in all the LC models. Table 4 shows similar results in relation to expected signs and parameter significance. Notably, only the TT_{car} parameter within the RUM classes of the LC models exhibited higher values.

The results of the alternative specific constants (ASCs) in all models with LOS attributes (Table 3) showed that the bus and rail alternatives were less popular than the car. It was also noted that individuals were more likely to choose public transport when sociodemographic attributes were included in the models, as shown in Table 4; an exception to this was the LC model that also had negative ASCs when sociodemographic attributes were included in the class allocation model.

The class specific constant (δ_{RRM}) was statistically significant and positive in all the LC models with LOS attributes (Table 3), showing that the population was likely to belong to the RRM class, and the opposite was found when the sociodemographic attributes were included in the class allocation model (Table 4). The shares of the class in the LC models showed that individuals had a high probability of belonging to the RRM class than to the RUM class in all models, whether the sociodemographic attributes were considered or not.

It is worth noting that the models with the generic μ parameter (μ_{gen}) indicated that individuals had a strong aversion to losses, despite its lack of significance at 95% confidence level in the μ*RRM* and μRMU models (Tables 3 and 4, respectively); however, it was significant at this level in the *LC* μ*RRM* models. Moreover, models with different values of the specific μ parameters entailed different behavior implications for each attribute. In all cases involving scale heterogeneity, μ_{TT} resulted in values

Table 3. Estimates of the Models with just LOS Attributes

	RUM	*CRRM*	*μRRM*	*2 μRRM*	*LC CRRM*	*LC μRRM*	*LC 2 μRRM*
ASC_{bus}	−0.4284**	−0.4175**	−0.5038**	−0.5369**	−0.8500**	−3.3616**	−11.3832**
ASC_{rail}	−0.2263**	−0.0802	−0.2217**	−0.2174**	−0.6296**	−1.1273**	−2.3201**
δ_{RRM}	na	na	na	na	0.5010**	0.6602**	1.3058**
RUM							
TT_{car}	−0.0364**	na	na	na	−0.1507**	−0.1000**	−0.1073**
TT_{bus}	−0.0385**	na	na	na	−0.0433**	−0.0560**	−0.0079**
TT_{rail}	−0.0240**	na	na	na	−0.0231**	−0.0267**	−0.0188**
TC	−0.3520**	na	na	na	−0.6084**	−1.1822**	−2.0818**
RRM							
TT_{car}	na	−0.0274**	−0.0276**	−0.0261**	−0.0578**	−0.0284**	−0.0342**
TT_{bus}	na	−0.0271**	−0.0264**	−0.0278**	−0.0525**	−0.0293**	−0.0345**
TT_{rail}	na	−0.0195**	−0.0196**	−0.0195**	−0.0368**	−0.0254**	−0.0266**
TC	na	−0.1982**	−0.1712**	−0.2195**	−0.1631**	−0.1006**	−0.7321**
μ_{gen}	na	na	0.1346	na	na	0.2673**	na
μ_{TT}	na	na	na	0.1814†,*	na	na	0.2217††,**
μ_{TC}	na	na	na	19.9413†,*	na	na	66.9425
π_{RUM}	100%	na	na	na	37.73%	34.07%	21.32%
π_{RRM}	na	100%	100%	100%	62.27%	65.93%	78.68%

Note: LOS = level of service; ASC = alternative specific constant; TT = travel time; TC = travel cost; RUM = random utility maximization; CRRM = classical random regret minimization; RMU = random modified utility; LC = latent class; na = not applicable.
**$p<0.05$ (t-test against 0.0000).
†$p<0.1$ (t-test against 1.0000); ††$p<0.05$ (t-test against 1.0000)

Table 4. LOS Estimates for Models with LOS + SOCIO Attributes

	RUM	CRMU	μRMU	2 μRMU	LC CRRM	LC μRRM	LC 2 μRRM
ASC_{bus}	9.5542**	9.2457**	8.6697**	9.0272**	−1.0002**	−5.3526**	−5.0186**
ASC_{rail}	6.3899**	6.0873**	5.1007**	5.9024**	−0.7864**	−5.9519**	−6.0013**
δ_{RRM}	na	na	na	na	−11.9923**	−11.0474**	−9.2453**
RUM							
TT_{car}	−0.0396**	na	na	na	−0.3130**	−0.8595**	−1.0670**
TT_{bus}	−0.0442**	na	na	na	−0.0473**	−0.0507**	−0.0590**
TT_{rail}	−0.0282**	na	na	na	−0.0281**	−0.0267**	−0.0314**
TC	−0.3139**	na	na	na	−0.5325**	−0.3969**	−0.3487**
RRM							
TT_{car}	na	−0.0308**	−0.0289**	−0.0281**	−0.0696**	−0.0692**	−0.0679**
TT_{bus}	na	−0.0301**	−0.0293**	−0.0306**	−0.0594**	−0.0868**	−0.5144**
TT_{rail}	na	−0.0217**	−0.0218**	−0.0219**	−0.0396**	−0.0558**	−0.0540**
TC	na	−0.1636**	−0.1470**	−0.1850**	−0.1387**	−0.8025**	−0.0213**
μ_{gen}	na	na	0.0613	na	na	0.2339**††	na
μ_{TT}	na	na	na	0.1361	na	na	10.5489*†
μ_{CO}	na	na	na	64.7908	na	na	50.9711
π_{RUM}	100%	na	na	na	32.33%	32.65%	35.59%
π_{RRM}	na	100%	100%	100%	67.67%	67.35%	64.41%

Note: LOS = level of service; SOCIO = sociodemographic; ASC = alternative specific constant; TT = travel time; TC = travel cost; RUM = random utility maximization; CRMU = classical random modified utility; CRRM = classical random regret minimization; RMU = random modified utility; LC = latent class; na = not applicable.
*$p<0.10$ (t-test against 0.0000); **$p<0.05$ (t-test against 0.0000).
†$p<0.1$ (t-test against 1.0000); ††$p<0.05$ (t-test against 1.0000)

Table 5. Parameter Estimates of Sociodemographic Attributes from Logit Models

	RUM	CRMU	μRMU	2 μRMU
$PEAK_{CAR}$	0.3665**	0.3400**	0.3326**	0.3001**
AGE	−0.0321**	−0.0315**	−0.0308**	−0.0309**
ED_1	−0.0465	−0.0421	−0.0281	−0.0466
ED_2	−0.3038**	−0.2564**	−0.2551**	−0.2483**
SEX_{BUS}	0.8079**	0.8024**	0.8029**	0.8074**
SEX_{RAIL}	0.5501**	0.5270**	0.5085**	0.5171**
INC_{BUS}	−0.9603**	−0.9443**	−0.8949**	−0.9431**
INC_{RAIL}	−0.5585**	−0.5277**	−0.4354**	−0.5254**
$HOUSE_{BUS}$	0.2714**	0.2638**	0.2638**	0.2611**
$HOUSE_{RAIL}$	0.2055**	0.1964**	0.1926**	0.1928**
$TRIPS_{BUS}$	−0.2381**	−0.2366**	−0.2334**	−0.2280**
$TRIPS_{BUS}$	−0.1585**	−0.1511**	−0.1429**	−0.1423**

Note: RUM = random utility maximization; RMU = random modified utility; CRMU = classical random modified utility.
**significant at 95% level of confidence.

Table 6. Parameter Estimates of the Sociodemographic Attribute of the Class Allocation Models

	LC CRRM	LC μRRM	LC 2 μRRM
$PEAK_{RRM}$	0.5226**	0.4661**	0.3163**
AGE_{RRM}	0.0531**	0.0477**	0.0364**
$ED_{1_{RRM}}$	0.1054	0.1419	0.1200
$ED_{2_{RRM}}$	0.6058**	0.5719**	0.4299**
SEX_{RRM}	−1.1214**	−1.0056**	−0.8620**
INC_{RRM}	1.2227**	1.1328**	0.9692**
$HOUSE_{RRM}$	−0.3774**	−0.3478**	−0.2876**
$TRIPS_{RRM}$	0.3207**	0.2930**	0.2292**

Note: LC = latent class; RRM = random regret minimization; CRRM = classical random regret minimization.
**significant at 95% level of confidence.

lower than 1 with statistical significance, except for the 2 μRMU model, showing that individuals imposed stronger regret in relation to travel times. Meanwhile, higher values of μ_{TC} indicated that individuals assigned equal importance to gains and losses, despite its statistical significance only in the $2\mu RRM$ model.

Furthermore, the μ parameters were not statistically significant at 95% level of confidence when the sociodemographic attributes were included in the μRMU or 2 μRMU models. Sociodemographic attributes affected the individuals' regret with regard to LOS attributes in the MNL models. However, this effect decreased when these attributes were taken into account in the choice process within the LC models (see Table 4).

The parameter estimates for the sociodemographic attributes in the MNL models are presented in Table 5. In general, similar results were found across the models for expected signs, values, and significance. The only nonsignificant parameter was the first category of education (between 8 and 10 years of study) in all models. Car was preferable to bus and rail during the morning peak and among older individuals, whereas public transportation was less favored among those with higher levels of education. Likewise, increments in household income decreased the probability of bus and rail being chosen, even though these effects were different for the two alternatives. Nevertheless, higher numbers of members within a household increased the probability of individuals choosing transit alternatives. Women were more likely to choose bus and rail, and higher numbers of daily trips increased the probability of choosing the car.

Table 6 presents the parameter estimates in the class allocation model. Only the parameter for the first category of level of education ($ED1_{RRM}$) was nonsignificant at 95% confidence level, similar to the MNL models with sociodemographic attributes. Factors such as traveling during the morning peak, being older, having higher level of education, higher income, and making more trips per day were associated with an increased likelihood of belonging to the RRM class. Being female and having more household members increased the probability of belonging to the RUM class, that is, individuals with these characteristics were more likely to maximize their utility for an alternative than minimize their regret. These findings were consistent across all the estimated LC models and exhibited similar magnitudes.

Elasticities

We calculated the elasticity measures only for models with all significant coefficients, that is, we excluded the μRRM models with nonsignificant μ parameters from the analyses. The aggregate direct point elasticities estimations are given in Table 7 (LOS) and Table 8 (LOS + SOCIO). From Table 7 it is evident that the RRM models provided the lowest elasticities compared with those based on the RUM approach, such that an increase in travel time or

Table 7. Direct Aggregate Point Elasticities for TC and TT for Model with LOS Attributes

		RUM	CRRM	μRRM	2μRRM	LC CRRM	LC μRRM	LC 2μRRM
RUM								
TC	Car	−0.94	na	na	na	−1.66	−1.55	−1.43
	Bus	−1.00	na	na	na	−1.02	−2.90	−5.41
	Rail	−1.10	na	na	na	−1.57	−3.93	−6.92
TT	Car	−0.40	na	na	na	−1.35	−0.53	−0.31
	Bus	−1.99	na	na	na	−1.35	−2.87	−0.57
	Rail	−1.20	na	na	na	−0.87	−0.69	−0.49
RRM								
TC	Car	na	−1.96	NS	−2.06	−1.55	−1.26	NS
	Bus	na	−1.25	NS	−1.43	−1.13	−0.63	NS
	Rail	na	−1.35	NS	−1.54	−1.21	−0.69	NS
TT	Car	na	−0.79	NS	−0.62	−1.00	−0.53	NS
	Bus	na	−3.27	NS	−3.45	−5.54	−3.09	NS
	Rail	na	−2.65	NS	−2.65	−4.41	−3.46	NS

Note: RUM = random utility maximization; LC = latent class; CRRM = classical random regret minimization; RRM = random regret minimization; na = not applicable; NS = attributes were not statistically significant.

Table 8. Direct Aggregate Point Elasticities for TC and TT for Model with LOS and Sociodemographic Attributes

		RUM	CRMU	μRMU	2μRMU	LC CRRM	LC μRRM	LC 2μRRM
RUM								
TC	Car	−0.83	na	na	na	−1.43	−0.56	−0.52
	Bus	−0.73	na	na	na	−0.69	−0.47	−0.36
	Rail	−0.94	na	na	na	−1.31	−0.94	−0.84
TT	Car	−0.43	na	na	na	−2.15	−2.65	−2.93
	Bus	−1.89	na	na	na	−1.14	−1.14	−1.16
	Rail	−1.33	na	na	na	−0.99	−0.98	−1.09
RRM								
TC	Car	na	−1.59	NS	NS	−1.29	−9.51	NS
	Bus	na	−0.93	NS	NS	−0.98	−5.38	NS
	Rail	na	−1.10	NS	NS	−1.04	−6.04	NS
TT	Car	na	−0.87	NS	NS	−1.13	−2.65	NS
	Bus	na	−3.38	NS	NS	−5.90	−6.59	NS
	Metro	na	−2.91	NS	NS	−4.48	−6.33	NS

Note: TC = travel cost; TT = travel time; RUM = random utility maximization; CRMU = classical random modified utility; RMU = random modified utility; LC = latent class; CRRM = classical random regret minimization; RRM = random regret minimization; na = not applicable; NS = attributes were not statistically significant.

cost significantly affected choices. The CRRM and the 2 μRRM elasticities were similar (inelastic for the car alternative in both cases), as well as for *TT* and *TC* in the MNL RUM, suggesting that travel time increments did not significantly change the probability of choosing this alternative. In addition, the LC models exhibited substantial differences compared with the MNL models, both in the RUM and RRM components. The travel time elasticity of rail was inelastic in all the RUM components of the LC models in opposition to the MNL model. This was analogous to the results for car in the LC μRRM, and bus and car in the LC 2μRRM. On the other hand, travel costs were found to be elastic for all alternatives in the LC 2μRRM for the RUM component, albeit with low values.

The outcomes of models incorporating sociodemographic attributes are presented in Table 8. The findings suggested that travel costs were inelastic for all alternatives, and for travel time only the car alternative showed inelasticity in the MNL RUM model. As for the RRM approach, only the elasticities of the MNL CRRM model are presented. In this context, the travel cost of the bus and travel time of the car alternatives were found to be inelastic. This suggested that an increase in these attributes did not significantly decrease the probability of choosing these alternatives. Similarly, the results of the LC models showed that the main difference between its RUM component and the RUM model was related to travel time by car, which was inelastic in the MNL case but elastic in all the LC models. For the RRM component, the elasticity of travel cost in the LC CRRM and all the elasticities in the LC μRRM were higher compared with the MNL CRRM model.

Conclusions and Policy Implications

Understanding the behavior processes underlying the decisions of individuals is an important task for transport policy-making. Although the RUM approach has been widely used in the field, other theories and approaches have been proposed such as the RRM, which has evolved from its first formulation to several variants such as the P-RRM and the μRRM. Although several studies have compared them, further research is required to understand the limitations and advantages of the RRM modeling paradigm, especially in the context of Global South countries such as Brazil.

This holds significant importance as urbanization and factors influencing mobility patterns vary significantly between southern and northern regions. Moreover, cities in Latin America have faced substantial adverse effects owing to the extensive reliance on individual motorized transport. Therefore, embracing innovative paradigms like the RRM becomes crucial, thus providing new perspectives on individual travel behavior. This, in turn, can aid policy makers in formulating more effective transport policies and uncovering aspects that conventional approaches, such as RUM, may have overlooked until now.

This research addressed certain gaps identified in the existing RRM literature by i) applying the approach to travel mode choice in São Paulo, Brazil, the largest city in Latin America; ii) concurrently examining heterogeneity in the decision rule and the scale regret parameter; iii) correcting the formulation for the elasticities in the μRRM model, firstly addressed by Belgiawan et al. (*10*). To achieve this, we utilized RP data obtained from a household survey conducted in the city of São Paulo, focusing on travel mode choices for commuting trips. We also presented a correct formulation for deriving elasticities and MRS of the μRRM model.

The LC μRRM model with specific μ parameters for travel time and travel cost attributes (LC 2μRRM) comprising sociodemographic attributes in the class allocation model showed the best results among the tested models. This suggests that individuals consider different strategies while choosing between travel alternatives, that is, maximizing utility or minimizing regret. For policy makers, this indicates that decisions based solely on the assumptions of one approach may not adequately address the needs of groups exhibiting one or other type of behavior.

Employing a combination of strategies derived from both approaches could be an effective method of changing mode shares, particularly in encouraging transitions from private car to public transport alternatives. Our findings indicated higher likelihood of individuals in São Paulo adopting the RRM approach (with an average probability of 66% across all LC models) as opposed to the RUM approach.

Moreover, engaging in a morning trip during peak hours, being older, having higher level of education, and greater income, as well as taking multiple trips per day, all contributed to an increased likelihood of individuals exhibiting semicompensatory behaviors. Conversely, being woman and having more household members increased the probability of belonging to the full compensatory behavior group (RUM). This pattern might be attributed to how women and larger families tend to have limited available alternatives, consequently reducing the probability of reproducing regret-related behaviors.

The RRM models demonstrated better performance than the RUM approach, regardless of the inclusion of sociodemographic attributes, in line with existing literature. Furthermore, the findings indicated that increasing flexibility in the decision process and the scale of regret significantly improved the goodness-of-fit of the estimated models. The μ parameter proved to be statistically significant when considering only minimized attributes (LOS) for the 2μRRM model and LC μRRM model, whereas for the hybrid models (LOS + SOCIO) it was significant only for the LC μRRM model.

Furthermore, a notable drawback in increasing the model complexity, that is, from MNL to LC models, was the occurrence of extreme values for elasticities in some cases, for example, in the elasticities of the RRM component of the LC μRRM model (LOS + SOCIO), and the elasticities of the RUM component of the LC 2μRRM model (LOS). Given the significance of these measures in guiding transport policies, analysts might prefer simpler models that yield more reasonable results, even at the expense of compromising improvements in model fit.

Moreover, from a policy standpoint, the findings underscored that individuals strongly dislike increases in travel time and cost. The travel cost elasticities of public transport alternatives were elastic in all models. In locations like São Paulo, where two-thirds of the population commute using both public transport and cars, alterations in transport fares and travel times could significantly influence their mode choices. In addition, the demand for travel times and costs was elastic, implying that policies affecting these attributes will have significant impacts on the demand for these alternatives.

Finally, for individuals exhibiting compensatory behavior, transport policies concentrating solely on one mode may not yield the expected results. Therefore, strategies such as the avoid-shift-improve approach could prove beneficial, emphasizing enhancements to transit and active modes through improved infrastructure, reduced travel times, and increased comfort, thereby discouraging car usage by raising its overall transport cost (*61*).

Policy making must incorporate a gender perspective, as the findings indicated higher likelihood for women to use public transport. Although such results are not novel, they underscore the importance of tailoring the planning and operation of bus and rail systems to accommodate the specific needs of women. In addition, initiatives aimed at promoting public transport should explore the use of incentives during off-peak hours, such as discounts or other types of incentives.

Future research could address the applicability of the RRM approach in diverse contexts and with alternative datasets, thereby broadening our understanding of the approach in cities across the Global South. Although some research has been conducted on this subject, the need for additional empirical evidence remains. Methodologically, it would be beneficial to explore alternative formulations of the RRM approach, such as the P-RRM model, and consider various types of heterogeneity, including unobserved taste and scale heterogeneity.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: G.P. Caldeira, C.A. Isler; data collection: G.P. Caldeira; analysis and interpretation of results: G.P. Caldeira, C.A. Isler; draft manuscript preparation: G.P. Caldeira, C.A. Isler. All authors reviewed the results and approved the final version of the manuscript.

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Supplemental Material

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