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The application of rational inattention theory in modelling residential location choices: A cross-sectional investigation using a stated preference dataset

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Abstract: The rational inattention theory aims to evaluate instances in which a decision is made in an information-rich environment where consumers cannot process all information due to limited cognitive capacity. In contrast to classical random utility-maximizing models, rational inattention discrete choice models do not assume that decision-makers make choices with complete knowledge of the alternatives. Today's information technology tools create a decision-making environment in which information is plentiful and easily accessible. Yet, it is cognitively impossible for households to be aware of every aspect of available options. This study uses rational inattention theory to investigate residential location choices in the Greater Toronto Area (GTA) during the COVID-19 pandemic, using an efficient-adaptive stated preference dataset collected in July 2021. The rational inattention theory requires identifying information processing costs and marginal probabilities as decision-makers' prior beliefs. The empirical model of this paper proposes using the time respondents spend on choice problems to measure their attention span and the latent preferences produced from the efficient-adaptive survey to measure their prior beliefs.

Keywords: rational inattention, residential location preferences, efficient-adaptive stated preference design, discrete choice models

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1 Introduction

The contribution of this study is to explore how Rational Inattention (RI) theory can be applied to discrete location choice modelling, an area where such an approach has not been widely examined. The classical Random Utility Maximization (RUM) theory, which assumes the Gumbel distribution for independent and identically distributed error terms, has formed the foundation of discrete location choice models in the literature (Schirmer et al., 2014; Zolfaghari, 2013). In RUM theory, implementing the workhorse multinomial logit model in location choice modelling imposes two major restrictive assumptions. First, the model assumes decision-makers have perfect information about all alternatives in their choice set. Second, the alternatives in their choice set satisfy the assumption of independence of irrelevant alternatives (IIA). As the alternatives in a location choice model are likely to be correlated due to unobserved spatial components, recent discrete

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location choice research focuses on relaxing the IIA assumption (Bhat & Guo, 2004; Guimaraes et al., 2004; Habib & Miller, 2009; Lee & Waddell, 2010; Sener et al., 2011). However, little attention has been devoted to addressing the rather unrealistic assumption that decision-makers make decisions with complete knowledge of all alternatives.

The rational inattention theory seeks to investigate circumstances in which information is abundant, but consumers have a limited cognitive capacity to absorb and process it. Nowadays, property listing websites, social media, and online virtual markets allow households to obtain as much information as they desire about the qualities of various listings before deciding on a future residence location. This creates a decision-making environment where information is abundant and easily accessible, yet households are cognitively unable to process all available information.

Modelling choice behavior in an information-rich environment should account for the fact that information consumes the decision-maker's attention and that an abundance of information results in a scarcity of attention (Simon, 1971). The rational inattention theory was initially proposed to model decisions involving continuous variables (Sims, 2003). Later, discrete choice models were theoretically incorporated into the theory, especially the multinomial logit model formulation by Matêjka and McKay (2015). Furthermore, the RI framework weakens the IIA assumption of the multinomial logit model by stating that for a pair of alternatives, the ratios of probabilities need only remain constant between consecutive information acquisition states instead of staying constant across all alternatives for all information acquisition states (Matêjka & McKay, 2015).

The main benefit of adopting rational inattention theory is that it relaxes the complete information assumption regarding the alternatives in a choice set. However, this benefit comes at a cost, making the RI modelling framework quite demanding regarding its data requirements, including the decision-maker's prior beliefs and heterogeneity in information processing. This article utilizes a novel Efficient-Adaptive Stated Preference (EASP) experiment for the empirical investigation. The EASP experiment meets the data needs of the rational inattention theory by capturing survey respondents' prior beliefs and heterogeneity in information processing, in addition to collecting discrete choice data on residential locations. This study uses the RI theory to efficient-adaptive cross-sectional data to investigate residential location preference in the Greater Toronto Area (GTA) post-COVID-19 pandemic era. The investigation elucidates the potential changes in residential relocation behavior in the aftermath of a pandemic.

To our knowledge, this is the first attempt to incorporate rational inattention theory into an empirical discrete choice model using cross-sectional data. The focus of prior research on rational inattention discrete choice models has been on introducing concepts and theories rather than their application (Caplin et al., 2016; Fosgerau et al., 2020; Joo, 2022; Matêjka & McKay, 2015). This paper contributes to the literature by developing an empirical discrete choice model based on rational inattention using a cross-sectional data set in the context of residential location choice.

Although this study is among the earliest attempts to develop an empirical framework incorporating rational inattention theory into discrete choice models using cross-sectional data, investigating decision-maker inattention is not a novel topic in discrete choice modeling. There has been a considerable amount of research done on attribute non-attendance in discrete choice models and choice experiments (Hensher, 2006; Hensher et al., 2005; Hensher et al., 2007; Hess et al., 2013; Rose et al., 2005; Scarpa et al., 2009). Attribute non-attendance is a form of decision-maker's inattention in which decision-makers are insensitive to particular attributes and their levels. Rational inattention provides a broader perspective on decision-maker inattention, as it does not distinguish between different types of inattention: (1) choice set inattention, where a decision-maker ignores a subset of alternatives with which they are unfamiliar; (2) attribute inattention, where a decision-maker disregards some attributes due to their perceived insignificance or limited cognitive capacity to process information; and (3) inattention to the decision environment, where the decision-maker appears disinterested in the decision-making context and exhibits passive behavior toward acquired information. Rational inattention aims to explain the decision-making process for Bayesian agents under any form of inattention. Still, the literature on attribute non-attendance has a specific objective: determining the correct marginal rate of substitutions. Consequently, rather than updating the underlying theory, the model structure is adjusted, and the decision-maker's behavior is still regarded as adhering to the random utility theory assumptions. Since the approach used in attribute non-attendance differs from that used in Rational inattention-based discrete choice, attribute non-attendance research will not be examined in further depth in this study. The work by Lew and Whitehead (2020) provides a thorough review of the current approaches to explore and model attribute non-attendance.

The paper is organized as follows: The next section reviews the literature on residential location choice from the perspective of studies with objectives similar to the RI framework. Then, the rational inattention theory's underlying principles and hypotheses are introduced. The fourth section describes the application of the RI for the Greater Toronto Area post-pandemic location choice data. The fifth part discusses the modelling results. In the final section, conclusions are provided, along with suggestions for future research.

2 Literature review

Since there are no direct applications of rational inattention theory to residential location choice, studies that employ a similar approach are reviewed in this section. The RI framework investigates the behavior of decision-makers who are not necessarily attentive to all alternatives in their choice set. In other words, rational inattentive decision-makers lack complete knowledge of their choice set and are influenced by their prior beliefs. The literature review is thus based on this assertion and covers location choice studies focused on: 1) The influence of prior beliefs on future home location choice. 2) The decision-maker's unawareness of all alternatives in the choice set.

2.1 The impact of prior beliefs on future home location choice

In the Rational Inattention (RI) framework, prior belief serves two key roles in decision-making. First, it shapes how individuals acquire and process new information. Second, it influences how past beliefs affect future choices (Caplin et al., 2016). Our examination of earlier studies on residential location preference reveals that investigations of prior belief mostly focus on the latter.

A panel study in Britain reveals that a significant proportion of residential relocations are within short distances, suggesting that people's prior belief may influence their attachments to a neighborhood over time (Böheim & Taylor, 1999). Likewise, a residential relocation preference study conducted in Denmark reveals a significant impact of prior residence on future relocation behavior, as people typically prefer to relocate to a neighborhood similar to where they grew up (ÆrØ, 2006).

Several studies in the literature that examine the effect of prior belief on future home location decisions rely on methods that, while treating residential location as a discrete variable, do not employ random utility theory as their basis (descriptive analysis, regression analysis, etc.). These studies often find inertia toward non-relocation or relocation to a comparable dwelling or neighborhood (ÆrØ, 2006; Blaauboer, 2011; Böheim & Taylor, 1999; Feijten et al., 2008; Kährik et al., 2016; Nivalainen, 2004;

Talen, 2001; Yang & O'Neill, 2014). Although such studies are the most relevant to the context of this research, there are fundamental methodological differences, as they do not focus on the nuances of the decision-making process.

The literature contains fewer studies that have attempted to incorporate the impact of prior residential experience into discrete choice models. Chen et al. (2009) utilize a distance-based generalized extreme value model to account for the historical deposition of decision-makers and spatial correlation between zones. In their proposed model, the systematic utility function coefficients are a function of a household's past location experience of marginal utilities. Their findings support the hypothesis that prior residential experience impacts location preferences. However, the influence differs among individuals, with some exhibiting tolerant behavior and inertia toward prior location experience, while others, likely those whose previous site was unsatisfactory, exhibited acquisitive behavior in their choice of future residence place (Chen et al., 2009).

Using the concept of discounted utilities in dynamic discrete choice generalized extreme value analysis, Yu et al. (2017) incorporated the influence of the previous residential location experience into examining the residential location preferences. Their study indicates that neglecting experience in residential location choice models could result in biased estimates.

This section of the literature evaluation concludes that past experiences substantially affect the future placement decisions of households and lead to heterogeneous behavior. In the rational inattention theory, prior belief is a broader concept than past residential experience. While experience only refers to the alternatives pertinent to a household's former location, prior belief covers the household's perspective on each option in their choice set. The lack of information on a household's previous beliefs in cross-sectional datasets is the fundamental cause for the absence of research on the prior state of households for every alternative in the choice set. This argument also applies to RI modelling, as reliable data for identifying prior beliefs is one of the primary obstacles associated with implementing rational inattention theory in empirical models. In the fourth section of this study, we will outline our assumptions and strategies for addressing this prevalent problem in the literature.

2.2 Awareness of all alternatives in the choice set

Because residential location choice is often associated with large choice sets, awareness of the alternatives in the choice set is a topic that has been widely explored in the literature. As perfect awareness of all alternatives does not exist in residential location choice (Chen et al., 2009), the generation of choice sets is a typical approach in the literature. This procedure determines a set of viable alternatives for particular decision-makers (Swait & Ben-Akiva, 1987). This sub-section focuses on the motivations underlying choice set generation procedures. Instead of discussing the details of choice set formation methods, it draws linkages to rational inattention theory.

The incentive for choice set formation is frequently linked to large sample sizes in the literature. Aside from including the universal choice set in the model is unrealistic regarding residential location behavior (Fotheringham, 1988; Huff, 1986, 2021), and large sample sizes in random utility discrete choice models flatten the choice probability distributions (Wegener, 2011). As a result, the models' performance will be affected by the logic behind choice set identification (Pagliara & Timmermans, 2009; van der Waerden et al., 2004). In this regard, understanding the search behavior of households is proposed as essential for identifying credible choice sets (Habib & Miller, 2007; Rashidi et al., 2012). The current study is based on similar reasoning and claims that customers' search behavior is influenced by their cognitive abilities. Consequently, a housing market with abundant information will result in diminished attention to some alternatives. As a result, consumers' limited attention will govern the alternatives they examine for their future relocation decisions.

The research on choice set formation has advanced a similar concept to customers' inattentive search behavior from a different perspective known as the two-stage choice paradigm (Manski, 1977). As per this perspective, in the first stage of the decision-making process, consumers do a non-compensatory screening to reduce the universal choice set to a handful of options, and in the second stage, they employ a compensatory approach to make a choice (Manrai & Andrews, 1998; Morikawa, 1996; Payne et al., 1993). Multiple studies in the literature on location choice modelling based their analysis on this concept to create models that are more compatible with realistic market behavior and generate more accurate results (Fatmi et al., 2016; Rashidi et al., 2012; Zolfaghari et al., 2012). While the two-staged choice paradigm effectively captures residential location preferences, it cannot reveal the full spectrum of consumer attention in the market. Understanding these nuances and analyzing the factors shaping heterogeneous market behavior due to varying levels of attention can provide valuable insights. This research contributes to the literature by demonstrating how the rational inattention discrete choice model can link consumer preferences to their attentiveness.

3 Rational inattention theory in discrete choice context

The rational inattention theory argues that rational decision-makers choose in the presence of imperfect awareness regarding the payoffs of alternatives. Therefore, they engage in a choice process with two objectives. First, they evaluate which alternatives will be used and to what extent information will be collected and processed. Second, they decide based on their prior beliefs and the signals acquired during the information acquisition phase. Since consumers have limited cognitive capacity, there will be a trade-off between the information acquisition and decision-making phases. Ultimately, this trade-off generates a decision-making environment where the customer has incomplete information regarding the available options' payoffs. The aforementioned procedure is expressed as the following optimization problem (Matêjka & McKay, 2015):

$$Max \sum_i P_i^0 \int v_i \ f(\boldsymbol{v}|i)d\boldsymbol{v} - \lambda \, I(\boldsymbol{v}, s) \quad (1)$$

subject to:

$P_i^0 \geq 0 \ ; \ \forall \boldsymbol{v} \in \mathbb{R}^N$ Marginal probabilities are non-negative real numbers. (1-1)

$\sum_{i=1}^{N} P_i^0 = 1 \ ; \ \forall \boldsymbol{v} \in \mathbb{R}^N$ Sum of marginal probabilities should be equal to one. (1-2)

$\sum_i P_i^0 f(\boldsymbol{v}|i) = G(\boldsymbol{v})$ Information acquisition is consistent with prior beliefs. (1-3)

In the above mathematical problem, the vector $\boldsymbol{v}$ is the payoffs of each alternative i. The cost of the information process by decision-makers is included via $I(\boldsymbol{v}, s)$, the information function, and λ, decision-maker's unit of information cost. Lastly, P_i^0 represents the marginal probabilities for alternative i, which includes information on the decision-maker's prior belief $G(\boldsymbol{v})$ and information cost unit λ. The intuition underlying this formulation is that decision-makers attempt to maximize their information about the expected payoffs of the alternatives relative to the cost of acquiring that information.

Finally, the decision-maker chooses the alternative with the highest expected payout based on the optimal solution to the preceding mathematical problem.

The objective function in Equation 1 is subjected to three conditions that control the formulation and the range of probabilities. Under the assumption that the information gathering process is consistent with the prior belief and the cost of information processing is determined using Shannon's entropy (Shannon, 1948):

$$I(\vec{v}, \vec{s}) = \int_{\boldsymbol{v}} \left(\sum_{i=1}^{N} P_i(\boldsymbol{v}) \cdot \log P_i(\boldsymbol{v}) \right) \cdot G(d\boldsymbol{v}) - \sum_{i=1}^{N} P_i^0 \cdot \log P_i^0 \tag{2}$$

Matêjka and McKay (2015) show that the mathematical problem (1) with Shannon's entropy (2) as its cost function will have a solution format that is comparable to the multinomial logit model:

$$P\big(i \big| E(\boldsymbol{v})\big) = \frac{P_i^0 \cdot e^{\frac{\boldsymbol{v}_i}{\lambda}}}{\sum_j P_j^0 \cdot e^{\frac{\boldsymbol{v}_j}{\lambda}}} \tag{3}$$

Based on the distribution that the modeller assumes for marginal probabilities P_i^0, the solution in Equation 3 may be either closed or non-closed form. For instance, under the assumption that P_i^0 is uniform (decision-makers do not possess prior beliefs and are irresponsive to the information signals to form their posterior belief.) and equal information process cost for all participants ($\lambda = c$); the rational inattention model converges to the conventional conditional logit random utility model (McFadden, 1978).

The sensitivity of Equation 3 to the modeller's assumption for decision-maker's prior belief and information process cost indicates that the performance of the rational inattention discrete choice model largely depends on the quality of the dataset. The rational inattention discrete choice model should, therefore, be regarded as a data-intensive technique applicable in instances where a reasonable identification of marginal probabilities P_i^0 and information cost λ is attainable.

4 The application of rational inattention

This section outlines the assumptions underlying the application of the rational inattention discrete choice model. This section is separated into two parts for this reason. In the first section, data properties are briefly summarized. The second section discusses the applicability of the rational inattention theory to the dataset, along with the model's assumptions and identification.

4.1 Efficient-adaptive stated preference data

In recent years, a body of studies has produced a wide range of methodological contributions to residential relocation choice modelling by implementing data acquired through stated preference (SP) experiments (Krueger et al., 2019; Liao et al., 2015; Russonello & Stewart, 2011; Walker & Li, 2007). Nevertheless, there is little investigation into whether the data acquired through these experiments accurately reflect actual residential relocation behavior. Generally, residential location decisions are tied to large choice sets. In such circumstances, conducting normal orthogonal SP experiments where the purpose is to balance the appearances of attribute levels in choice experiments could result in choice sets that are irrelevant to the participant. Consequently, decision-makers in such surveys are likely to demonstrate inattentiveness in a decision-making environment where they are not fully familiar with their choice set. Moreover, tracking the time participants spend on repeated orthogonal SP experiments shows that individuals lose focus on the tasks after a few choice experiments.

This study employs a modified stated preference design (efficient-adaptive) that considers participants' attentiveness by incorporating prior beliefs and present answers into scenario generation. In summary, the idea of efficient-adaptive design is to increase respondent engagement in choice experiments by generating real-time SP experiments for heterogeneous variables while maintaining the efficiency of the design for homogeneous attributes. To accomplish this, the efficient-adaptive survey seeks to forecast the likelihood that each respondent will be interested in each alternative by learning their preferences as they reply to the survey. The likelihood detected by efficient-adaptive surveys is referred to as latent preference and is based on survey questions the participant has already answered. For example, a participant's region latent preference considers their present residence, workplace, school location, adjacent neighborhoods, and responses to earlier choice scenarios. Afterward, a Monte Carlo simulation of their latent preferences generates each respondent's choice scenarios. Those interested in the specifics of the efficient-adaptive experiment designs are encouraged to read Shakib & Habib (2022).

This study implements efficient-adaptive data obtained in July 2021 to identify residential location preferences in the Greater Toronto Area post-COVID-19 pandemic. A market research panel was contracted to distribute the efficient-adaptive survey to Greater Toronto Area residents. The market research panel employed in this study used a double opt-in authentication process and cash incentives. The regional distribution of respondents was controlled and matched with the regional distribution of the latest available census population to ensure that the collected sample is representative of the population distribution in the Greater Toronto Area. The data underlying this study cannot be shared publicly as it is bound by confidentiality agreements specified in the data collection ethics approval.

4.2 RI model identification

To apply the rational inattention theory to the dataset, it is necessary to identify the prior beliefs and information process cost, which will be covered in the following section. In this empirical study, we make the following hypotheses to identify the rational inattention, discrete choice model:

1. Latent preferences obtained during the efficient-adaptive stated preference survey serve as marginal probabilities in the rational inattention discrete choice model (P_i^0 in Equation 3). According to the rational inattention theory, marginal probabilities should depend solely on prior beliefs and information costs. As a result, latent preferences that take into account respondents' previous location choices and their heterogeneity in preferences towards different neighborhoods are appropriate for identifying marginal probabilities in a rational inattention discrete choice model.
2. Information processing costs can be determined by monitoring the participant's attention span. In other words, respondents with a longer attention span can concentrate on choice tasks more easily, and, as a result, they can process more information. This assumption fits the notion that information consumes attention (Simon, 1984).
3. While cognitive capacity is expected to vary among survey participants, we assume a uniform cognitive capacity to isolate choice heterogeneity from participants'

attention spans in this study. Consequently, when a respondent takes longer to complete a choice task, a greater quantity of information is processed using their constant cognitive capacity, indicating a lower information cost unit for that individual. In technical terms, Information process cost λ has an inverse relationship with the attention span of participants in the survey.

4. The attention span of individuals varies based on the subject matter of the choice tasks. Consequently, different demographics have varying attention spans for varied topics.

Based on the four hypotheses stated above, model identification for the rational inattention discrete choice model is presented in Equation 4:

$$P_n(i) = \frac{\sqrt{LP^0_{idw} * LP^0_{irg}} \cdot e^{\frac{V_i}{\lambda_n}}}{\sum_j \sqrt{LP^0_{jdw} * LP^0_{jrg}} \cdot e^{\frac{V_j}{\lambda_n}}} \tag{4}$$

Where:

$$\lambda_n = 1/e^{att_n}$$

$$att_n = \mu_n . Y_n + \gamma_n . Z_n + \varepsilon_n$$

$$V_i = \beta_i . X_i + \alpha_{n\_rg} . rg_i$$

A closer examination of Equation 4 indicates that the rational inattention discrete choice model integrates two main models into a single function and estimates both models simultaneously. First is modelling the probability of person n choosing alternative i given the attention span att_n. The second is modelling participants' information process cost λ_n using the attention span att_n given the sociodemographic characteristics Y_n and individuals' latent attitudinal variables Z_n.

It is essential to note that attention span att_n, which is obtained from tracking the amount of time the users spend on each choice task t_n and is not an absolute measurement. For instance, it is unclear whether a respondent who spends two minutes on a choice task is attentive or inattentive without knowing the time spent by other respondents on choice tasks. Therefore, the time individuals have spent on choice tasks is scaled according to the median time $\tilde{t}$ spent on choice tasks ($att_n = t_n/\tilde{t}$). To reduce the impact of outliers on scaling, the median has been chosen over the mean for central tendency measurement.

Prior probabilities are derived directly from the efficient-adaptive SP data in the model. Terms LP^0_{idw} and LP^0_{irg} relate to an individual's latent preferences for particular dwelling types and neighborhoods. The payoff function explanatory variables V_i are constructed from SP survey attributes X_i and dummy variables for the regions rg_i which capture unobserved payoffs for each region. Since individuals are not attentive to all regions, the term α_{n_rg} , which is determined by the efficient-adaptive survey, is multiplied by each region to exclude irrelevant regions from the payoff function of each person.

For the estimation of the attention span, modellers can assume a variety of error distributions ε_n to find the optimal fit. For this investigation, we assumed a linear model with a Gaussian noise term and estimated the rational inattention model parameters (β_i , μ_n, γ_n) using the GAUSS 22 Maximum Likelihood MT package.

To provide a clearer understanding of the methodological workflow, Figure 1 presents a conceptual framework illustrating the relationship between the stated preference survey and the RI model with the presented hypotheses above.

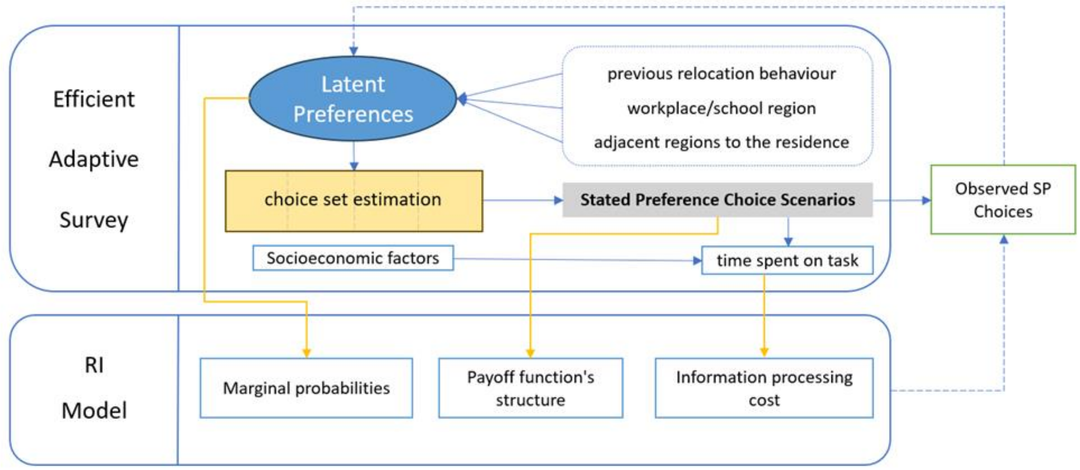


Figure 1. Conceptual framework of the proposed RI model identification

Finally, the measurement of attention span represents an important component in our model specification. We operationalize this construct using time spent on choice tasks, interpreting longer durations as indicative of more thorough information processing. This approach finds indirect support in survey methodologies that use response times to identify inattentive respondents (Brownell et al., 2015; King et al., 2019), as well as in latent class studies linking extended decision times to more systematic choice patterns under bounded rationality (Zhu & Timmermans, 2010). While this proxy advances rational inattention applications, we acknowledge that time spent may reflect not only attention but also external factors like distractions or interface familiarity. Future research using eye-tracking or other direct attentional measures could help disentangle these effects and validate the approach.

5 Empirical analysis[1]

This section presents the empirical study of the rational inattention discrete choice model utilizing the stated preference dataset gathered in the Greater Toronto Area in July 2021. In the first part of this section, the implemented SP data is introduced briefly, and in the second, the model results are discussed.

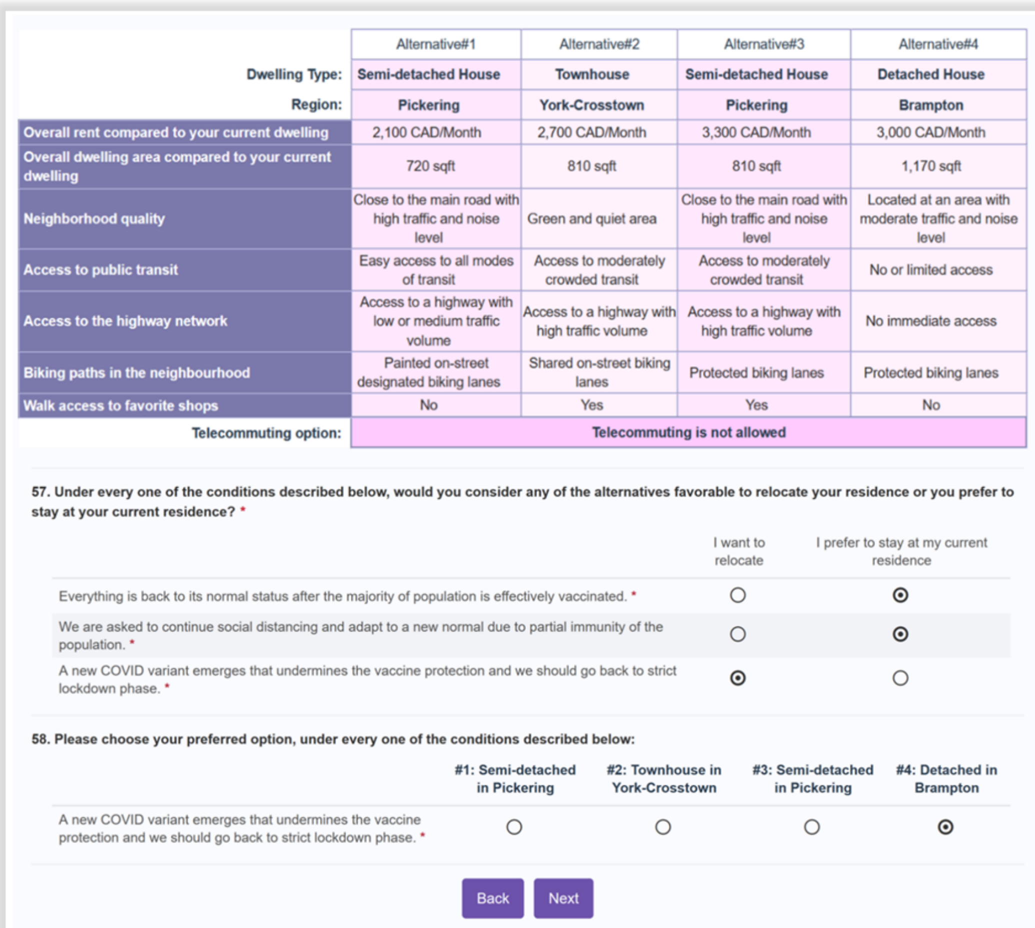
5.1 SP data

This research utilizes a residential location choice SP dataset collected using a web-based questionnaire. A local market research panel in the Greater Toronto Area was recruited to collect the data. The timeline of data collection was July 11th through July

[1] While this study focuses on the identification and empirical application of the RI model, we refer readers to (Shakib, 2023) for a technical comparison of the RI model against conventional models (e.g., MNL, Nested Logit, Scale-Mixed Logit, and Mixed Logit), evaluating its performance, challenges, and explanatory advantages when information processing costs and payoff structures are well-defined.

29th in 2021. The purpose of the survey design was to understand the residential location preferences of households and, if possible, to link relocation trends in the dataset to the COVID-19 pandemic experience of households. Thus, in addition to gathering SP data via repeated choice tasks, the survey collected data on participants' attitudes and lifestyle changes during the COVID-19 pandemic.

For data analysis, a sample of 672 respondents, each of whom had completed nine choice tasks, remained after data cleaning. Figure 2 illustrates an example of a scenario generated for a survey participant. When respondents face each table, the first question is if they are willing to relocate. Then, if they choose to move out of their existing residence, they must choose one of the available options.



	Alternative#1	Alternative#2	Alternative#3	Alternative#4
Dwelling Type:	Semi-detached House	Townhouse	Semi-detached House	Detached House
Region:	Pickering	York-Crosstown	Pickering	Brampton
Overall rent compared to your current dwelling	2,100 CAD/Month	2,700 CAD/Month	3,300 CAD/Month	3,000 CAD/Month
Overall dwelling area compared to your current dwelling	720 sqft	810 sqft	810 sqft	1,170 sqft
Neighborhood quality	Close to the main road with high traffic and noise level	Green and quiet area	Close to the main road with high traffic and noise level	Located at an area with moderate traffic and noise level
Access to public transit	Easy access to all modes of transit	Access to moderately crowded transit	Access to moderately crowded transit	No or limited access
Access to the highway network	Access to a highway with low or medium traffic volume	Access to a highway with high traffic volume	Access to a highway with high traffic volume	No immediate access
Biking paths in the neighbourhood	Painted on-street designated biking lanes	Shared on-street biking lanes	Protected biking lanes	Protected biking lanes
Walk access to favorite shops	No	Yes	Yes	No
Telecommuting option:	Telecommuting is not allowed			

57. Under every one of the conditions described below, would you consider any of the alternatives favorable to relocate your residence or you prefer to stay at your current residence? *

	I want to relocate	I prefer to stay at my current residence
Everything is back to its normal status after the majority of population is effectively vaccinated. *	○	⦿
We are asked to continue social distancing and adapt to a new normal due to partial immunity of the population. *	○	⦿
A new COVID variant emerges that undermines the vaccine protection and we should go back to strict lockdown phase. *	⦿	○

58. Please choose your preferred option, under every one of the conditions described below:

	#1: Semi-detached in Pickering	#2: Townhouse in York-Crosstown	#3: Semi-detached in Pickering	#4: Detached in Brampton
A new COVID variant emerges that undermines the vaccine protection and we should go back to strict lockdown phase. *	○	○	○	⦿

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Figure 2. A sample scenario of choice experiment design

In Figure 2, the second and third-row levels for dwelling type and region are generated using an adaptive Monte Carlo simulation based on respondents' latent preferences collected through the survey. The remaining attribute levels are derived from the efficient design. For the price and area attributes, values are calculated and provided based on the price and area of the respondent's present residence to produce comparable alternatives to the respondent's current residence. The other attributes considered in the choice tasks are neighborhood quality, public transit accessibility, highway accessibility, biking lanes in the neighborhood, telecommuting days, and walk access to favourite shops.

5.2 Model results

In the previous section, it was stated that the purpose of the survey was to discover residential location preferences in the aftermath of the COVID-19 pandemic and to establish a connection between location choice behavior and the changes participants experienced during the pandemic. This part applies a rational inattention discrete choice model to answer the aforementioned questions.

Section 4 describes the rational inattention model, which has two main outputs. First are the parameters of the payoff function, which reflect the observed residential location preferences and provide the response to the survey's primary question. The second are the factors contributing to respondents' attentiveness to choice tasks. This study uses the second group of outcomes to draw linkages between location choice behavior and pandemic experience.

5.2.1 Payoff function discussions

Each choice task required respondents to choose between five choices. One alternative is their current residence, while the remaining options are those generated by the SP survey. Literature indicates that when households consider a dwelling, they use their current residence as a reference point (Habib & Miller, 2009). Thus, the quantitative variables such as price and area are modelled relative to the price and area of the current residence. In contrast, the qualitative variables such as neighborhood quality, biking paths in the neighborhood, and so on are separated for the "no relocation" and "relocation" alternatives.

The estimation results for the payoff function and the model's overall goodness of fit are presented in Table 1. In Table 1, variables that appear in both the "no relocation" and "relocation" alternatives with different coefficients are separated and presented, starting with the name of the respective alternative.

Table 1. Rational inattention model results - payoff estimations

			95% confidence intervals	
Variable	**Estimate**	**P-Value**	**Lower limit**	**Upper limit**
Dwelling-type variables: (Base dummy: Condo apartments)				
detached	0.8288	<0.001	0.7440	0.9136
semi-detached	0.5934	<0.001	0.4970	0.6898
townhouse	0.3577	<0.001	0.2609	0.4545
Region variables: (Base dummy: Halton Hills)				
Ajax	1.7679	<0.001	1.5145	2.0213
Brampton	0.6306	<0.001	0.4439	0.8173
Downtown	1.7105	<0.001	1.5309	1.8901
East End Toronto	1.5219	<0.001	1.3489	1.6948
Etobicoke	1.1743	<0.001	1.0016	1.3470
Markham	1.5786	<0.001	1.4041	1.7532
Milton	0.9560	<0.001	0.7318	1.1801
Mississauga	0.7161	<0.001	0.5644	0.8678

Variable	Estimate	P-Value	95% confidence intervals: Lower limit	Upper limit
North York	1.3699	<0.001	1.2203	1.5194
Oakville	1.1700	<0.001	0.9580	1.3820
Oshawa	1.5970	<0.001	1.3656	1.8285
Pickering	1.8734	<0.001	1.6386	2.1081
Richmond Hill	1.8575	<0.001	1.6499	2.0651
Scarborough	1.5473	<0.001	1.3720	1.7225
Vaughan	1.3822	<0.001	1.2058	1.5587
West End Toronto	1.4643	<0.001	1.2882	1.6404
Whitby	1.6516	<0.001	1.4162	1.8871
York	1.2989	<0.001	1.0993	1.4985
SP table attributes:				
price change	-0.1126	<0.001	-0.1354	-0.0899
Floorspace area change	0.1308	<0.001	0.1108	0.1508
Neighborhood quality variables: (Base dummy: High noise level)				
no relocation: quality moderate noise	0.5768	<0.001	0.4950	0.6586
no relocation: quality green and quiet	1.0597	<0.001	0.9510	1.1683
relocation: quality moderate noise	-0.0327*	0.4349	-0.1146	0.0493
relocation: quality green and quiet	0.2897	<0.001	0.2104	0.3691
Public transit variables: (Base dummy: Limited access)				
no relocation: transit moderate access	1.3955	<0.001	1.2758	1.5153
no relocation: transit quick access	1.5452	<0.001	1.4275	1.6628
relocation: transit moderate access	-0.0124*	0.7578	-0.0909	0.0662
relocation: transit quick access	0.1283	0.001	0.0521	0.2046
Highway access variables: (Base dummy: No immediate access)				
no relocation: highway moderate access	0.0089*	0.8567	-0.0880	0.1058
no relocation: highway immediate access	0.2460	<0.001	0.1557	0.3362
relocation: highway moderate access	0.0280*	0.4882	-0.0513	0.1074
relocation: highway immediate access	-0.0238*	0.5661	-0.1052	0.0575
Biking access variables: (Base dummy: shared with auto traffic)				

Variable	Estimate	P-Value	95% confidence intervals: Lower limit	95% confidence intervals: Upper limit
no relocation: bike lane painted	0.2307	<0.001	0.1495	0.3119
no relocation: bike lane protected	0.2112	0.0002	0.1004	0.3220
relocation: bike lane painted	0.2440	<0.001	0.1695	0.3185
relocation: bike lane protected	0.2269	<0.001	0.1496	0.3041
Shopping access variable: (Base dummy: No walking access)				
shopping walk access change to yes	0.2383	<0.001	0.1881	0.2885
Telecommuting variable: (Number of available days for remote work)				
no relocation: telecommuting change	-0.0388	0.0016	-0.0628	-0.0148
Goodness of fit measures:				
Rho squared	0.4781			
Log-likelihood	-7067.13			
Log-likelihood (no predictors)	-13539.95			

*The marked coefficients in the table are statistically insignificant at the 0.05 significance level. While no behavioral inferences are drawn from the signs and magnitude of these coefficients, the results are kept for reference.

In payoff functions, dwelling-type variables are entered as dummy variables, and the reference dummy is set to condo dwelling types. The coefficients for detached, semi-detached, and townhouse dwelling types are positive and statistically significant, indicating that respondents prefer these three dwelling types to condo dwelling types. Due to the lack of comparable data on pre-pandemic dwelling type preferences in the region, it is impossible to determine whether this is a continuation of an existing trend or the effect of the pandemic experience on households. In the following section, where pandemic latent factors will be associated with respondents' attentiveness, it will be argued whether the pandemic has intensified this suburbanization tendency.

In this investigation, 19 regions represented in Figure 3 were studied. To make the payoff functions for each region identifiable, each region's payoff function was entered as a dummy variable, with the Halton Hills region acting as the reference dummy. The selection of Halton Hills as the reference region was to ensure the coefficients of other regions were positive and facilitate comparisons. The region coefficients represent unspecified payoffs not captured by the attributes in the choice tasks, and their precise nature is unclear. These dummy variables account for latent factors such as regional demographics, ethnicity, proximity to jobs, proximity to friends and family, perceived safety, and income segregation. They are not tied to geographical considerations but reflect broader regional trends in residential location preferences. According to the model outputs, Pickering and Richmond Hill have the highest coefficients, which may indicate higher overall demand for these regions. This aligns with market data from the Toronto Regional Real Estate Board (2021), which shows that Pickering and Richmond Hill have the highest benchmark prices in York and Durham municipalities among the neighborhoods included in this study.

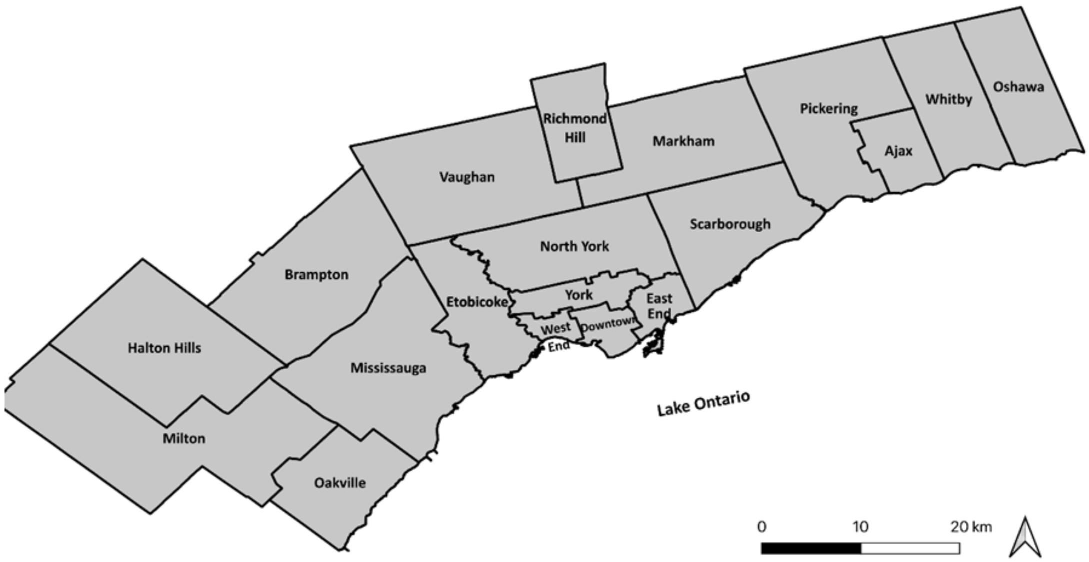

Figure 3. SP regions in the Greater Toronto Area

Regarding the attributes in the choice tasks, coefficient values are found to be indicative of the expected behavior. The coefficients for the price and area variables entered the model relative to the current property prices were negative and positive, respectively. In other words, the payoff for the decision-maker would be greater if they could obtain larger square footage for a lower price if all other features remain fixed.

The "quality" attribute has been incorporated as dummy variables for the "no relocation" and "relocation" payoff alternatives separately, with the lowest quality level set as the reference value. For relocating households, quality improvements in housing do not influence their decision unless they move from a low-quality neighborhood to a future high-quality one. This finding also suggests that households already living in mid- to high-quality neighborhoods are unlikely to relocate solely to increase neighborhood quality.

Regarding the accessibility of public transportation attributes, the model predicts comparable results to the neighborhood quality results. Households are only willing to move to a new residence if they increase the accessibility of their current residence to public transportation from the lowest level (reference dummy) to the highest level. The payoff values for the "no relocation" alternative are higher than those for the relocation alternatives, reflecting respondents' stronger preference for their current residences.

The findings of the highway accessibility attribute demonstrate respondents' indifference towards highway accessibility improvements for their future residence. Similar to transportation accessibility, the lowest level of accessibility was assigned as the reference dummy variable. However, the results do not indicate a tendency to relocate if the only enhancement to the dwelling type is its proximity to the highway network. This finding may reflect the specific context of the GTA, which is known for its highly congested highway systems. For residents, proximity to highways may not necessarily translate into improved accessibility due to frequent congestion, potentially reducing its perceived value. Additionally, the insignificance of highway accessibility in our study does not imply a reversal of its role in land-use models. Rather, it suggests that, within our hypothetical scenarios, it was deemed less influential compared to other attributes such as housing type, price, and neighborhood characteristics. This highlights the importance of contextual factors and the need to prioritize attributes based on local conditions and resident preferences.

Not having bike lanes was the reference dummy variable for the biking attribute. The model results indicate that respondents are concerned with improving the availability of bicycle pathways in their prospective relocation. Still, they do not differentiate between off-street and on-street biking trails. This finding is consistent with earlier research conducted in the Greater Toronto Area (Habib et al., 2014). In addition, an earlier study on cyclists' attitudes toward on-street and off-street bike lanes indicates that cyclists' preferences for off-street and on-street biking lanes depend on the geometry and traffic of the road (Li et al., 2012).

The model examines telecommuting's impact on residential preferences through the no-relocation payoff function. The negative coefficient for increased telecommuting days suggests respondents with more remote workdays showed a greater likelihood of relocating. This finding aligns with the broader phenomenon where mandatory telecommuting during the pandemic may have enabled residential mobility in the Greater Toronto Area by decoupling work location from home location. However, our study uses data collected in Summer 2021, reflecting a period when telecommuting was largely mandatory rather than voluntary. Future research should examine how residential preferences evolve as telecommuting transitions from a pandemic necessity to an optional work arrangement, including investigating its long-term adoption patterns in post-pandemic society.

The payoff function findings show the homogenized residential preferences in the area and generate results comparable to the conventional random utility-based discrete choice models. The major advantage of the rational inattention model will be highlighted in the subsequent section, in which respondents' decision behavior will be differentiated according to their demographic and altitudinal factors in choice tasks.

5.2.2 Attentiveness discussions

In classical random utility-maximizing discrete choice models, heterogeneity in choice behavior is commonly captured using mixed logit models by permitting random distribution of coefficients. Although mixed logit models identify variations in preferences, they cannot pinpoint the origins of the observed heterogeneity because they rely on simulation approaches for estimation. In the context of scale heterogeneity in generalized multinomial logit models (G-MNL) (Fiebig et al., 2010), the model does not identify the scale parameter separately, and the sources of variation could well be correlated with other parameters in the model. Accordingly, sources of scale heterogeneity are not distinguishable in G-MNL models. Nevertheless, rational inattention discrete choice models identify the scale parameter as the information processing unit. In contexts where data is available, these models can reveal the spectrum of heterogeneous behavior in terms of which behavior is associated with which group of decision-makers.

The rational inattention discrete choice model allocates rational customers depending on their attentiveness to a spectrum of rational consumers. Before discussing the results of this empirical investigation, it is necessary to explain the intuition behind the different information process cost λ values in the model. To clarify how λ values help identify respondent attentiveness, we introduce the choice behavior among rational consumers for the two extreme values of λ.

The rationally perfectionist consumer ($\boldsymbol{\lambda \to 0^+}$): When the information processing unit cost is infinitesimally small, consumers are willing to receive an abundance of information signals to update their prior beliefs regarding the alternatives in their choice set. Due to the impossibility of acquiring perfect knowledge, these customers are permanently in the process of gathering data and would never settle on a decision.

The rationally inattentive consumer ($\boldsymbol{\lambda \to +\infty}$): When the cost per unit of information processing approaches infinity, consumers find the task of information processing overwhelming. A fully rational, inattentive consumer takes no effort to create a posterior belief. This type of consumer makes a snap judgment based on their prior beliefs and does not value additional information.

These two described behaviors represent opposite ends of the spectrum of attentiveness. The information processing cost unit is conceptual and cannot be linked to absolute measurements. However, relative metrics can be developed using reference behavior to differentiate consumer attention discrepancies.

Section 4 established a connection between attention span and information processing. Since the time spent on a choice task does not give any information about the origins of heterogeneity, sociodemographic and latent attitudinal variables are included as explanatory variables. While sociodemographic characteristics provide valuable insights, our analysis reveals that they alone cannot explain heterogeneity in information processing costs. This underscores the importance of incorporating latent attitudinal variables, which capture additional dimensions of individual differences, to understand the complexity of decision-making behavior better. In this empirical study, the combined effects of sociodemographic characteristics and latent variables reflecting a person's pandemic experience on the attention span of respondents during choice tasks are investigated.

Pandemic-related factors are included in the modeling of attention span by deriving latent variables using factor analysis from questions about respondents' attitudes and lifestyle changes during the pandemic. Exploratory Factor Analysis (EFA) is conducted to evaluate the correlation structure of the responses to the pandemic questions. The optimal number and combination of latent factors are determined using parallel analysis and the maximum likelihood method. Regarding EFA's reliability tests, Cronbach's Alpha values for two suggested factors satisfy the 0.70 threshold (Kline, 2015). Then, a Confirmatory Factor Analysis (CFA) is done to validate the latent factor structure and ensure the consistency of EFA-derived factors. CFA results for the final latent factor structure, loadings, and reliability measurements are presented in Table 2.

Table 2. Factor structure and factor loadings

Factors structure[a]	**Factor Loadings**
Factor 1: Pandemic fear factor (Cronbach's α = 0.897)	
Concerned about the high number of active COVID-19 cases	1.000
Concerned about emergence of a new COVID-19 variant	0.978
Concerned about the possible increase in COVID-19 mortality rates	0.950
Concerned about the low rate of COVID-19vaccination rates in the population	0.812
Concerned about the possible low efficiency of COVID-19 vaccines	0.790
Factor 2: Change in daily routines during the pandemic (Cronbach's α = 0.865)	
Having to follow social distancing rules often in daily activities	1.000
Significant effect of lockdown on daily activities	1.057
Having to avoid social gatherings regularly	1.154
Using the mask for long periods during daily activities	0.978
Goodness-of-fit measures for CFA	
Root Mean Square Error (RMSE)	0.079
Standardized Root Mean Square Residual (SRMR)	0.045
Tucker-Lewis Index (TLI)	0.934
Comparative Fit Index (CFI)	0.952

a- All questions in the defined factors are in a five-level Likert scale

Subsequently, the latent factors defined by the confirmatory factor analysis were included beside sociodemographic variables and the rational inattention model in Equation 4 was estimated simultaneously for attention span and residential preferences. Table 3 displays the estimation findings for the information process cost heterogeneity.

Table 3. Rational inattention model results - attention span estimations

Variable
Gender: male
Household type[a]: couple no children
Household type: single individual
Household type: roommates
Pandemic fear factor[b]
Pandemic lifestyle change factor[c]

a- Household type entered the model as dummy variables, and the dummy reference is "Family with children."

b- A latent variable derived from Table 2 which measures respondents' level of concern about COVID-19 case counts and vaccination status.

c- A latent variable derived from Table 2 which captures the degree to which respondents' daily routines were disrupted during the pandemic

The coefficients in Table 3 estimate respondents' attention span in the choice tasks as the dependent variable, which has an inverse relationship with information processing costs (i.e., higher attention span = lower processing costs). A positive coefficient indicates a greater attention span and lower information processing costs.

For the gender variable, the reference value is set to female. A negative sign for men implies that males, compared to females, are more likely to exhibit inattentive behavior than perfectionist behavior while making residential location decisions. This discovery can be analyzed differently when considering interval estimations in the payoff function in Table 1. For example, for the gender variable, men have larger information processing values, which results in narrower predicted coefficient ranges. Consequently, one may conclude men's residential location preferences are less variable and more consistent compared to women.

Using the data in Table 3, it is possible to link the respondents' pandemic experience to their residential choice behavior. The model results suggest that individuals who were more fearful of the pandemic, as measured by their responses to attitudinal questions regarding their concern over case counts and vaccination status, were less likely to be interested in relocating. On the other hand, respondents whose daily routines were substantially disrupted during the pandemic—for a given level of pandemic fear—appeared more attentive and flexible in choice tasks, showing a greater willingness to contemplate relocation. While this finding aligns with the idea that significant disruptions to the status quo may prompt individuals to reconsider their living situations, it is important to acknowledge the possibility of noise in captured variations or unobserved factors influencing these results. Further research would be needed to validate and understand the underlying mechanisms driving this behavior.

Combining all information in Table 3, it is possible to determine which set of respondents exhibits behavior closest to the two extreme ends of the rational inattention model. For this empirical investigation on residential location preferences, the closest group to rational perfectionist behavior consists of females who live alone and whose lifestyles have altered significantly after the COVID-19 pandemic. Still, they do not exhibit fear of the pandemic status. This group was the most adaptable in shifting their residence and participated actively in the choice tasks. In contrast, the least attentive respondents in the choice scenarios were men who lived in households with children who feared the pandemic the most and whose daily routines have not changed dramatically since the COVID-19 outbreak began.

6 Conclusions

This research proposed and implemented a framework for a rational inattention discrete choice model for residential location preferences. Currently, discrete choice models are predominantly based on conventional random utility maximization models that assume error terms are independent, identically distributed, and follow the Gumble distribution. Consequently, the work in this field is influenced by the constraints of the assumptions regarding the sources of randomness. In this regard, McFadden et al. (1999) state: "most cognitive anomalies operate through errors in perception that arise from the way information is stored, retrieved, and processed." Thus, rational inattention, from a random utility perspective, is a theory that ties the sources of randomness in the random utility theory to the process in which decision-makers receive information. This ambitious quest leads to a data-demanding modelling approach that requires the modeller to identify the decision-maker's prior beliefs and information process cost heterogeneity. For identifying prior beliefs and information process cost heterogeneity, the empirical model provided in this paper uses latent preferences generated from efficient-adaptive survey data and the amount of time respondents spent on the choice task. However, researchers can also make other assumptions satisfying the rational inattention model's requirements.

The empirical application of rational inattention theory illustrated in this study offers a novel contribution to policymaking by enabling targeted policy design. This approach allows for detailed behavioral analysis, revealing how policies impact different demographic groups based on their attentiveness. By identifying which groups are most attentive in each choice environment, policymakers can predict which populations will be most responsive to policy changes. This insight facilitates the creation of targeted policies that address the unique needs and challenges of specific demographics. However, it is important to note that the empirical findings in this study are hypothetical and based on stated preference data. While conclusive statements about real-world policymaking, such as in the context of COVID-19-induced residential relocation choices, cannot be made, the theoretical framework provides a foundation for future applications.

The key findings of this empirical study can be separated into two categories: payoffs and attentiveness. Payoff function findings are equivalent to traditional random utility discrete choice models regarding policy implications. The attentiveness analysis, which captures response heterogeneity, creates the difference. From the perspective of policy implications, the attentiveness findings can reveal which groups of individuals will most affect the policy inferred by payoff analysis. This is why the respondent's attention span was not directly utilized in model identification but instead was linked to demographic variables and pandemic latent factors.

In terms of residential location preferences, the overall findings indicated the unwillingness of households to relocate. Cases in which households were eager to move were solely associated with circumstances in which a household could change an attribute of their residence from the worst to the best category (except for highway accessibility). Regarding the telecommuting factor, it was observed that offering more telecommuting days increases the possibility of a relocation decision.

This research also investigated linking participants' attentiveness to explanatory variables through a separate estimation of information processing cost by monitoring respondents' attention span. A Gaussian noise model was assumed for the attention span, and sociodemographic and pandemic-related factors were examined. Regarding sociodemographic characteristics, it was observed that females living alone are the most attentive respondents and the most flexible in relocating their residences.

For the pandemic-related variables, it was discovered that individuals who are more concerned with the current and future state of the pandemic are less likely to relocate. On the other hand, people whose daily habits were considerably altered by the pandemic displayed greater interest and involvement in residential relocation choice tasks. The current findings on attentiveness only apply to residential preferences; a change in the subject of decision-making could shift individuals along the attentiveness spectrum toward perfectionism or inattentiveness.

The primary recommendation offered by the authors for future studies that want to implement the rational inattention discrete choice model is the selection of a balanced and suitable attentiveness measuring approach. As attention values are scale parameters in the choice model, they will likely induce estimation instability. Using a measurement method that excessively diversifies the attentiveness of the participants increases the likelihood of the presence of outliers in the attention spectrum. Outliers generate extreme values in the model estimation calculations, challenging the numerical calculation of the gradient and Hessian matrix. Future research seeking measurement methods for information processing heterogeneity should consider the trade-off between adding more details to the attention spectrum and the stability of numerical optimization of model estimation.

Future research could address and improve the limitations of the current study. One of the primary shortcomings of the current study is the modelling approach's failure to account for the impact of the housing market on respondents' decisions. This study's methodology creates an unrealistic choice environment that disregards market competition and assumes the respondent's desired residence is always available on the market. Another weakness of this study is that the possible changes in telecommuting social acceptance during the pandemic are not incorporated in the modelling. As a result, the reported conclusions about the telecommuting effect are subject to future changes in how telecommuting is conceived and embraced.

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Author contribution

The authors confirm their contribution to the paper as follows: study conception and design: K. M. N. Habib; data collection: S. Shakib; analysis and interpretation of results: S. Shakib and K. M. N. Habib; draft manuscript preparation: S. Shakib and K. M. N. Habib. All authors reviewed the results and approved the final version of the manuscript.

Data availability

The original data was obtained through a market research panel in July 2021, where a Stated Preference (SP) survey was distributed to residents of the Greater Toronto Area. The data was collected in digital survey format and contains detailed information on respondents' socio-demographic attributes, residential locations, and adaptive choice experiment responses regarding post-COVID-19 relocation preferences. The data underlying this study cannot be shared publicly due to confidentiality and ethical restrictions associated with the survey's collection and participant privacy protections.

References

ÆrØ, T. (2006). Residential choice from a lifestyle perspective. *Housing, Theory and Society, 23*(2), 109–130. https://doi.org/10.1080/14036090600773139

Bhat, C. R., & Guo, J. (2004). A mixed spatially correlated logit model: formulation and application to residential choice modeling. *Transportation Research Part B: Methodological, 38*(2), 147–168. https://doi.org/10.1016/S0191-2615(03)00005-5

Blaauboer, M. (2011). The impact of childhood experiences and family members outside the household on residential environment choices. *Urban Studies, 48*(8), 1635–1650. https://doi.org/10.1177/0042098010377473

Böheim, R., & Taylor, M. (1999). *Residential mobility, housing tenure and the labour market in Britain*. Institute for Social and Economic Research, University of Essex.

Brownell, B., Cechanowicz, J., & Gutwin, C. (2015). Gamification of survey research: Empirical results from gamifying a conjoint experiment. In *Gamification in education and business* (pp. 569–591). Springer International Publishing. https://doi.org/10.1007/978-3-319-10208-5_29

Caplin, A., Leahy, J., & Matejka, F. (2016). *Rational inattention and inference from market share data.* [Unpublished Working Paper]. NYU and CERGE-EI.

Chen, C., Chen, J., & Timmermans, H. (2009). Historical deposition influence in residential location decisions: A distance-based GEV model for spatial correlation. *Environment and Planning A*, *41*(11), 2760–2777. https://doi.org/10.1068/a41323

Fatmi, M. R., Chowdhury, S., & Habib, M. A. (2016). *A two-stage panel model of residential search and location choice decisions*. Transportation Research Board.

Feijten, P., Hooimeijer, P., & Mulder, C. H. (2008). Residential experience and residential environment choice over the life-course. *Urban Studies*, *45*(1), 141–162. https://doi.org/10.1177/0042098007085105

Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The generalized multinomial logit model: Accounting for scale and coefficient heterogeneity. *Marketing Science*, *29*(3), 393–421. https://doi.org/10.1287/mksc.1090.0508

Fosgerau, M., Melo, E., de Palma, A., & Shum, M. (2020). Discrete choice and rational inattention: A general equivalence result. *International Economic Review*, *61*(4), 1569–1589. https://doi.org/10.1111/IERE.12469

Fotheringham, A. S. (1988). Note—consumer store choice and choice set definition. *Marketing Science*, *7*(3), 299–310. https://doi.org/10.1287/mksc.7.3.299

Guimaraes, P., Figueiredo, O., & Woodward, D. (2004). Industrial location modeling: Extending the random utility framework. *Journal of Regional Science*, *44*(1), 1–20. https://doi.org/10.1111/J.1085-9489.2004.00325.X

Habib, K. N., Mann, J., Mahmoud, M., & Weiss, A. (2014). Synopsis of bicycle demand in the City of Toronto: Investigating the effects of perception, consciousness and comfortability on the purpose of biking and bike ownership. *Transportation Research Part A: Policy and Practice*, *70*, 67–80. https://doi.org/10.1016/j.tra.2014.09.012

Habib, M. A., & Miller, E. J. (2007). *Modeling residential and spatial search behaviour: Evidence from the greater Toronto area*. Paper presented at the 6th Triennial Symposium on Transportation Analysis, Phuket Island, Thailand.

Habib, M. A., & Miller, E. J. (2009). Reference-dependent residential location choice model within a relocation context. *Transportation Research Record*, *2133*(1), 92–99.

Hensher, D. A. (2006). Attribute processing in choice experiments and implications on willingness to pay. *Valuing Environmental Amenities Using Stated Choice Studies*, 135–157. https://doi.org/10.1007/1-4020-5313-4_6

Hensher, D. A., Rose, J., & Bertoia, T. (2007). The implications on willingness to pay of a stochastic treatment of attribute processing in stated choice studies. *Transportation*

Research Part E: Logistics and Transportation Review, *43*(2), 73–89. https://doi.org/10.1016/J.TRE.2005.07.006
Hensher, D. A., Rose, J., & Greene, W. H. (2005). The implications on willingness to pay of respondents ignoring specific attributes. *Transportation, 32*(3), 203–222. https://doi.org/10.1007/S11116-004-7613-8
Hess, S., Stathopoulos, A., Campbell, D., O'Neill, V., & Caussade, S. (2013). It's not that I don't care, I just don't care very much: Confounding between attribute non-attendance and taste heterogeneity. *Transportation*, *40*(3), 583–607. https://doi.org/10.1007/s11116-012-9438-1
Huff, J. O. (1986). Geographic regularities in residential search behavior. *Annals of the Association of American Geographers*, *76*(2), 208–227. https://doi.org/10.1111/j.1467-8306.1986.tb00113.x
Huff, J. O. (2021). Spatial aspects of residential search. In *Modelling housing market search* (pp. 106–129). Routledge.
Joo, J. (2022). Rational inattention as an empirical framework for discrete choice and consumer-welfare evaluation. *Journal of Marketing Research*, *60*(2). https://doi.org/10.1177/00222437221110173
Kährik, A., Temelová, J., Kadarik, K., & Kubeš, J. (2016). What attracts people to inner city areas? The cases of two post-socialist cities in Estonia and the Czech Republic. *Urban Studies*, *53*(2), 355–372. https://doi.org/10.1177/0042098014567444
King, C. V., Labas, R., & Renaudin, C. (2019). Using conjoint analysis to understand preference for online survey layout. *International Journal of Market Research*, *61*(6), 621–634. https://doi.org/10.1177/1470785319873249
Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
Krueger, R., Rashidi, T. H., & Dixit, V. V. (2019). Autonomous driving and residential location preferences: Evidence from a stated choice survey. *Transportation Research Part C: Emerging Technologies*, *108*(October), 255–268. https://doi.org/10.1016/j.trc.2019.09.018
Lee, B. H. Y., & Waddell, P. (2010). Residential mobility and location choice: A nested logit model with sampling of alternatives. *Transportation*, *37*(4), 587–601. https://doi.org/10.1007/s11116-010-9270-4
Lew, D. K., & Whitehead, J. C. (2020). Attribute non-attendance as an information processing strategy in stated preference choice experiments: Origins, current practices, and future directions. *Marine Resource Economics*, *35*(3), 285–317. https://doi.org/10.1086/709440
Li, Z., Wang, W., Liu, P., & Ragland, D. R. (2012). Physical environments influencing bicyclists' perception of comfort on separated and on-street bicycle facilities. *Transportation Research Part D: Transport and Environment*, *17*(3), 256–261. https://doi.org/10.1016/j.trd.2011.12.001
Liao, F. H., Farber, S., & Ewing, R. (2015). Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis. *Urban Studies*, *52*(2), 314–337. https://doi.org/10.1177/0042098014527138
Manrai, A. K., & Andrews, R. L. (1998). Two-stage discrete choice models for scanner panel data: An assessment of process and assumptions. *European Journal of Operational Research*, *111*(2), 193–215. https://doi.org/10.1016/S0377-2217(98)00145-3
Manski, C. F. (1977). The structure of random utility models. *Theory and Decision*, *8*(3), 229.

Matêjka, F., & McKay, A. (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review*, *105*(1), 272–298. https://doi.org/10.1257/AER.20130047

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, *673*, 72–77. https://onlinepubs.trb.org/Onlinepubs/trr/1978/673/673-012.pdf

McFadden, D., Machina, M. J., & Baron, J. (1999). Rationality for economists? *Elicitation of Preferences*, 73–110. https://doi.org/10.1007/978-94-017-1406-8_4

Morikawa, T. (1996). A hybrid probabilistic choice set model with compensatory and noncompensatory choice rules. In *World transport research: Proceedings of the 7th World Conference on Transport Research* (Vol. 1). Pergamon.

Nivalainen, S. (2004). Determinants of family migration: Short moves vs. long moves. *Journal of Population Economics*, *17*(1), 157–175. https://doi.org/10.1007/s00148-003-0131-8

Pagliara, F., & Timmermans, H. (2009). Choice set generation in spatial contexts: A review. *Transportation Letters, 1*(3), 181–196. https://doi.org/10.3328/TL.2009.01.03.181-196

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.

Rashidi, T. H., Auld, J., & Mohammadian, A. K. (2012). A behavioral housing search model: Two-stage hazard-based and multinomial logit approach to choice-set formation and location selection. *Transportation Research Part A: Policy and Practice*, *46*(7), 1097–1107. https://doi.org/10.1016/j.tra.2012.01.007

Rose, J. M., Hensher, D. A., & Greene, W. H. (2005). Recovering costs through price and service differentiation: Accounting for exogenous information on attribute processing strategies in airline choice. *Journal of Air Transport Management*, *11*(6), 400–407. https://doi.org/10.1016/J.JAIRTRAMAN.2005.05.005

Russonello, B., & Stewart, L. (2011). *Community preference survey: What Americans are looking for when deciding where to live*. National Association of Realtors.

Scarpa, R., Gilbride, T. J., Campbell, D., & Hensher, D. A. (2009). Modelling attribute non-attendance in choice experiments for rural landscape valuation. *European Review of Agricultural Economics*, *36*(2), 151–174. https://doi.org/10.1093/ERAE/JBP012

Schirmer, P. M., Van Eggermond, M. A. B., & Axhausen, K. W. (2014). The role of location in residential location choice models: A review of literature. *Journal of Transport and Land Use*, *7*(2), 3–21. https://doi.org/10.5198/jtlu.v7i2.740

Sener, I. N., Pendyala, R. M., & Bhat, C. R. (2011). Accommodating spatial correlation across choice alternatives in discrete choice models: An application to modeling residential location choice behavior. *Journal of Transport Geography 19*(2), 294–303. https://doi.org/10.1016/j.jtrangeo.2010.03.013

Shakib, S. (2023). *Capturing residential preference changes through perception detections of rationally inattentive decision makers* [Doctoral thesis, University of Toronto]. TSpace, University of Toronto. http://hdl.handle.net/1807/129971

Shakib, S., & Habib, K. M. N. (2022). *A hybrid efficient-adaptive choice experiment design for investigating post COVID-19 pandemic residential mobility and location choice in Greater Toronto Area.* Paper presented at the Transportation Research Board 101st Annual Meeting, Washington, DC.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Simon, H. A. (1971). Designing organizations for an information-rich world. *Computers, Communications, and the Public Interest*, *72*, 37.

Simon, H. A. (1984). *Models of bounded rationality, volume 1: Economic analysis and public policy*. MIT Press Books.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, *50*(3), 665–690. https://doi.org/10.1016/S0304-3932(03)00029-1

Swait, J., & Ben-Akiva, M. (1987). Incorporating random constraints in discrete models of choice set generation. *Transportation Research Part B: Methodological, 21*(2), 91-102. https://doi.org/10.1016/0191-2615(87)90009-9

Talen, E. (2001). Traditional urbanism meets residential affluence: An analysis of the variability of suburban preference. *Journal of the American Planning Association*, *67*(2), 199–216. https://doi.org/10.1080/01944360108976229

Toronto Regional Real Estate Board. (2021). MLS ® Home Price Index MLS HPI ®. Retrieved from https://trreb.ca/market-data/mls-home-price-index/mls-home-price-index-archive/

van der Waerden, P., Borgers, A., & Timmermans, H. (2004). *Cyclists' perception and evaluation of street characteristics.* Paper presented at the 83rd Annual Meeting of the Transportation Research Board (A3B07-Commitee on Bicycle Transportation), Washington, DC.

Walker, J. L., & Li, J. (2007). Latent lifestyle preferences and household location decisions. *Journal of Geographical Systems*, *9*(1), 77–101. https://doi.org/10.1007/s10109-006-0030-0

Wegener, M. (2011). *The IRPUD model* [Working paper]. Spiekermann & Wegener Urban and Regional Research.

Yang, Y., & O'Neill, K. (2014). Understanding factors affecting people's attitudes toward living in compact and mixed-use environments: A case study of a New Urbanist project in Eugene, Oregon, USA. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, *7*(1), 1–22. https://doi.org/10.1080/17549175.2013.827585

Yu, B., Zhang, J., & Li, X. (2017). Dynamic life course analysis on residential location choice. *Transportation Research Part A: Policy and Practice*, *104*, 281–292. https://doi.org/10.1016/j.tra.2017.01.009

Zhu, W., & Timmermans, H. (2010). Modeling simplifying information processing strategies in conjoint experiments. *Transportation Research Part B: Methodological*, *44*(6), 764–780. https://doi.org/10.1016/j.trb.2009.12.007

Zolfaghari, A. (2013). *Methodological and empirical challenges in modelling residential location choices* [Doctoral thesis, Imperial College London]. Spiral repository, Imperial College London. https://doi.org/10.25560/12565

Zolfaghari, A., Sivakumar, A., & Polak, J. W. (2012). Choice set pruning in residential location choice modelling: A comparison of sampling and choice set generation approaches in greater London. *Transportation Planning and Technology*, *35*(1), 87–106. https://doi.org/10.1080/03081060.2012.635420