Pricing the Unseen: Revenue Management under Rationally Inattentive Travellers

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SHORT SUMMARY

Ongoing research in transport modelling is gradually shifting from the traditional Rational Expectations framework, premised on the assumption of fully informed, optimizing, and self-interested decision-makers, to a more nuanced understanding of traveller behaviour under Bounded Rationality. However, the focus is typically targeted on developing advanced choice models to forecast travellers' behaviour, with less emphasis on the subsequent response of competing suppliers. Recognizing the cognitive cost of acquiring and processing information (e.g., price, travel time) this paper explores the implications of Rational Inattention in the context of revenue management from the perspective of the transport service provider. Through a series of numerical experiments, we compare optimal pricing strategies in a duopolistic taxi/ride-hailing market, contrasting the outcomes derived from neoclassical models with those incorporating information capacity constraints and the formulation of prior, unconditional probabilities of choice. Our findings suggest that traditional Random Utility models (e.g., MNL) might overestimate the market share capture of minor, economical market players, failing to account for the influence of prior perceptions, and the scarcity of consumers' attentional resources. This can lead to suboptimal pricing strategies, especially when introducing heterogeneity in the population. Through the analysis of varying levels of information acquisition cost, we observe a distinct advantage accruing to established providers, which is magnified as information costs increase, when other profitable opportunities are easily missed. Interestingly, beyond a certain threshold, minor competitors are also incentivized to obfuscate their pricing, leading to mutually profitable obfuscation pricing strategies and underscoring the need for market regulation. By incorporating discrete choice models of Rational Inattention into revenue management, this paper contributes to an alternative, potentially more realistic portrayal of travel demand and supply interaction, highlighting biases in conventional forecasts and identifying risks related to the exploitation of travellers' cognitive capacity constraints.
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Keywords: Choice modelling, Revenue management, Optimal pricing, Rational inattention, Information constraints

1. INTRODUCTION

The field of transportation planning and policy is typically reliant on predictive models that delineate and anticipate the behavioural patterns of travellers. Traditionally based on the Rational Expectations theory of economics, these models are grounded on the assumption that decision-makers are optimizing, strategic, and self-motivated in their choices. This conventional paradigm, however, does not sufficiently account for the observed inertia and aversion to change in travel behaviour under conditions of uncertainty, nor for the presence of strong prior beliefs formed through, for example, the accumulation of experience or observation of other travellers. Several theories have emerged as alternatives, aiming at extending the scope of rationality. Prominent examples include Bounded Rationality (Simon, 1955), Prospect Theory (Kahneman and Tversky, 1979), and lately Rational Inattention (Sims, 2003).

The rising interest in the Rational Inattention (RI) hypothesis, initially proposed by Christopher Sims in 2003, introduces a nuanced explanation for the above phenomena. The theory entails that individuals may intentionally select what appear to be suboptimal decisions, influenced by information costs associated with the acquisition and processing of information. Expanding upon this premise, Matejka and McKay in 2015 applied the RI hypothesis to discrete choice models, under the constraints of imperfect information and cognitive limitations. This progression in theoretical understanding has brought RI to a prominent position, providing a framework for analysing decision-making processes in complex and dynamic transportation settings. Notable past applications of the theory in transportation include the work of Fosgerau (2019), and subsequently Jiang (2020), who focused on route and departure time choice under the RI framework and presented a series of numerical experiments. Fosgerau et al. (2020) proceeded to establish the general equivalence between Random Utility (RUM) and RI models, creating an alternative point of view in the interpretation of conventional modelling methods. In terms of empirical applications, Habib (2022) concentrated on the estimable use-cases of discrete choice models within the Rational Inattention framework, and specifically the RI-MNL and RI-NL models.

With the landscape of transport services offerings becoming more diverse, an evolving field of application for behavioural models is the examination of choice within the context of a systems' optimisation. While revenue management has been discussed in transport for decades, initial efforts assumed decision-making being deterministic or implemented model simplifications and linearization with tractable representations (e.g. Talluri and Ryzin, 2004; Andersson, 1998) due to convexity and linearity conditions. However, those model structures did not allow for the integration of behaviourally advanced representations, which commonly require simulation, and they are in most cases non-convex and non-linear. An emerging stream of research bases the integration of more advanced choice models utilising the utility function and deploying simulation for the random component (Pacheco Paneque et al., 2021). This approach has been the basis for subsequent studies that integrate the utilization of choice models broadly within optimization, thus also applicable to revenue management (e.g. Pacheco Paneque et al., 2022; Haering et al., 2023). Recently, this premise was also applied to generate a framework for equilibrium solutions in oligopolistic markets, with consumer choices being modelled according to the random utility theory (Bortomiol et al., 2022).

Although forming a set of seminal studies, the above pertinent literature is bounded by the neoclassical assumptions, and specifically that decision-makers evaluate the entirety of the choice set and process all available information. However, this assumption is challenged by the dynamic nature of information provision which has become commonplace within competitive markets of multiple providers and the increased complexity of offerings (e.g. Mobility as a Services, Ridesharing, Airline markets). In the economics literature there exist studies which investigate pricing using such novel behavioural theories, aiming to explain several real-world phenomena such as rigid pricing (Matejka 2015), and the emerging of information obfuscation equilibria (Janssen et al., 2024). However, their association in transport planning and policy remain relatively unexplored.

Building upon the findings of previous literature, in this study we investigate the implications of Rational Inattention in the context of revenue management from the perspective of the transport service provider. Through a series of numerical experiments, we compare optimal pricing strategies in a duopolistic taxi/ride-hailing market, contrasting the outcomes derived from neoclassical models with those incorporating information capacity constraints and the formulation of prior, unconditional probabilities of choice. This remainder of this paper is structured as follows: we first present the methodology including the RI revenue maximisation formulation (Section 2). Then we apply the methodology and compare the findings to a RUM-based approach (Section 3). We proceed to analyse the results, interpret different market strategies, and provide policy-related recommendations with regards to regulation in transport markets (Section 4). Finally, we summarize and outline the future work directions (Section 5).

2. METHODOLOGY

We proceed with the outline of the revenue estimation methodology under the Rational Inattention behavioural framework, based on the work of Matejka and McKay (2015) and Caplin, Dean and Leahy (2019).

<u>Problem Definition</u>

The agent observes an unknown state x (e.g., price, travel time), with their initial belief represented by the probability density function $g(x)$. The decision-making process involves two stages: firstly, the selection of signal s through the information strategy $f_{sx}(s|x)$, where the agent refines their belief about the state in face of uncertainty, and secondly, the choice of action y, described by the action strategy $f_{ys}(y|s)$, The objective (1) is to maximize the expected utility $U(y,x)$ while minimizing the cost associated with acquiring information, denoted as $C(f_{sx})$.

$$\max_{f_{sx}, f_{ys}} \mathbb{E}[\mathbb{E}U(y,x)|s] - C(f_{sx}(s|x)) \quad (1)$$

Although this is a two-stage choice, the joint probability $f(y,x)$ is sufficient to describe both the choice of information signal and action, as they should be derived such that no two signals lead to the same action. Otherwise, the agent would be wasting attentional resources by distinguishing between signals that do not directly affect their actions. As a result, it is possible to make a one-to-one association between the signal and action and analyse the relationship between attention, allocation, information acquisition, and decision-making in a unified framework. Therefore, the objective function (2) is maximized subject to the Bayesian rationality constraint (3), ensuring the consistency between prior and posterior beliefs,

$$\max_{f} \int U(y,x) f(y,x)dxdy - C(f) \quad (2)$$

$$\int f(y,x)dy = g(x) \quad (3)$$

The cost function (4) is conceptualized as a representation of the resources and cognitive effort expended by the agent in acquiring and comprehending information regarding the observed variable. It is measured by contrasting the entropy of the initial distribution of x with that under knowledge of y. The parameter λ, often referred to as the "attention cost" or "information cost," serves as a metric for the cognitive and computational resources allocated to the process of information acquisition and processing.

$$C(f) = \lambda \cdot I(y; x) \equiv \lambda \cdot \left[H(x) - E[H(x|y)]\right] \quad (4)$$

The entropy under Shannon's formulation (5) is typically used to quantify this uncertainty reduction, which measures the amount of information present in the probability distribution of x. As such, $I(y; x)$ is the Shannon mutual information of the random variables x and y (6).

$$H[g(x)] = -\int g(x) log\, g(x) dx \quad (5)$$

$$I(y; x) \equiv \int f(x, y) \log \left(\frac{f(y,x)}{g(x)p(y)}\right) dxdy \quad (6)$$

Therefore, the cost function imposes penalties on the observation of the unknown state, depending on the desired precision, due to the cognitive burden associated with the acquisition and processing of the information signal.

Choice Probability

The general solution of the agent’s problem for an unknown state of the network x has the following probabilistic logit form, where $p(y)$ is the unconditional (marginal) probability of each action y.

$$f(y|x) = \frac{p(y)e^{U(y,x)/\lambda}}{\int_z p(z)e^{U(y,x)/\lambda} dz} \quad (7)$$

Specifically for the case of a discrete alternative set $y \equiv i \in \{1, \dots, N\}$, the following choice probabilities are derived,

$$P(\mathrm{i}|\mathrm{x}) = \frac{e^{\frac{U(i,x)+a(i)}{\lambda}}}{\sum_{j=1}^{Y} e^{\frac{U(j,x)+a(j)}{\lambda}}} \quad (8)$$

Any experience, existing knowledge and approach towards processing information are reflected in the probability form via the weights $\alpha(i)$, allocated to each alternative in the choice set. These priors adjust the probabilities in line of alternatives that were considered favorable, and they are entirely unrelated to the current utility of these options. With an increase in the information processing cost, the observed choices become less influenced by the utility and more by the initial beliefs and prior unconditional probabilities.

Identification of Priors

While initial research was focused on the derivation of the probability form, Caplin et al. (2019) described the solution process for obtaining the unconditional probabilities $P(i)$, by proving the following slackness condition. It has been shown that the information strategy of the agent is optimal if and only if for all actions,

$$\sum_{x \in X} \frac{e^{U(i,x)/\lambda} P(x)}{\sum_{j=1}^{Y} e^{U(j,x)/\lambda} P(j)} \leq 1 \quad (9)$$

To compute the probability $P(i)$ for each action, we begin with an initial guess $P_0(y)$ for each y in Y. The initial estimate is updated through iteration until convergence is achieved, with each subsequent probability vector derived from the previous one using the iterative algorithm. Choice alternatives where $P_1(y) < \xi$ are set to 0.

$$P_{l+1}(i) = \sum_{x \in X} \frac{e^{U(i,x)/\lambda} P(x)}{\sum_{j=1}^{Y} e^{U(j,x)/\lambda} P(j)} P_l(i) \quad (10)$$

Therefore, we observe the unique capability of the Rational Inattention framework to account for endogenous choice set formulation, as some alternatives will not even be considered, which would not be the case in typical RUM models.

Expected Revenue Calculation

Once the unconditional probabilities (priors) and choice probabilities have been derived, the total revenue of a supplier s for a product i with price x can be calculated as,

$$R_{i,s} = \sum_{m=1}^{M} N_m \, P_m(i|x) x_{i,s} \quad (11)$$

, where N is the size of a specific market segment m.

The multi-step methodological approach presented in this Section allows for a comprehensive and disaggregate analysis of revenue generation, with regards to the interplay between market segmentation, consumer behaviour, and suppliers' pricing strategies.

3. NUMERICAL EXPERIMENTS

To evaluate the properties of the methodological framework for transport revenue management, we proceed to conduct a series of simulation experiments. We consider a duopolistic taxi/ride-hailing market, competing over a standard origin-destination (OD) route, such as the one between an airport and a city center. Within this market, the standard taxi service (STS) operates under a fixed fare of 15 units. In contrast, the ride-hailing flexible service provider (FLS), a new and more economical player, has adopted adaptive pricing, fluctuating between 10 and 17 units.

We proceed to introduce a level of heterogeneity within the population, by clustering it into two distinct segments: "Convenience Seeker" and "Price Sensitive" travellers. The former, favors the readily available STS service which is easily accessible and might not necessitate pre-booking or the use of a smartphone-based application, while the latter, comprises of individuals who seek cost efficiency (e.g., students), exhibit a weaker preference for the STS and are more inclined to consider the FLS service. Assuming linear in parameters utility functions, the simulation parameters are summarized in Table 1.

Our initial goal is to identify the revenue management strategies for the two service providers, first based on the theory of Rational Expectations, using the traditional Multinomial Logit model (MNL), and second under the Rational Inattention framework presented in Section 2. For the latter, we adopt a uniform prior for agent beliefs over the FLS price distribution, denoted by $X \sim U(10,17)$, while the information parameter λ is normalized to 1 for both models. It is important to note that there is no requirement for the agents' beliefs to mirror the actual simulated price distribution, but that would incur potentially higher “mistakes” in the case of a bounded rational decision maker.

Table 1 Simulation experiment parameters

Population Segments	Convenience Seeker		Price Sensitive	
Description	Param.	Value	Param.	Value
Alternative specific constant for Standard Service	$ASC_{STS,1}$	2.8	$ASC_{STS,2}$	1.9
Price coefficient	$\beta_{PRICE,1}$	-0.9	$\beta_{PRICE,2}$	-2.1
Number of people in the segment	N_1	550	N_2	450

With regards to the RI model, the optimality of the iterative solution assumes the choice set is extensive enough to cover all possible choices. Given that our analysis accounts for the entirety of the duopoly market structure, it is ensured that the algorithm yields the optimal priors solution.

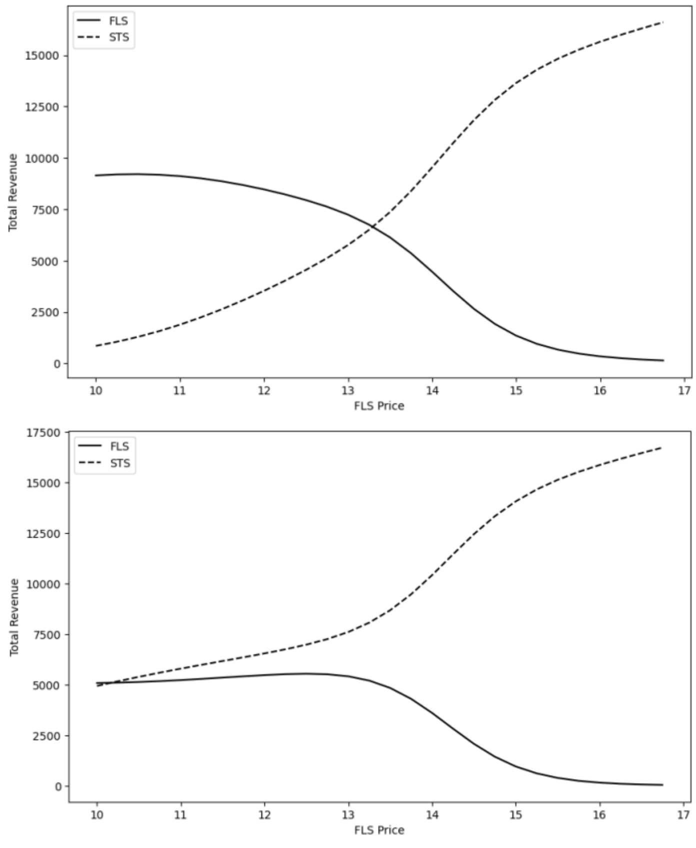

Figure 1Total revenue for different price levels assuming Neoclassical (top) and Rationally Inattentive travellers (bottom)

Figure 1 presents the total revenue projections of the two service providers for different levels of the FLS price. Under the neoclassical model, we observe a significant overestimation of revenues for the FLS particularly at lower price levels. This discrepancy is attributed to the model's assumption of complete price transparency, which posits that consumers, being fully informed, will invariably opt for the most opportunistic solution. This assumption, however, does not hold when consumers' attention is limited, even in abundance of information. In contrast, the RI framework accounts for these real-world consumer behavior complexities. The prior algorithm estimates a very low unconditional probability of FLS choice by Convenience Seekers, at 1.5%. Even for the lowest FLS price of 10 units, we find that the Convenience Seekers will not be identifying this opportunity at a probability higher than 10%, justifying the ~50% reduction in expected revenue. Conversely, Price Sensitive travellers are to prefer the FLS 64.2% of the time.

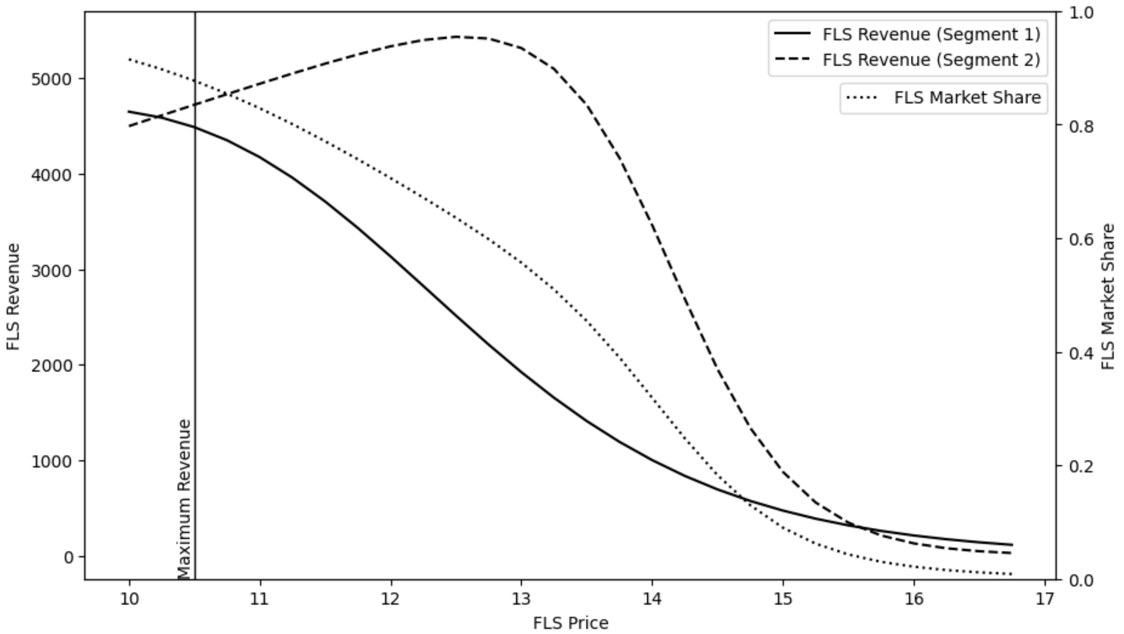

Figure 2 FLS revenue for each population segment and total market share (Neoclassical)

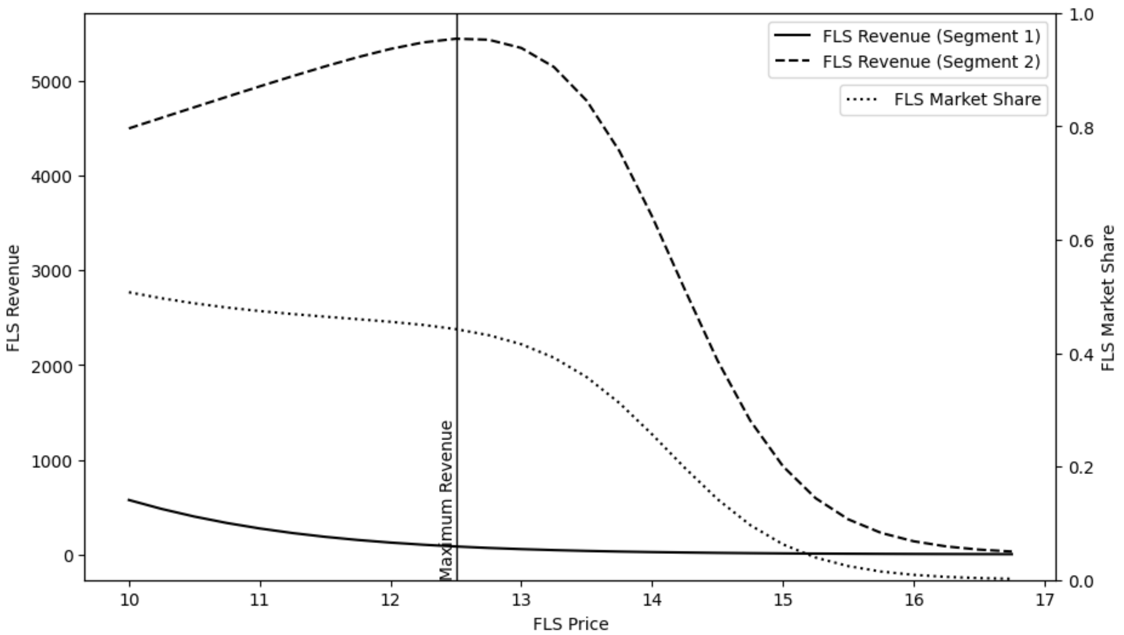

Figure 3 FLS revenue for each population segment and total market share (Rational Inattention)

These figures suggest a nuanced consumer decision landscape, where the traveller heterogeneity greatly affects the likelihood of choosing the FLS and its expected revenue. The next step of the analysis process is to evaluate different pricing strategies from the perspective of the FLS. In Figure 2 (Rational Expectations-MNL), the optimal price point is estimated at 10.50 units. At this price, the cumulative revenue for both segments is maximized. As such, the optimal strategy would entail FLS being competitively priced (4.5 units cheaper that the STS) to attract consumers from both segments with a total market share higher than 80%. Contrastingly, in the case of RI (Figure 3) the optimal price point is estimated at 12.50 units. This higher optimal price reflects a strategic decision of targeting the Price Sensitive travellers for a market share of 40%, as they have a higher propensity to select the FLS, even at smaller magnitudes of a pricing discount.

4. RESULTS AND DISCUSSION

The above findings lead to the natural question of how increasing the cost of information processing and overall transparency affects the market from a policy and regulation perspective. As visualized in Figure 4, a sharp decline in FLS revenue and market share is observed as information processing cost increases, suggesting that in a market influenced by Rational Inattention (RI), larger players with established customer bases could benefit from more opaque pricing schemes (prior effect). Thus, from the FLS perspective, there is an initial necessity to lower prices to maintain visibility. However, the optimal strategy pivots towards an increase of price once a certain threshold of obfuscation is reached, as the FLS service becomes less noticeable, thus having to target the “loyal” Price Sensitive segment of the population.

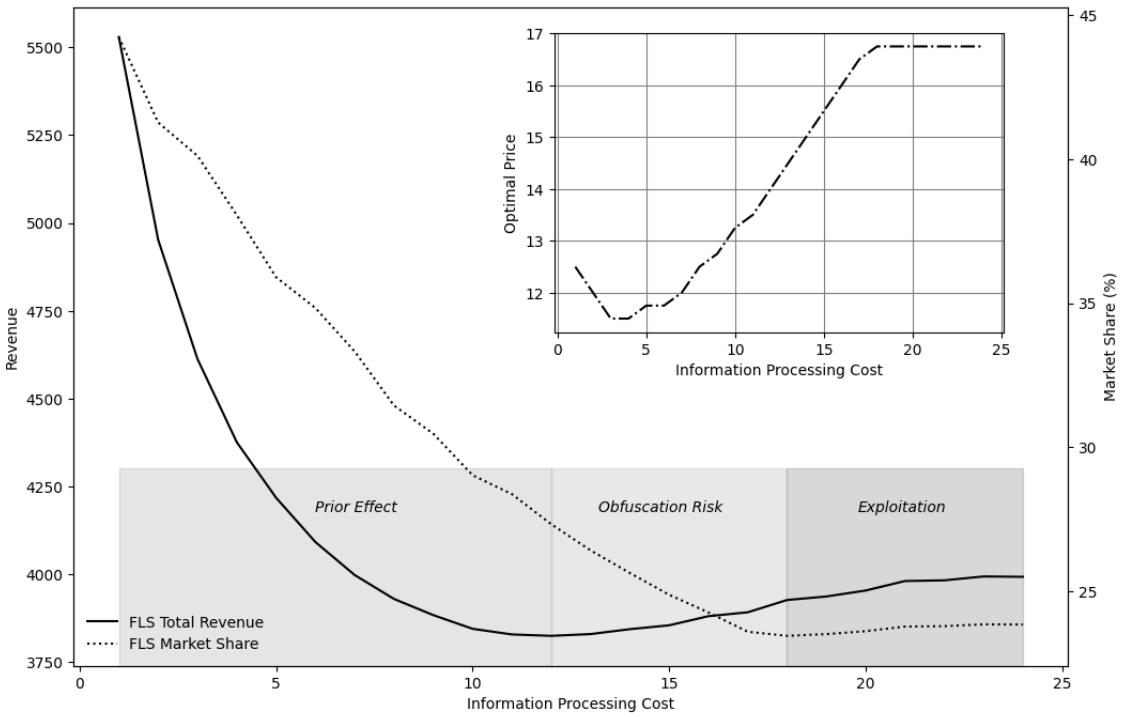

Figure 4 FLS optimal pricing, revenue and market share for varying levels of information processing cost

Interestingly, we observe that beyond a certain level of information opacity, smaller market players can also build their revenue through the increase of the price. This counterintuitive strategy leads to a unique situation where both suppliers could potentially increase their revenues simultaneously by altering the opacity of their pricing schemes. Such a scenario raises concerns about regulation, as it suggests the possibility of market manipulation where both providers benefit from the implementation of less transparent strategies (obfuscation risk) due to travellers' information capacity constraints. Eventually, when the cost of information becomes too high, FLS providers may rely on exploiting consumers with even higher pricing, to balance their already diminished market share. They might resort to hidden fees, bundling, or other tactics that could result in consumers paying more for less desirable options. These observations emphasize the need for regulatory oversight to ensure fair market play and protect consumers from potentially manipulative practices (exploitation).

Ultimately, we find that the presence of Rational Inattention among travellers with strong prior beliefs results in a significantly inelastic response to price changes. It also becomes evident that decoding heterogeneous populations and how they are affected by the cognitive costs of processing information is key in the formulation of robust pricing strategies.

5. CONCLUSION

The proposed approach for studying transport revenue management opens several directions for further exploration. Firstly, we have assumed that the Standard Service (STS) adheres to a fixed fare structure, remaining unresponsive to the pricing strategies employed by the Flexible Service (FLS). A natural extension of this research would involve examining the various equilibrium states that could emerge, considering mutual pricing adjustments and other dynamics, such as the evolution of consumers' prior beliefs. Moreover, the discrepancies in the pricing and revenue management strategies that we have uncovered necessitate empirical validation. Applying the methodology to real-world data will help ascertain which behavioural theory more closely aligns with travellers' rationale. Lastly, to tackle the inherent complexity of larger scale optimization problems under Rational Inattention, it will be essential to employ advanced analytical techniques, designed specifically to address the non-linearity challenges, as been done successfully in the case of Random Utility models.

In conclusion, by integrating Rational Inattention into the analysis of revenue management, we demonstrate that traditional neoclassical models applied in transportation research may not adequately capture the dynamics of a market that includes heterogeneous consumers acquiring noisy information signals. Ultimately, this interplay between market behaviour and information costs underscores the potential need for regulatory oversight to protect travellers' interests and prevent pricing and market manipulation.

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