The Effect of Incentives on the Actions Transit Riders Make in Response to Crowding

Bogdan Kapatsila*[1], Dea van Lierop[2], Francisco J. Bahamonde-Birke[3], Emily Grisé[4]

[1] Ph.D. Candidate, School of Urban and Regional Planning, University of Alberta, Canada

[2] Assistant Professor, Human Geography and Spatial Planning, Utrecht University, Netherlands

[3] Assistant Professor, School of Social and Behavioral Sciences, Tilburg University, Netherlands

[4] Assistant Professor, School of Urban and Regional Planning, University of Alberta, Canada

SHORT SUMMARY

Public transit crowding influences riders' satisfaction and needs to be tackled using both demand and supply management approaches. In this study, we focus on the policy response to public transit crowding using customer incentive schemes. We used statistical tests and an an Integrated Choice and Latent Variable model to analyze data collected in Metro Vancouver, Canada, during the COVID-19 pandemic. Our findings suggest that people who favor incentives tend to be more likely to change their travel behavior in response to crowding and that incentives that reduce the cost of travel have more potential to shift riders' travel time, while other incentives have a more pronounced effect on the decision to travel via a less crowded route. These findings are aimed at public transit agencies interested in employing policy instruments to manage transit crowding and researchers seeking to advance the knowledge about the influence of personal attitudes on travel behavior.

Keywords: Incentives, Transportation Demand Management, Transit Crowding, Transportation Behavior, Discrete Choice Modelling

1. INTRODUCTION

Overcrowded public transit impacts customer satisfaction and can lead some riders to opt for other modes (Cho & Park, 2021; de Oña & de Oña, 2015; dell'Olio et al., 2011; Eboli & Mazzulla, 2007; Haywood et al., 2017). Accordingly, effective strategies must be utilized for public transit crowding management that tackle the issue both quickly and efficiently. The traditional approach of adding system capacity offers a long-term solution to the challenges of transit crowding, however, such an approach is usually a prolonged and expensive endeavor that requires years of planning and execution. On the other hand, managing demand on public transit using policy tools might be an equally feasible intervention, able to provide much faster and more affordable congestion relief. Some cities, including Washington D.C., Melbourne, Sydney, Tokyo, and Hong Kong, use pre-peak hour free fares, discounts at off-peak hours, and fee increases during rush hours to manage the demand among public transit riders. More elaborate approaches attempted to use the knowledge about the human tendency to gamble (Anselme & Robinson, 2013) and engaged riders via smartphone games that offer opportunities to win prizes more valuable than a discounted or free fare, though this approach did not become widespread. To better equip public transit agencies with guidance regarding the incentives schemes that can engage riders to avoid the most congested routes or travel at less congested times, this study aims to systematically assess the riders' preferences for various incentives in the context of crowding reduction and investigate whether the favorable view of incentives increases the likelihood of behavioral change necessary to reduce system crowding.

2. METHODOLOGY

This study pursued two objectives. To understand the differences in preferences between the offered incentives, we compared the values of collected indicators, as well as disaggregated them by income groups to gain further insights. Given the nonparametric nature of the attitudes measured on a Likert scale, the significance of the differences was evaluated using the Wilcoxon T-test (Siegel, 1956).

To achieve the second objective, we investigated the influence of the attitudes toward incentives on the decision to either change travel time or public transit route using an Integrated Choice and Latent Variable (ICLV) approach (Ben-Akiva et al., 2002). This modeling technique allows connecting the choices individuals make and attitudes they express via unobservable constructs (i.e. latent variables) and understanding the strength of the effect that attitudes have on the choices. The final integrated likelihood function for the estimated model comprised the likelihood of a selected outcome, the likelihood of observing the considered attitudinal indicators, and the distribution of the latent variable (LV). It took the following form:

$$L_q = \int_{\eta} P(y|X_q, \eta_q;\ \beta_X, \varepsilon_q) \cdot P\left(I_q \middle|\ \eta_q; \gamma_\eta, \varsigma_q\right) \cdot f\left(\eta_q \middle| X_q, Y_q, \alpha_y, \upsilon_q\right) \cdot d\upsilon \quad (1)$$

There is no closed-form expression to the equation above, so it is commonly solved via numerical techniques, like a maximum simulated likelihood estimation (Ben-Akiva et al., 2002). We performed the modeling using the Apollo package (Hess & Palma, 2019) in the R statistical software (R Core Team, 2013). A 1000 Sobol draws (Sobol', 1967) were used to approximate the integration distribution and multiple starting values were tested to avoid obtaining the results for only a local optimum.

3. RESULTS AND DISCUSSION

The analysis was performed using data collected by the means of two waves of a survey disseminated in December 2020 and May 2021. Hard age and gender quotas were used to recruit a sample of respondents representative of Metro Vancouver from the panel managed by a marketing research company. Given the public transit focus of the survey, we only kept respondents who frequently commuted to work or education via transit before the COVID-19 pandemic. The final sample used for the analysis includes 1,201 respondents, the majority of whom (57.1%) did not stop using public transit during the pandemic. On top of the demographics of the individuals, we also recorded their attitudes toward incentives and actions in response to crowding using a 5-point Likert scale. Admittedly, government restrictions remained unchanged between the two waves of the survey, though the general shift towards remote employment and more private vehicle use has been observed (Kapatsila et al., 2022).

Figure 1 reveals that a fare discount is the type of incentive that had the highest support in our sample (median=4, IQR=2), followed by a 20$ credit for a monthly pass (median=3, IQR=2) and a free coffee, or a discount coupon for a meal (median=3, IQR=3). The other options like a discount for other modes, the opportunity to participate in a raffle, or make a donation to a charity seem to be less preferable, with a median score of 2 and an equal spread. At the same time playing a smartphone game with an opportunity to win points and exchange them for a cash reward seems to be appealing at least to some respondents. Though the median score for it is also 2, the interquartile range is as high as observed for the food coupons/discounts - 3. Lastly, an advantage over peers on a leadership board was the least preferable incentive (median=1, IQR=2), though a comparison to other options spread indicates that some people might consider it as well. All differences described above were found to be statistically significant.

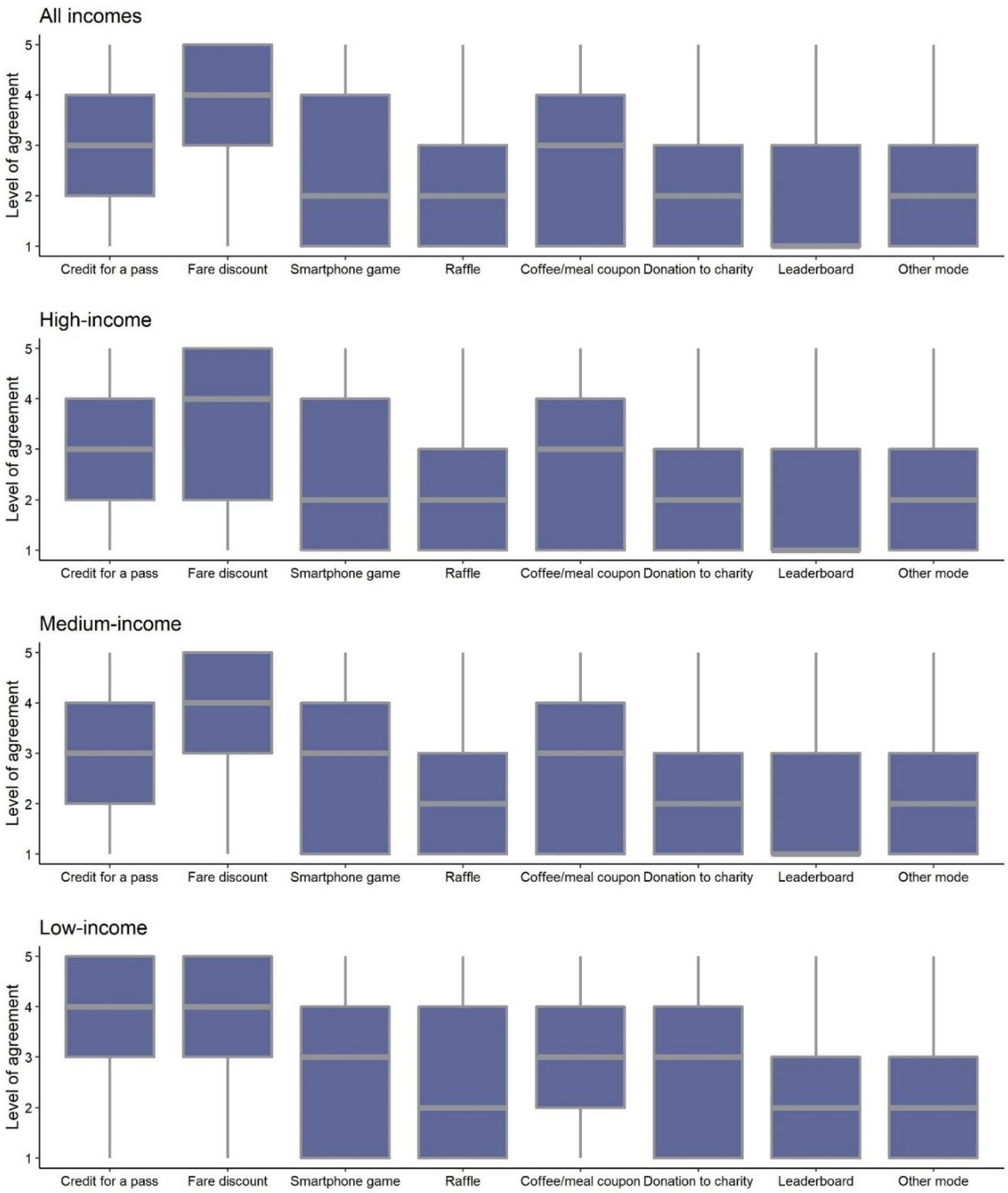

Figure 1: Attitudes towards incentives by income

Comparing the preferences towards incentives by different income groups provides additional insights. Although a fare discount remains the top choice across all income groups, the high-income earners (those making more than $200,000 annually) display a larger range, suggesting that some of them (most likely those at the top of the category) have a comparatively low preference for incentives in general. This, of course, is of no surprise, as it is expected that small rewards would have lower benefits for those with higher incomes. Another finding that stands out is that both medium- (making between $50,000 and $100,000 a year) and low-income (those earning less than $50,000 annually) earners have a higher preference for winning points in a smartphone game when compared to high-income ones, and that difference is statistically significant (p=0.074 and p=0.021 respectfully).

In the second stage of the analysis, we simultaneously estimate two ICLV models, one evaluating the probability of changing the travel start time, and the other the probability of changing the public transit route, with both being subject to the influence of the identified LVs that captured attitudes towards incentives. Given the similar nature of the dependent variables, we introduced a normally distributed error term for both outcomes to capture the correlation effect of the parameters that could not be included in the model (e.g. social norms, trip context). The diagrammatic representation of the selected model is visualized in Figure 2.

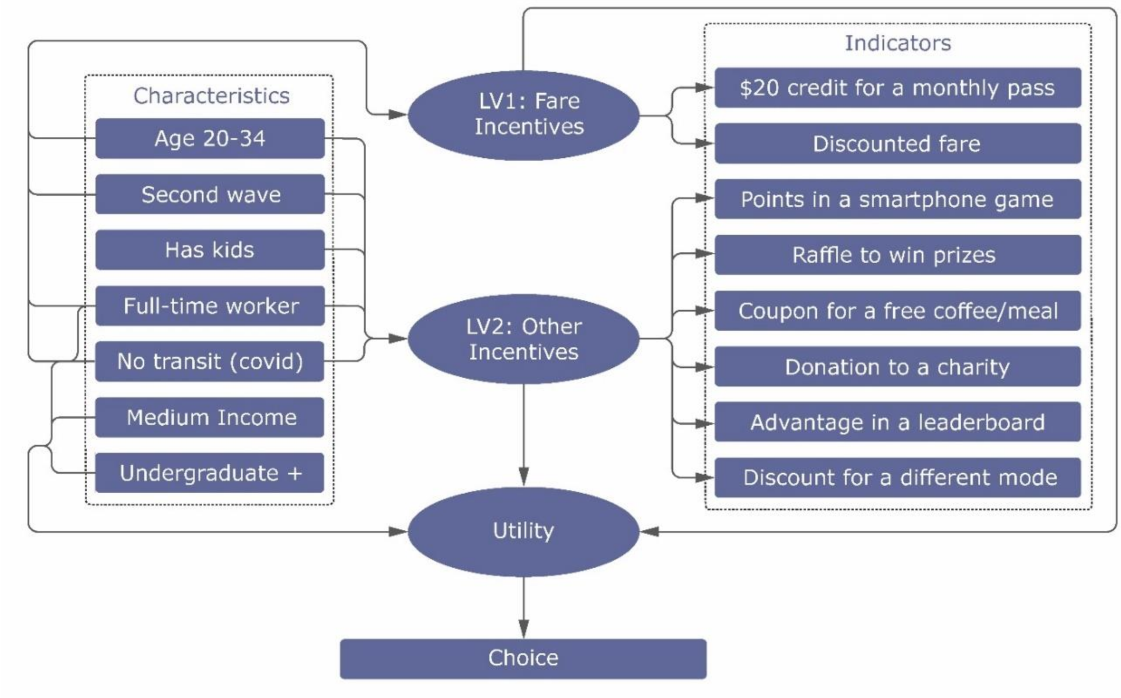

Figure 2: Diagrammatic representation of the selected ICLV model

The results of the model are presented in Table 1. Inspection of the structural equations estimates highlights the influence of several individual characteristics. Importantly, for both LVs they are nearly identical, with the only difference being individuals with kids influencing LV Other Incentives. As for other characteristics, individuals in the 20-34 age group are generally more likely to favor incentives, which goes along the lines of findings from other studies that pointed engagement with incentives to go down with aging (Dhingra et al., 2020). It is also natural that full-time workers are less likely to respond to consider incentives as they are caught between professional and domestic responsibilities and have little flexibility for any changes. The fact that people who stopped using public transit during the COVID-19 pandemic are less likely to favor incentives on transit is also fairly intuitive. It is hard to imagine for people who abandoned public transit out of concern or necessity to see incentives to change travel behavior on public transit in a positive light. The ebb and flow of the pandemic tide can also explain the more positive view of incentives that respondents from the second wave of the survey had. In May 2021 Metro Vancouver saw a gradual increase in vaccination and a decline in COVID-19 hospitalizations (British Columbia Provincial Health Services Authority & BC Centre for Disease Control, 2022), which most likely improved the uneasiness towards public transit in general, and incentives on it as well.

Table 1: Results of the Model

Variable	Equation	Estimate	SD	t-test
Age 20-34	S.E. LV1: Fare Incentives	0.165	0.066	2.498
Full-time worker		-0.194	0.064	-3.045
No transit use (pandemic)		-0.181	0.063	-2.855
Second wave of the survey		0.133	0.063	2.122
Age 20-34	S.E. LV2: Other Incentives	0.364	0.066	5.506
Full-time worker		-0.134	0.062	-2.133
No transit use (pandemic)		-0.415	0.063	-6.642
Second wave of the survey		0.111	0.062	1.801
Has kids		0.306	0.069	4.416
ASC Change Route	Utility Change Route	2.396	0.221	10.844
Medium income		0.414	0.179	2.315
Undergraduate degree or higher		0.250	0.189	1.325
Full-time worker		-0.050	0.187	-0.272
No transit use (pandemic)		-0.262	0.184	-1.422
LV 1: Fare Incentives		0.255	0.118	2.158
LV 2: Other Incentives		0.663	0.117	5.678
Threshold 1		0	-	-
Threshold 2		1.504	0.102	-
Threshold 3		3.675	0.149	-
Threshold 4		5.504	0.194	-
ASC Change Route	Utility Change Travel Time	3.102	0.236	13.131
Medium income		0.436	0.180	2.423
Undergraduate degree or higher		0.472	0.190	2.486
Full-time worker		-0.652	0.189	-3.447
No transit use (pandemic)		0.895	0.187	4.780
LV 1: Fare Incentives		0.722	0.123	5.862
LV 2: Other Incentives		0.472	0.115	4.109
Threshold 1		0	-	-
Threshold 2		1.530	0.120	-
Threshold 3		3.638	0.162	-
Threshold 4		6.069	0.213	-
Correlation Change Route & Change Travel Time		2.325	0.111	20.89
Number of observations: 1201				
Number of parameters: 70				
Log-likelihood of the whole model: -15422.72				

Shifting focus from the LVs to their impact on the choices, we can see that both LVs have a positive influence on the likelihood of either changing travel time or public transit route in response to crowding. This confirmation is a piece of encouraging evidence suggesting that at least in the stated preference design setting people who are more likely to respond to incentives and change their travel habits also tend to have a higher probability of changing travel behavior in response to crowding. Another insight worth noting is the size of the effect each LV has on the choices. Looking at the choice to change the public transit route, we can see that it is more likely to pertain to the individuals favoring other incentives since the respective LV has a higher impact than LV Fare Incentives on that choice. On the other hand, the reverse is true for the choice to change travel time. One explanation for this difference can be the familiarity of respondents with the fare price change in Metro Vancouver where it is more expensive to travel on light rail and ferries between the 3 zones at peak hours (TransLink, n.d.). As for the higher influence of LV Other Incentives on the likelihood to change the public transit route, several explanations can be hypothesized. There might be a correlation in the skills and preferences needed to both opt for another transit line and to play a game on a smartphone to win points, as both can be achieved using a smartphone (e.g. getting navigation via a route planning mobile application in the case of the former), however, the latter is impossible without a smartphone. Similarly, there is potentially a positive relationship between the propensity to switch to other public transit routes and responding to a discount for the use of other modes, as both require a change in the usual means of commuting.

4. CONCLUSIONS

This study investigated the differences in preferences towards various incentive schemes on public transit and assessed the relationship between the riders' eagerness to modify their travel patterns in response to crowding and the likelihood to respond to incentives that influence them to do the same. We found that people who favor incentives tend to be more likely to change their travel behavior in response to crowding and that incentives that reduce the cost of travel on public transit have more potential to shift riders' travel time, while other incentives have a more pronounced effect on the decision to travel via a less crowded public transit route. Similarly, we identified the incentive schemes that received the highest support and the demographics of potential users who favor those. Nevertheless, this study was subject to several limitations that should be acknowledged. First, the analysis was performed using a stated choice survey, which does not necessarily mean that the opinions respondents expressed would reflect their actual behavior. Similarly, some people might be highly favorable to incentives but have very limited options to change their travel time or route in practice. As such, future research should explore the opportunities to analyze the revealed choices of public transit riders when it comes to incentives. Secondly, both waves of the survey data were collected during the COVID-19 pandemic, and this time of heightened attention to public health and fewer systematic professional and personal travel needs could have affected the results obtained.

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