The hidden cost of fast delivery: Consumer willingness to trade delivery time and cost for food delivery rider safety

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Short summary

The online meal delivery services base speed and convenience as central service attributes, but this emphasis on fast delivery may compromise rider safety. Existing research has mainly focused on supply-side factors, such as rider behavior, to address the issue of safety, while little is known about whether consumers are willing to support safer delivery practices. This study addresses that gap through a stated-preference experiment with consumers of online food delivery services in Amsterdam and Copenhagen. Respondents chose between labelled cuisine alternatives that varied in delivery time, meal cost, delivery cost, and rider safety risk. A hybrid latent class choice model with random error terms was estimated to capture class-based heterogeneity and unobserved preferences. The results reveal two distinct consumer segments. One group is largely indifferent to rider safety, whereas the other is strongly safety-sensitive and willing to pay more or wait longer for safer delivery. These findings suggest that consumer-facing safety information in ordering apps could complement platform and regulatory interventions to improve the safety of delivery riders.
Keywords: consumer behaviour; discrete choice experiment; online meal delivery; rider safety; stated preference

1 Introduction

The rapid growth of online meal delivery services is reshaping food consumption patterns in urban areas worldwide (Wang & He, 2021; Statista, 2023). Digital platforms such as Uber Eats, Deliveroo, and Just Eat have embedded fast, on-demand delivery into everyday consumption, establishing speed and convenience as central service attributes (Lord et al., 2023). To meet these expectations, platforms routinely prioritise short delivery times as a key performance metric. This emphasis on speed has raised growing concerns regarding the safety of delivery riders, who often operate under time pressure in dense and complex urban traffic environments (Allen et al., 2021). Empirical studies show that food delivery riders face increased exposure to crashes and near-miss incidents, along with adverse effects on their physical well-being, mental health, and job satisfaction (Christie & Ward, 2023; Choi et al., 2022; Nguyen-Phuoc et al., 2022; Fan et al., 2022).

Delivery speeds, which are central to rider safety, are influenced by a range of supply-side factors, including performance-based incentives and penalties imposed by platforms, competition among delivery workers for future tasks, and broader competitive dynamics between platforms. Existing research and policy efforts aimed at improving safety in platform-based food delivery have predominantly focused on these supply-side dimensions, such as labour conditions, rider behaviour, and regulatory oversight (Wood et al., 2019; Apouey et al., 2020; Dong et al., 2021; Kavta et al., 2025). While these efforts have generated valuable insights into the risks faced by riders and the effectiveness of supply-side interventions, they have largely overlooked the role of consumers, who shape the demand for these services. As the demand side of the system, consumers influence delivery speed expectations, pricing structures, and platform operational practices. This study therefore explores the role of consumers and their willingness to support improvements in rider safety. Importantly, the analysis does not imply that responsibility for rider safety should shift to consumers. Rather, it examines whether consumer preferences can complement platform and

regulatory interventions, particularly when safety-related information is made transparent within the decision-making process.

From an economic perspective, safety risks associated with food delivery generate broader social costs, including increased crash risks for other road users, traffic disruptions, and additional strain on emergency services. These impacts represent negative externalities, as the social costs generated by delivery activities are not fully reflected in the prices paid by consumers (Pigou, 2017). Whether consumers are willing to internalise rider safety risks by accepting longer delivery times or higher prices in exchange for safer delivery practices therefore remains an open empirical question.

Building on this gap, this study employs a stated preference experiment to examine how consumers trade off delivery time and cost for improvements in rider safety in online food delivery services. The contributions of this study are fourfold. First, it extends the literature by explicitly incorporating rider safety as a decision attribute within a consumer choice framework. Second, it provides empirical estimates of willingness-to-pay (WTP) and willingness-to-wait (WTT) for safety improvements. Third, it captures multiple sources of behavioural heterogeneity by integrating latent variables, class-based segmentation, and random utility components. Fourth, it offers policy-relevant insights by linking consumer preferences to potential platform-level interventions to improve rider safety.

2 Methodology

Data were collected through an online survey administered in Amsterdam and Copenhagen in January 2025. Respondents were required to be at least 16 years old and regular users of online food delivery services. After data cleaning, the final sample consisted of 350 respondents and 1,400 observations. The questionnaire included sections on food ordering habits, a stated preference experiment, socio-demographic information, and attitudinal indicators.

In the stated preference experiment, respondents first identified their most recently ordered cuisine from a predefined list. This cuisine served as the reference alternative. They then identified their second and third preferred cuisines in the event that their primary choice was unavailable. These three cuisines were used as labelled alternatives. This design improves behavioural realism by ensuring that all alternatives are relevant to the respondent.

Each alternative was described by four attributes: delivery time, delivery cost, meal cost, and rider safety risk. The first three attributes reflect common elements in online food ordering, while the fourth captures the safety conditions faced by delivery riders. To reduce hypothetical bias, a pivoting design was employed, in which the attribute levels for the reference cuisine were anchored to the respondent's most recent order and the remaining alternatives were generated by pivoting around this reference (Rose et al., 2008; Hess et al., 2008; Tversky & Kahneman, 1981). A D-efficient design developed in Ngene produced 24 choice tasks divided into 6 blocks, with each respondent completing one randomly assigned block of four tasks (ChoiceMetrics, 2012; Rose & Bliemer, 2009, 2013).

Safety risk was represented as the hypothetical probability that a rider would experience a crash or near-miss incident during a delivery trip. This framing was adopted because annual crash frequencies are difficult to interpret within a single choice situation, while purely qualitative labels do not support quantitative trade-off estimation (Antoniou, 2014; Flügel et al., 2015; Rizzi & de Dios Ortúzar, 2006; Gössling & McRae, 2022; Harrison et al., 2014). The risk attribute was presented using numerical probabilities together with colour-coded labels and alphabetical grades to support comprehension (Carroll et al., 2022; Garcia-Retamero & Cokely, 2013). Following Heinrich's safety triangle, the measure combines crashes and near-miss incidents to capture broader safety conditions (Heinrich, 1941).

Choices were analysed using a Hybrid Latent Class Choice Model (HLCCM), which combines a class membership model, a class-specific utility model, and latent variables capturing attitudes toward road safety and rider safety. Figure 1 illustrates the conceptual framework.

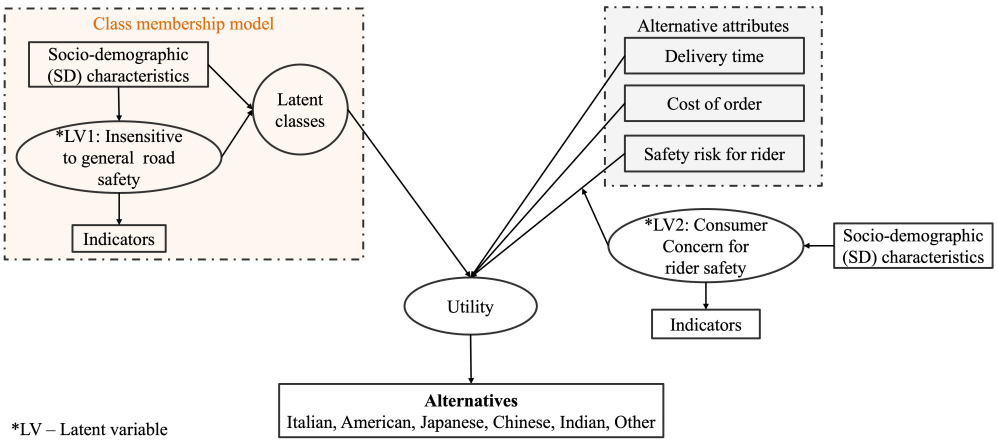


Figure 1: **Conceptual framework of the Hybrid Latent Class Choice Model**

The unconditional probability of individual n choosing alternative i in choice task t is defined as a weighted sum of class-specific choice probabilities:

$$P_{int} = \sum_{q=1}^{Q} \hat{H}_{nq} \cdot P_{int|q} \tag{1}$$

where $\hat{H}_{nq}$ denotes the class membership probability and $P_{int|q}$ is the probability of choosing alternative i conditional on membership in class q.
The class-specific utility function is given by:

$$\begin{aligned} U_{int|q}^{(p,s)} = \alpha_{i,q} + \beta_{cost,q} \cdot \text{Cost}_{int} + \beta_{time,q} \cdot \text{DelTime}_{int} + \beta_{risk,q} \cdot \text{Risk}_{int} \\ + \beta_{interaction,q} \cdot \left(LV2_n^{(p)} \times \text{Risk}_{int} \right) + \eta_n^{(s)} \end{aligned} \tag{2}$$

where $\alpha_{i,q}$ is the alternative-specific constant, $\beta_{cost,q}$, $\beta_{time,q}$, and $\beta_{risk,q}$ are class-specific taste parameters, $LV2_n$ captures concern for rider safety, and η_n is an individual-specific random error component. The model was estimated by simulated maximum likelihood in Apollo using Modified Latin Hypercube Sampling draws (Train, 2009; Hess & Palma, 2019). The final specification used 5,000 draws per individual and proved stable when re-estimated with 10,000 draws.

3 Results and discussion

Latent class enumeration was based on both statistical criteria and behavioural interpretability. Although the AIC marginally improved with more classes, the BIC and the interpretability of the results supported a two-class specification (Etzioni et al., 2021; Marcucci et al., 2015; Chen & He, 2023; Roeder et al., 1999). The two classes are referred to as Class-IRS (Insensitive to Road Safety) and Class-SRS (Sensitive to Road Safety).
The class membership results show that age, education, and latent attitudes toward general road safety significantly influence the probability of belonging to the safety-sensitive class. Older individuals, respondents with school-level education, and those with higher insensitivity toward road safety are less likely to belong to Class-SRS. The two segments are almost equal in size, with class probabilities of 49.7% and 50.3%, respectively.

Table 1: Class membership model estimates

Parameter	**Estimate**	**t-ratio**	**p-value**
Constant (Class-SRS)	1.598	3.296	0.001
Age	-0.307	-2.767	0.006
School-level education	-0.755	-2.361	0.018
$LV1$ (insensitivity to road safety)	-0.742	-4.038	< 0.001
Class probability (Class-IRS)		49.7%	
Class probability (Class-SRS)		50.3%	

Table 2 presents the main modelling results. Cost and delivery time are negative and significant in both classes, indicating that consumers prefer lower prices and shorter waiting times. The rider safety risk attribute, however, is only significant for Class-SRS. This implies that one segment of consumers responds strongly to safety-related information, whereas the other remains largely unaffected. The interaction between risk and concern for rider safety is also significant and negative in the safety-sensitive class, suggesting that attitudinal concern strengthens the behavioural response to objective safety information.

Table 2: Selected class-specific model estimates

Parameter	**Estimate**	**t-ratio**	**Significance**
Order cost (Class-IRS)	-0.0493	-3.4659	***
Order cost (Class-SRS)	-0.2430	-7.4919	***
Delivery time (Class-IRS)	-0.0320	-5.3485	***
Delivery time (Class-SRS)	-0.0526	-5.3944	***
Risk for riders (Class-IRS)	-0.0061	-0.1991	NS
Risk for riders (Class-SRS)	-0.9876	-7.8648	***
Risk $\times LV2$ (Class-IRS)	-0.0077	-0.2928	NS
Risk $\times LV2$ (Class-SRS)	-0.3032	-4.9505	***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, NS = not significant.

To interpret these estimates in more practical terms, marginal rates of substitution (MRS) were calculated. These indicate how much additional money or waiting time consumers are willing to trade for a reduction in rider risk. The contrast between the two classes is substantial. For a 10% reduction in rider crash and near-miss risk, the safety-insensitive class shows essentially no statistically meaningful willingness to pay or wait, while the safety-sensitive class is willing to pay approximately €4.06 or wait 18.75 additional minutes. By contrast, the safety-insensitive class values time savings more strongly.

Table 3: MRS indicators with 95% confidence intervals

MRS indicator	**Class-IRS**	**Class-SRS**
Risk reduction (€ per 10% reduction)	0.12 [-1.19, 1.43]	4.06 [2.78, 5.34]
Risk reduction (minutes per 10% reduction)	0.19 [-1.88, 2.26]	18.75 [9.52, 27.98]
Delivery time (€ per minute)	0.64 [0.20, 1.08]	0.21 [0.11, 0.31]

These findings make three main contributions. First, they show that safety can be incorporated into a consumer choice framework as a meaningful attribute in platform-based services. Second, they highlight the demand side as a relevant component of safety outcomes in digitally mediated delivery systems. Third, they underline the importance of accounting for behavioural heterogeneity: average preferences conceal a strong divide between safety-sensitive and safety-insensitive consumers.

The practical implications are also noteworthy. The results do not imply that responsibility for rider safety should be transferred to consumers. Platforms and regulators remain the primary actors responsible for safe working conditions and safe operational practices. However, the findings suggest that consumer preferences can complement these interventions. Platforms could introduce optional "safer delivery" modes, present safety information through in-app risk labels, or experiment with adaptive pricing and delivery-time settings that reflect users' willingness to pay and wait for safer delivery. Such interventions may help internalise safety considerations without assuming that all consumers respond in the same way.

Several limitations should nevertheless be noted. First, the analysis is based on stated preference data and therefore reflects intended rather than actual behaviour. Second, the study focuses on Amsterdam and Copenhagen, two cities with relatively strong cycling cultures and road safety awareness. The identified segments may therefore not transfer directly to other contexts.

4 Conclusions

This paper examined whether consumers are willing to trade delivery time and cost for safer food delivery rider conditions. Using a stated preference experiment and a Hybrid Latent Class Choice Model, the study identified two distinct consumer segments. One segment is largely indifferent to rider safety and places greater value on rapid delivery. The other is strongly safety-sensitive and is willing to pay more and wait longer for safer delivery conditions.

The key implication is that the consumer market is not uniformly speed-driven. A sizable share of consumers appears willing to support safer delivery practices when safety is made visible in the decision context. This creates room for platforms to test safety-oriented service design, such as optional safer-delivery modes or in-app safety labels, in ways that complement platform and regulatory measures.

Future research should examine whether these stated preferences translate into real behaviour through field experiments or platform pilots. It should also explore alternative ways of communicating safety risk and extend the analysis to other urban and institutional contexts. Even with these limitations, the findings show that the hidden cost of fast delivery is recognised by a meaningful segment of consumers and that this recognition can inform safer and more socially sustainable platform design.

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