The road less travelled: A route choice experiment focusing on the safety of food delivery riders

Kuldeep Kavta*[1], Shadi Sharif Azadeh[2], Yousef Maknoon[3], Gonçalo Homem de Almeida Correia[2]

[1]Postdoc researcher, Delft University of Technology
[2]Associate Professor, Delft University of Technology
[3]Assistant Professor, Delft University of Technology

SHORT SUMMARY

This study investigates the aspect of food delivery riders' safety against crashes, focusing on route choices within urban areas. The rise of online food delivery platforms has highlighted the role of delivery riders, yet their safety concerns remain underexplored. The research utilizes stated preference experiments and tests two nudging strategies: 'information nudging,' providing riders with crash probability data for route safety, and 'monetary incentives,' offering extra compensation for choosing safer routes. The descriptive findings reveal that riders are mostly young, male, and less educated. The Multinomial Logit (MNL) model results reveal the impact of nudging strategies on route choices, with information nudging influencing riders to opt for safer routes, and monetary incentives motivating reconsideration for those choosing shorter and less safe routes. Post-processing calculations yield valuable indicators, including the 'Value of Risk Reduction' and 'Willingness to Accept,' providing insights into the trade-offs riders make between travel time and safety nudging strategies.

Keywords: food delivery rider, safety, route choice, discrete choice experiment, wellbeing, gig economy.

1. INTRODUCTION

The emergence of online food delivery platforms has revolutionized the way consumers access their meals especially in the modern urban context. The convenience and efficiency offered by aggregator platforms like Just Eat, Deliveroo, Uber Eats, meituan, etc. have reshaped the restaurant business all around worldwide (Ray et al., 2019). Estimates suggest that online food delivery business will grow by 10.06% Compounded Annual Growth Rate from 2024 to 2028 (statista, 2023). All this has become possible with the real-time digital availability of the delivery riders (also referred to as couriers), who play a pivotal role in ensuring the seamless functioning of the delivery chain in the overall system (Lord et al., 2023). Although, other aspects of demand such as consumer preferences have been thoroughly investigated in the literature, the riders' side concerns remain unexplored (Oviedo-Trespalacios et al., 2022). As the demand for quick and reliable food delivery services continues to soar, so does the significance of addressing the concerns associated with the central element of this system – the riders (Christie & Ward, 2023).
This paper addresses a critical facet of this unexplored domain, specifically focusing on the safety of riders during the expedited delivery of orders within urban areas. The escalation in the number of food delivery riders navigating the thoroughfares of cities has resulted in a reported increase in accidents, attributable to a multitude of factors (Nguyen et al., 2023; Wang et al., 2021). One

strategy to mitigate the probability of crashes involves encouraging riders to adopt routes that prioritize safety over expediency. Predominantly, riders rely on navigation applications such as 'Google Maps' or those provided by food delivery platforms, which typically optimize routes based on the shortest duration. While these routes ensure swift deliveries, they may disregard the safety implications for riders, specifically in terms of crash probability.
This paper explores an alternative approach, investigating riders' preferences for safer routes through stated preference experiments and systematically testing two nudging strategies designed to incentivize riders toward the selection of safer routes. The data to test the interventions is currently being collected from the riders working in Amsterdam, the Netherlands, and Copenhagen, Denmark.
The organizational structure of the paper comprises four sections including the introduction section: Section 2 focuses on design of Stated Preference (SP) experiment and data collection. Section 3 elaborate on the methodology and descriptive results and section 4 concludes the study.

2. METHODOLOGY

Stated preference experiment design.

This study aims to gauge riders' safety preferences in route choices by assessing the effectiveness of two nudging strategies. Firstly, riders were exposed to 'Information Nudging,' providing crash probability details for routes, usually unavailable in navigation apps. Those who still opted for less safe routes were then introduced to 'Monetary Nudging,' involving additional money as an incentive to encourage safer route choices.
Representing route safety is challenging; while some studies incorporate objective statistics like 'Fatal crash per year' in SP experiments (Antoniou, 2014), respondents may struggle to relate these statistics to real-life decision-making. Subjective representations using categorical levels like 'low,' 'medium,' and 'high' pose challenges, lacking the precision needed for policy analysis. Our approach involves using crash probabilities as an objective statistic, providing a simpler and more understandable representation. Attribute details and corresponding levels for the stated preference experiment are outlined in the table below:

Table 1: Attributes and levels

Attributes	**Route suggested by Platform app**				**Alternative route that you know**			
Travel time (minute)	18	20	22	25	8	10	12	15
Safety level	20% lower chance of accident than all other routes	40% lower chance of accident than all other routes	60% lower chance of accident than all other routes	80% lower chance of accident than all other routes	-			
Extra payment for choosing route	€ 0.5	€ 1.0	€ 1.5	-	€ 0			

Ngene software was utilized to generate an efficient stated preference design (Rose & Bliemer, 2009), a total of 24 choice tasks were generated and were divided into 8 blocks. The design featured choice sets requiring riders to decide between a shorter route and a longer route that consistently offered higher safety levels. Each task had two alternatives: ‘Platform app route’ the platform/company-suggested route, and ‘route that you already know’. The design choice questions are hypothetical, suggesting that the route suggested by platform will prioritizes safety by providing explicit safety information. Participants responded to three tasks, with changing attribute levels. Figure 1 and Figure 2 illustrates how choice tasks were presented in the survey.

It take(s) **15 minutes** to reach the delivery place of your next request using a **route that you already know**.

In the **platform app** on your phone another route is proposed to you:

Travel time	18 minutes
Safety level	60% lower chance of accident than all other routes

1a - Which route would you choose?

Platform app route

Route that you already know

Figure 1: Choice question example (information nudging)

It take(s) **15 minutes** to reach the delivery place of your next request on the **route that you already know**.

In the **platform app** on your phone another route is proposed to you:

Travel time	18 minutes
Safety level	60% lower chance of accident than all other routes

New information: You get **extra € 1.5** if you choose **platform app route.**

Which route would you choose now?

Platform app route

Route that you already know

Figure 2: Choice set example (monetary incentive)

Survey instrument and data collection

The survey for this study had four sections. The first focused on demographics, covering gender, age, education, citizenship, and related aspects. The second delved into stated preference (SP) questions about route choices. The third explored employment arrangements, including working hours, contract type, job location, and satisfaction. The final section concentrated on riders' behavior and delivery patterns, encompassing metrics like kilometers ridden, cell phone usage, crash history, safety awareness, and quantity of deliveries. The survey, accessible through a Qualtrics link, took an average of 12 minutes to complete. Distribution began in the final week of December 2023, facilitated by a major online food delivery company in Amsterdam and Copenhagen. Currently, 157 samples have been collected, and data collection is ongoing, with an anticipated completion date at the end of February 2024.

3. MODELLING APPROACH

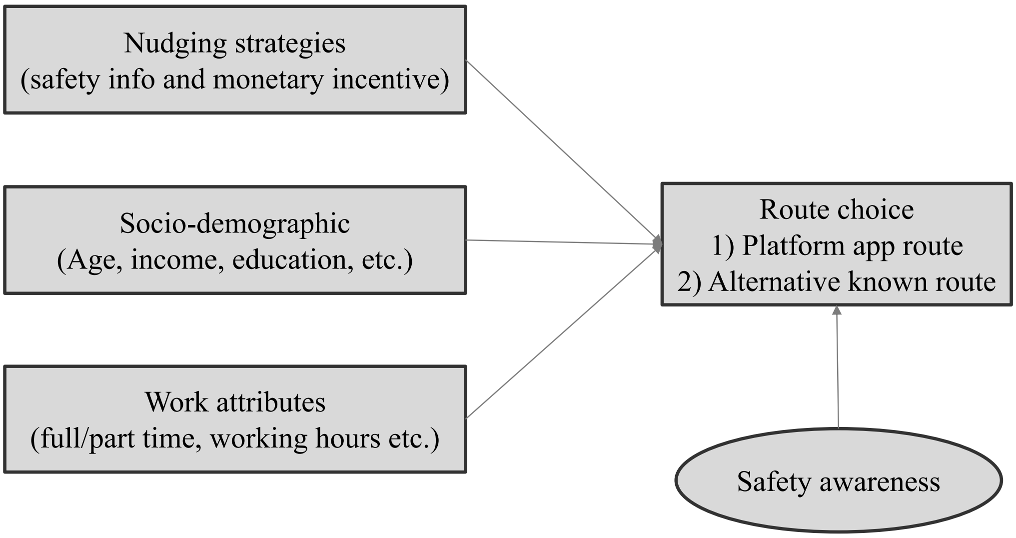

Figure 3: Conceptual model

The methodological approach of this research is grounded in a conceptual model shown in the above **Error! Reference source not found.** that explains the relationships of different independent variables with the route choice decision which is serving as the dependent variable. Drawing from prior literature on route choice, the exploration of causal relationships extends to respondents' socio-demographic profiles and their choices (Rizzi et al., 2006). The research also explores the potential influence of riders' working arrangements on their route selection. Specifically, the decision-making process of opting for a safer route may be contingent upon factors such as the rider's employment status (full-time or part-time), geographical location of work (e.g., Amsterdam or Copenhagen), and other relevant variables. In addition to the observed variables, the study delves into latent factors pertaining to riders' general awareness of road safety, recognizing their potential influence on route decisions. Models that neglect these latent aspects may fall short in explaining the heterogeneity in route choice decisions (Kamargianni et al., 2015; Vij, 2013). Lastly, we test the impacts of nudging strategies in motivating riders into choosing safer route based on their responses to stated preference questions.

In line with the conceptual model, different specification of random parameter logit and hybrid choice models will be developed, with the aim of identifying the most efficient and parsimonious model that accurately explains the underlying behavior. Below are the generic details of potential model formulation of a hybrid choice model with random parameters:

The probability of choosing alternative i by respondent n in task t is given by:

$$P_{i,n,t} = \int_{\beta}\int_{\eta} \frac{e^{V_{i,n,t}}}{\sum_{j=1}^{J} e^{V_{i,n,t}}} (\beta|\Omega) * g(\eta)\, d\beta\, d\eta$$

Where $\beta \sim f(\beta \mid \Omega)$ for random parameters and $g(\eta)$ for indicators of latent variables.

Utility of the route is represented by $V_{i,n,t} = f\ (\beta_n, x_{i,n,t}, \alpha_n, \tau, z_n)$

β_n represents vector of sensitivity of respondent n.
$x_{i,n,t}$ is vector of attributes of alternative i as shown to respondent n in task t.
z_n is the vector of variables related to respondent n.

α_n is the vector of latent variable related to respondent n.
τ is the vector of sensitivity of latent variable on alternative.

4. RESULTS

Descriptive statistics

The descriptive statistics from our sample provide insights into demographic profile and initial indication of preferences. Figure 4 illustrates the socio-demographics of the sample:

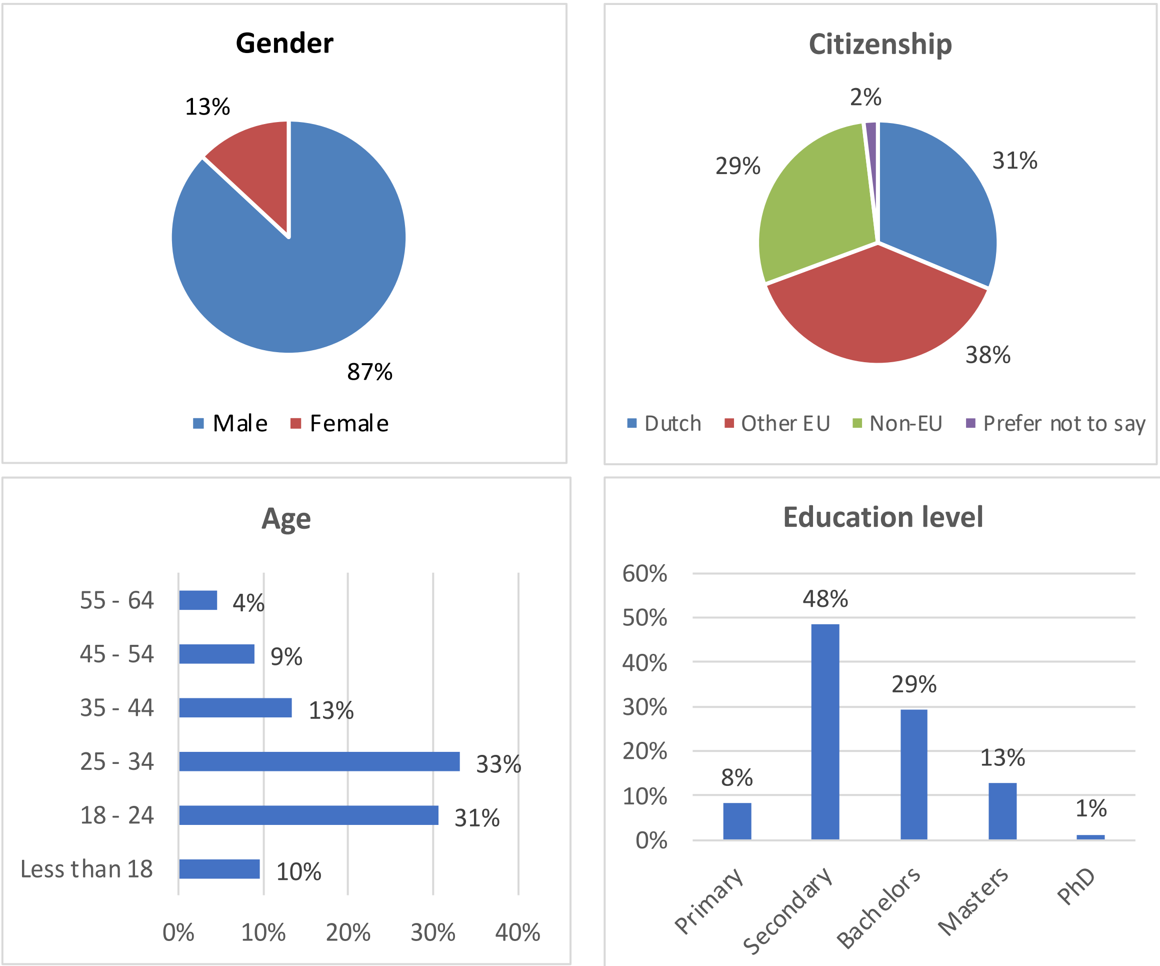

Figure 4: Socio-demographics

The socio-demographic patterns reveal that a majority (74%) of food delivery riders fall within the younger age group, less than 35 years old. In terms of education, 56% of riders have completed secondary schooling or have an education level below it. The sample is predominantly male, making up 87% of the total data, while women account for only 13%. Regarding citizenship, a significant portion of riders are European (38%), closely followed by Dutch citizens (31%), with non-EU citizens constituting 29% of the sample.

Multinomial Logit model

Based on our collected data, we initially employed a Multinomial Logit (MNL) model to explore the effects of nudging strategies and other variables on route choices. Recognized for its simplicity and widespread use, the MNL model, rooted in random utility theory, is often the initial choice due to its ease of development. The model operates under the assumption that the random error term in utility follows a type 2 extreme value distribution, resulting in a closed form for the calculation of probabilities. While advantageous in explaining choices, the model has limitations, such as the Independence from Irrelevant Alternative (IIA) property and challenges capturing parameter heterogeneity and serial correlation (Train, 2009). To address these, we are developing more advanced models. Despite its drawbacks, the MNL model provides valuable insights into relationships. The Table 2 below outlines outcomes from separate models for 'information' and 'monetary' nudging, revealing their impact on riders' route choices:

Table 2: MNL model

Platform route choice (Base – Known alternative route)				
	Information nudging model		**Monetary nudging model**	
	Parameters	*t-ratio*	*Parameters*	*t-ratio*
ASC platform route	0.3827	0.9738	-0.3307	-0.4350
Travel time	-0.0813	-3.7796	-0.2137	-4.8522
N1: Information on reduction in crash probability	0.0124	2.9838	-	-
Fulltime work	0.8976	3.2618	-	-
Experience: less than one year	0.5020	1.9388	-	-
Age: Less than 34	-0.7022	-2.8069	0.7156	1.5232
Citizen: Non-EU country	0.5636	2.4165	-	-
High weekly information	-0.4625	-1.6974	-	-
N2: Monetary incentive	-	-	2.1265	4.3382
Experience: More than 5 years	-	-	-1.9532	-1.8153
Marital status: Bachelor	-	-	1.6215	3.9450
Delivery mode: Car	-	-	-1.7235	-2.3144
Weekly income (scaled)	-	-	-0.1573	-1.6609
Number of individuals	157		108	
Starting Log Likelihood	-326.47		158.04	
Final Log Likelihood	-300.06		-107.99	
Adjusted Rho-squared	0.0557		0.2184	

The results presented in the table above depict the influence of various independent variables on the decision-making process related to choosing the platform app route, which is characterized by being longer yet safer. The dataset was segmented based on two distinct nudging strategies, leading to the estimation of two separate Multinomial Logit (MNL) models. All estimated parameters achieved significance at a minimum 90% confidence interval, with one parameter being near the threshold and retained in the model.

In the 'information nudging model,' the provision of information regarding crash probabilities for routes exhibited a statistically significant impact on the decision. We coded the reduction in crash probabilities as continuous variable in the model. The positive value suggests that as this value goes up, the likelihood of selecting the platform route also goes up. From policy perspective this suggests that if food delivery apps start providing safety information for their suggested routes, it would positively influence riders to choose those routes over shorter ones. The negative sign of the travel time parameter indicates that as travel time increases, the likelihood of choosing the route decreases. Notably, full-time riders exhibited a preference for the route suggested by the

Platform app compared to their part-time counterparts, potentially influenced by the higher distance covered by full-time riders, making them more sensitive to safety considerations. Furthermore, novice riders with less than a year of experience in food delivery preferred the Platform app-suggested route when compared to more experienced riders. Riders immigrating from non-EU countries displayed a positive preference for Platform routes compared to those with EU citizenship. Preferences also varied based on income, with riders who were earning higher weekly income from platform (Quartiles 3 and 4) favoring familiar and shorter routes.
The 'monetary nudging model' revealed a statistically significant positive impact of monetary incentives on decisions, indicating that riders were willing to choose a longer route for extra compensation. Interestingly, contrary to the information nudging model, riders under the age of 34 opted for the Platform route when influenced by monetary incentives. Unmarried riders showed a willingness to take longer routes if provided with additional compensation. More experienced riders (with over 5 years of experience) preferred their known routes over the Platform route, possibly due to increased confidence in navigating unsafe routes. Regarding the vehicle used for food delivery, riders driving cars tended to favor their familiar routes over those suggested by Platform, suggesting a perception of higher safety associated with car delivery. Similar to 'information nudging model', increasing income had a negative impact on choosing the Platform route, aligning with the intuitive notion that monetary incentives may be less relevant for high-earning riders.
Based on the estimates derived from the model parameters, we conducted post-processing to calculate two critical indicators: the 'Value of Risk Reduction (VRR)' and 'Willingness to Accept (WTA).' These metrics are founded on the trade-off that riders make between travel time and nudging strategies, where additional travel time is considered a cost for opting for a safer route and additional monetary incentive. In the case of the information nudging model, dividing the parameter for the reduction in crash probability by travel time yields the VRR. Based on the estimated values, the average VRR for riders is calculated to be 0.15 minutes per percentage point reduction in accident probability. In simpler terms, a rider is willing to travel 3 minutes extra if it means there is a 20% lower probability of a crash on the chosen route. This metric signifies the additional travel time a rider is willing to undertake for every percentage point decrease in the probability of a crash. Similarly, for the monetary nudging model, dividing estimates of travel time by monetary nudging provides the WTA, which is determined to be 0.1 Euro per minute. The WTA represents the additional compensation that rider is willing to accept for additional minute of extra travel. While these calculations provide preliminary insights, it is essential to note that the heterogeneity surrounding these indicators is not fully captured in the Multinomial Logit (MNL) model. We emphasize that these values may evolve as we progress with the development of more advanced models aimed at providing a more comprehensive explanation of rider behavior. Our ongoing work aims to refine and expand upon these initial findings.

5. CONCLUSIONS

Our paper explores factors influencing the safety of food delivery riders against traffic crashes and evaluates two nudging strategies affecting route decisions. By integrating safety considerations into stated preference experiments, our approach offers a unique perspective, ensuring simplicity for riders and aiding future predictions and policy analysis. Preliminary findings, including demographic insights, highlight a predominant demographic of young, mostly male, and less-educated riders. The multinomial Logit model reveals the significant impact of crash probability information on route choice decisions. Monetary nudging successfully influenced riders who initially chose lesser safe routes even after being aware of the chances of crash. In addition to nudging, socio-demographic and work-related variables also played a role. Our model suggests that food delivery companies could enhance safety by incorporating crash information into route suggestions and providing monetary incentives if needed. Post-processing involves calculating Value of Risk Reduction (VRR) and Willingness to Accept indicators, with a note that these indicators may evolve as we develop more advanced models, currently in progress.

ACKNOWLEDGEMENTS

This research was undertaken as part of the project SINERGI, funded by JPI-Urban Europe and NSFC.

REFERENCES

Antoniou, C. (2014). A stated-preference study of the willingness-to-pay to reduce traffic risk in urban vs. rural roads. *European Transport Research Review*, *6*(1), 31–42. https://doi.org/10.1007/s12544-013-0103-3

Christie, N., & Ward, H. (2023). Delivering hot food on motorcycles: A mixed method study of the impact of business model on rider behaviour and safety. *Safety Science*, *158*. https://doi.org/10.1016/j.ssci.2022.105991

Kamargianni, M., Dubey, S., Polydoropoulou, A., & Bhat, C. (2015). Investigating the subjective and objective factors influencing teenagers' school travel mode choice - An integrated choice and latent variable model. *Transportation Research Part A: Policy and Practice*, *78*, 473–488. https://doi.org/10.1016/j.tra.2015.06.011

Lord, C., Bates, O., Friday, A., McLeod, F., Cherrett, T., Martinez-Sykora, A., & Oakey, A. (2023). The sustainability of the gig economy food delivery system (Deliveroo, UberEATS and Just-Eat): Histories and futures of rebound, lock-in and path dependency. *International Journal of Sustainable Transportation*, *17*(5), 490–502. https://doi.org/10.1080/15568318.2022.2066583

Nguyen, M. H., Nguyen-Phuoc, D. Q., & Oviedo-Trespalacios, O. (2023). Non-fatal traffic crashes among food delivery riders in Vietnam: What is the problem? *Traffic Injury Prevention*, *24*(8), 686–692. https://doi.org/10.1080/15389588.2023.2238862

Oviedo-Trespalacios, O., Rubie, E., & Haworth, N. (2022). Risky business: Comparing the riding behaviours of food delivery and private bicycle riders. *Accident Analysis and Prevention*, *177*. https://doi.org/10.1016/j.aap.2022.106820

Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. *Journal of Retailing and Consumer Services*, *51*, 221–230. https://doi.org/10.1016/j.jretconser.2019.05.025

Rizzi, L. I., De Dios, J., & Ortu´zar, O. (2006). *Road Safety Valuation under a Stated Choice Framework*.

Rose, J. M., & Bliemer, Mi. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, *29*(5), 587–617. https://doi.org/10.1080/01441640902827623

statista. (2023). *Online Food Delivery: market data & analysis*. https://www.statista.com/outlook/dmo/online-food-delivery/worldwide

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Vij, A. (2013). Incorporating the Influence of Latent Modal Preferences in Travel Demand Models. In *University of California, Berkeley* (Vol. 15, Issue 4). https://doi.org/10.11436/mssj.15.250

Wang, Z., Neitzel, R. L., Zheng, W., Wang, D., Xue, X., & Jiang, G. (2021). Road safety situation of electric bike riders: A cross-sectional study in courier and take-out food delivery population. *Traffic Injury Prevention*, *22*(7), 564–569. https://doi.org/10.1080/15389588.2021.1895129