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Estimating the value of safety against road crashes: A stated preference experiment on route choice of food delivery riders

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ABSTRACT

The rapid growth of the online food delivery industry has led to a significant increase in the number of delivery riders navigating urban streets, predominantly using bikes and e-bikes. This growth has been accompanied by a concerning rise in crashes involving these riders, posing a critical challenge for city authorities and policymakers. Promoting safer riding behavior, such as choosing safer routes while delivering food, can potentially reduce crash risks. With this motivation, this paper aims to evaluate the effectiveness of strategies that encourage riders to choose safer routes and estimate the value riders place on reducing the risk of road crashes. The paper presents a stated preference experiment conducted with food delivery riders in Amsterdam and Copenhagen to assess two targeted strategies: 'safety information' and 'monetary incentives', designed to encourage riders toward selecting safer routes. The results from the route choice model show that presenting information about safety against crashes on different routes and offering monetary incentives can effectively motivate riders to choose safer routes, even if these are longer. The trade-offs riders make between safer and shorter routes were quantified by calculating the Value of Risk Reduction (VRR) and Willingness to Accept (WTA) indicators, which offer valuable insights into riders' safety preferences. These indicators highlight how much riders value risk reduction and the compensation required to choose safer routes. Furthermore, the findings reveal that factors related to riders' working arrangements and socio-demographic profiles significantly influence their route choice decisions. The paper concludes with a discussion about the practical challenges associated with implementing the strategies to enhance rider safety and proposing potential solutions that can be useful for food delivery platforms and policymakers.

1. Introduction

Food delivery riders play a critical role in maintaining the efficiency and reliability of food delivery services (Lord et al., 2023). As demand for these services continues to rise (Statista, 2023), the number of riders navigating urban environments has also increased. Typically using bicycles, e-bikes, and mopeds, they often operate under tight time constraints, increasing the pressure to complete deliveries quickly. Globally, crashes involving delivery riders are on the rise (Choi et al., 2022; Wang et al., 2021), raising significant

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concerns among urban planners and policymakers. For example, the Malaysian Institute of Road Safety Research (MIROS) reported four fatalities and over 120 injuries among food delivery riders within a three-month period (Tamrin, 2020). In Europe, a study in Milan, Italy, found that 39% of food delivery riders had experienced at least one road accident in the past year, with e-bike riders being particularly vulnerable (Boniardi et al., 2024). Broader global estimates suggest that between 25% and 35% of delivery riders have been involved in crashes (Prakobkarn et al., 2024; Qian et al., 2024; He et al., 2023; Papakostopoulos and Nathanael, 2021). Despite these alarming trends, research aimed at mitigating crash risks for food delivery riders remains scarce (Christie and Ward, 2023).

In this paper, rider safety is defined as reducing the likelihood of food delivery riders being involved in crashes or near-miss incidents. Crash risks for food delivery riders arise from a combination of factors such as traffic volume, vehicle mix, infrastructure design, adjacent land use, rider behavior, etc. This multifaceted challenge has been approached from various perspectives in the existing literature, with interventions ranging from soft measures such as awareness campaigns (Wundersitz et al., 2010; Delaney et al., 2004) to engineering solutions involving infrastructure modifications (Yannis et al., 2016). This study specifically focuses on reducing crash risk by influencing riders' route choice behavior, a critical and integral aspect of their daily operations.

Food delivery riders often select between multiple route options to reach their destinations, presenting an opportunity to implement interventions that could enhance their safety against crashes. Navigation tools such as Google Maps or delivery platform applications typically prioritize efficiency by minimizing travel time. While shorter routes are not inherently unsafe, there may be longer alternatives that offer greater safety, an aspect that traditional navigation systems generally overlook. Furthermore, riders may deviate from suggested routes based on personal preferences or experience, further complicating the situation (Liu et al., 2021). Consequently, riders either follow efficiency-driven navigation routes or rely on habitual choices, possibly exposing them to higher crash risks.

This study attempts to address these challenges by examining how the integration of safety-focused interventions into route recommendations can better protect delivery riders from crash and near-miss risks. Using a Stated Preference (SP) experiment, the study quantifies the trade-offs riders make between travel time and route safety by presenting them with hypothetical choices between a shorter route and a longer but safer alternative. The behavioral insights from this research can inform the design of nudging strategies within navigation systems, encouraging safer route selection without compromising operational efficiency.

The paper is organized into six sections after the introduction. Section 2 covers the state-of-the-art literature on factors influencing route choice behavior and different approaches to representing safety as an attribute in the SP experiment. Section 3 presents the structure of the questionnaire and the SP experiment. Section 4 explains the data collection process and the sample descriptive statistics. Section 5 presents the mathematical formulation and estimation of the route choice model. Section 6 elaborates on the empirical findings, followed by discussions on practical implications and limitations. Section 7 concludes with a summary of the key findings of the research.

2. Literature review

This section reviews existing research on the safety of food delivery riders, organized into two parts: factors influencing route choice and approaches to representing safety in SP experiments. These insights are crucial for informing the design and implementation of SP experiments in this research.

2.1. Factors influencing route choice behavior

Route choice refers to the decision-making process by which riders select a route between two locations, such as traveling from a restaurant to a delivery destination. This decision is shaped by various factors, explored here based on prior research. Given the limited studies specifically on food delivery riders, insights from broader route choice research across different user groups are incorporated.

The determinants of route choice can be broadly categorized into route-specific attributes, individual characteristics, and external factors. Among route-specific attributes, travel time is consistently identified as a primary determinant, with longer travel times negatively influencing route selection across different modes, including bicycles (Gan and Bai, 2014; Stinson and Bhat, 2003). Variability in travel time also plays a distinct role compared to average travel time (Palma and Picard, 2005; Liu et al., 2004; Shiftan et al., 2011). Travel distance is another critical factor, with shorter routes generally preferred when other conditions are equal (Scott et al., 2021). For cyclists, travel time and distance are highly correlated and can often be used interchangeably in modeling (Broach et al., 2012). Additional physical route characteristics, such as the number of intersections, presence of bike lanes, and surrounding built environment, also influence preferences (Cubells et al., 2023; Sener et al., 2009), with dedicated cycling infrastructure improving route attractiveness by reducing interactions with motorized traffic (González et al., 2016).

In terms of individual characteristics, socio-demographic factors significantly influence route preferences (Charoniti et al., 2017; Dane et al., 2020; Dill and Gliebe, 2008). Research has shown that both women and men generally avoid high-stress traffic environments; however, female cyclists are more likely to avoid arterial roads and steeper routes compared to their male counterparts (Lilasathapornkit et al., 2024). A study by Misra and Watkins (2018) found that traffic characteristics influence route choice decisions differently for female and male cyclists. Age also plays a role, as middle-aged and older cyclists tend to prefer shorter and more direct routes than younger riders (Lilasathapornkit et al., 2024). In addition to observed individual traits, psychometric factors such as time pressure and anxiety have been shown to influence route choice decisions (Charoniti et al., 2017)

Several external factors also influence decision-making. For example, noise levels have been shown to affect cyclists' route selection (Koch and Dugundji, 2021), and weather conditions impact overall travel behavior, including route choice (de Palma and Rochat, 1997). Aesthetic preferences further drive some users to select visually appealing routes over shorter options (Krenn et al., 2014). Safety, encompassing perceived and actual risk, is another crucial external factor. Prior studies demonstrate that accident history and safety perception substantially influence route decisions (Huang et al., 2020; Chandra, 2014). For instance, Politis et al. (2023) showed that past crash occurrences along different road segments significantly affected cyclists' route choices.

2.2. Representing safety in SP experiments

A key objective of this research is to test strategies encouraging riders to select safer routes. This requires determining how best to represent safety as an attribute in the SP choice experiment. Previous studies have typically represented safety either implicitly or explicitly. Implicit representation involves indirectly portraying safety through other attributes without a distinct safety-specific attribute. For example, Poudel and Singleton (2022) examined the preference of cyclists for different design and operational aspects of roundabouts and linked it to the improvement of cyclists' safety based on their previous work, which established this connection (Poudel and Singleton, 2021).

Explicit representation, on the other hand, involves a dedicated attribute defining safety in the choice experiment, allowing for a direct examination of the safety attribute's influence on choice. Within explicit representations, two distinct approaches have been utilized in previous studies: quantitative and qualitative. The quantitative approach reflects direct risks associated with choosing an alternative, often using metrics such as "accidents per year" based on historical crash data (Antoniou, 2014; Flügel et al., 2015; Rizzi and de Dios Ortúzar, 2006). In contrast, the qualitative approach describes safety using ordinal scales, such as the Likert scale, where each point represents a subjective perception of safety. For instance, Gössling and McRae (2022) assessed the perceived safety of cycling infrastructure using a four-point Likert scale (safe, rather safe, rather unsafe, unsafe).

The healthcare domain provides useful insights for representing safety attributes in discrete choice experiment. Harrison et al. (2014) reviewed 117 healthcare-related discrete choice experiments and found that risk is typically represented in several ways: by expressing it as a frequency (for example, "5 in 100 experience side effects"), as a percentage or likelihood (such as "5% chance of side effects"), or through a combination of both frequency and percentage. Risk has also been conveyed qualitatively, using scales such as "low", "moderate", or "high", or by combining qualitative descriptors with quantitative values (e.g., "low – 1 in 100"). In addition, visual aids such as charts, icons, and images are often employed to improve respondents' comprehension of the risk information presented. These approaches offer valuable guidance for designing safety attributes in transportation-related discrete choice experiments.

Considering the above discussions of the existing literature, this paper contributes to the existing literature by:

- Evaluating the determinants of route choice for food delivery riders and quantifying the value of lowering the risk of road crashes.
- Proposing a novel approach to represent riders' safety within the stated preference experiment, which can enhance interpretability and facilitate policy analysis post-model estimation.
- Providing empirically supported recommendations for food delivery platforms to enhance the safety of delivery riders through navigation-related operations.

3. Survey design

3.1. Structure of the questionnaire

Designing a survey questionnaire that effectively captures all the necessary information for this study was a critical step in the research process. Given the considerable variations in business and operational practices among food delivery companies, tailoring the survey to resonate with the respondents was essential. For instance, riders employed by the company facilitating data collection are paid weekly based on their working hours, regardless of the number of deliveries completed. Moreover, there are no strict penalties for late deliveries; riders receive warnings if they consistently deliver late. Several consultation meetings were held between August 2023 and November 2023 with stakeholders from the food delivery platform company supporting the data collection to ensure the survey's relevance and relatability.

The questionnaire comprised four parts. The first part captured basic socio-demographic details, such as gender, age, education, marital status, household size, and income. The second part focused on Stated Preference (SP) questions about route choice, detailed in Section 3.2. The third part explored riders' working arrangements, including hours worked, contract type, work experience, location, income, tipping frequency (number of times a rider received tips out of every 10 deliveries), and well-being. The final part addressed riding behavior and delivery patterns, covering daily kilometers traveled, phone usage, crash history, safety awareness, number of deliveries, riding speed, and vehicle type.

3.2. Stated preference (SP) choice experiment

At the beginning of each choice task, respondents were given a delivery scenario and asked to choose between two routes: a longer but safer ‘Platform App Route’ and a shorter ‘Alternative Known Route’. While shorter routes are not necessarily unsafe in real-world conditions, this experimental framing was deliberately adopted to evaluate how riders prioritize safety when faced with trade-offs between travel time and crash risk, as in prior stated preference studies evaluating similar trade-offs (Antoniou, 2014; Flügel et al., 2015). Without such a trade-off, the choice scenario would involve a clearly dominant alternative, thereby limiting the opportunity to observe meaningful decision-making behavior.

Both route alternatives were defined by multiple attributes. The first attribute, travel time, is expressed in minutes. The levels for travel time were determined in consultation with the food delivery platform company to reflect the typical travel durations experienced by riders between origin and destination points. The second attribute relates to the additional monetary incentive for selecting the safer route, which, in this case, was the “Platform app route”. As monetary incentives are not currently part of delivery operations, the levels were approximated so that they could be effective in motivating riders toward choosing safer routes. The third and critical attribute to represent was the safety level of the route.

As discussed in the literature review (Section 2.2), quantitative representations of safety, such as the “number of accidents per year”, may fail to convey meaningful risks. For instance, low figures (e.g., eight crashes annually) can appear negligible to respondents, and being based on historical data, may feel detached from the immediate decision-making context. In contrast, qualitative descriptors like “rather unsafe” are often too subjective and imprecise for policy-relevant analysis.

To address these limitations, this study adopts a percentage-based representation of safety, drawing from practices in healthcare literature, particularly Harrison et al. (2014). These values (0–100) reflect the relative reduction in the likelihood of crashes or near misses compared to other routes. The percentage value serves as a composite proxy for various underlying risk factors, including traffic conditions, infrastructure quality, and land use characteristics. However, the specific quantification of these factors and their relative contributions to the composite value lie beyond the scope of this study. This simplified representation helps respondents intuitively grasp safety differences between route options and offers a framework for policy evaluations. Combining crashes and near misses into a single percentage allowed for the use of higher values in the choice tasks, which would not have been feasible if only crashes were considered. This approach is supported by Heinrich’s safety triangle (Heinrich, 1941), which highlights that near misses occur far more frequently than crashes. Road safety studies show that addressing near-miss risks can significantly reduce the likelihood of severe crashes (Matsui et al., 2013; Park et al., 2023). The final route attributes and their levels are presented in Table 1.

Table 1
Attributes and their levels used in the SP experiment.

Attribute	Platform app route	Alternative known route
Travel time (minutes)	18, 20, 22, 25	8, 10, 12, 15
safety level	(20, 40, 60, 80) % lower chance of accident or close-calls than all other routes	–
Additional incentive (€)	0.5, 1, 1.5	0

To generate the efficient design, an initial set of priors was selected, drawing partly from the coefficient estimates reported by Rizzi and de Dios Ortúzar (2006). For attributes being tested for the first time, prior values were assigned based on the expected sign of the coefficients (positive for safety information and monetary incentives). These initial priors were subsequently refined based on insights from a pilot survey, which assessed the clarity of the questionnaire and the realism of attribute levels. The final design was generated using Ngene software and comprised 24 choice tasks divided into eight blocks. Each respondent was assigned between three and six tasks, requiring them to make trade-offs between travel time and the proposed nudging strategies. Figs. 1 and 2 illustrate how the tasks were presented across the two experimental stages.

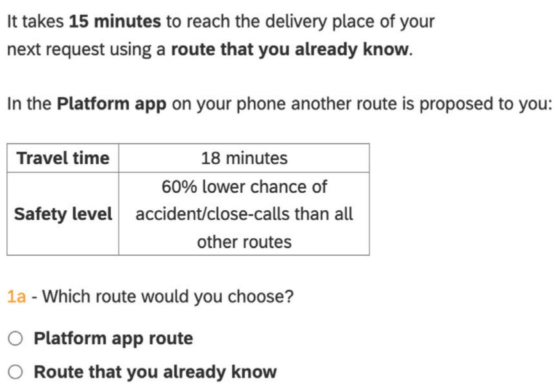
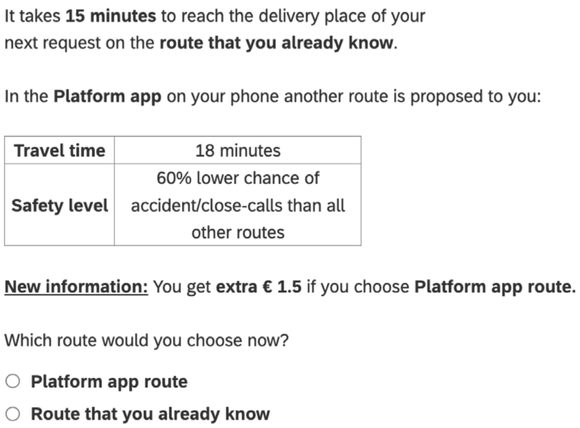


Fig. 1. Stage 1 - Safety information.


It takes **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/close-calls 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**

Fig. 2. Stage 2 - Monetary incentive.

4. Data collection and descriptive statistics

The questionnaire, designed using Qualtrics software, was available in English and Dutch and took around 12 min to complete. Since most riders in Denmark understood English, no Danish translation was provided. A pilot test with selected riders refined question clarity and relevance, with feedback incorporated into the final version. Survey distribution began in late December 2023 through a food delivery company operating in Amsterdam and Copenhagen, using email, internal WhatsApp groups, and local hubs where riders started their shifts. Respondents were informed of a cash prize of €25 via a post-survey lucky draw to encourage participation and quality responses. After excluding incomplete responses, 202 of 250 submitted questionnaires were valid for analysis, similar to the sample sizes in some other European studies. (Boniardi et al., 2024; Aguilera et al., 2022).

The descriptive summary statistics provide insights into the characteristics of food delivery riders, drawing comparisons with similar studies where possible. These statistics are categorized into three sections: socio-demographics, working arrangements, and riding behavior patterns.

4.1. Riders' socio-demographic profile

Fig. 3 shows the socio-demographic profile of the riders in the sample.

The socio-demographic analysis reveals a predominant profile among food delivery riders, with 75% aged under 35. In terms of education, 58% have completed high school or hold lower qualifications. Male riders form the majority at 85%, while females account for 15%. Regarding citizenship, 29% are non-EU nationals, while 26% are Dutch, 5% Danish, and 37% from other European countries. Marital status data shows 67% are unmarried, with 27% married or previously married. These findings align with earlier studies, such as Nguyen et al. (2023), which reported 88% male and 12% female respondents, and Christie and Ward (2023), which found 77% of riders in the UK under 35. The similarity in socio-demographic distribution across studies supports the representativeness of the sample. Overall, the typical profile of a food delivery rider in this study is that of a young, unmarried, European male with secondary education.

4.2. Riding behavior

Fig. 4 depicts the descriptive statistics related to riding behavior.

The delivery vehicles utilized by the riders encompass a variety of options, including e-bikes, regular bikes, cars, and other mopeds. 83% of riders utilize either bikes or e-bikes, and only 17% use other modes of delivery vehicles, including mopeds and cars. The use of mobile phones while riding is widespread, with 82% of riders reporting usage, often for navigation. 66% of riders avoid using headphones or earphones while riding, raising safety concerns. Some survey respondents also shared additional details about their involvement in crashes and receiving penalties for traffic violations in the past, reinforcing city authorities' concerns about the rising number of accidents involving riders.

4.3. Riders' working patterns

Fig. 5 presents the descriptive statistics about the working arrangement of riders with the food delivery company.

Riders can work either full-time (40 h a week) or part-time. In the sample, 73% of riders are part-time workers. This result contrasts with studies in Asian countries, where a higher proportion of riders is reported to be working full-time (Chen, 2023). Part-time riders were also asked about their complimentary occupations. About 50% are students, 16% work for other food delivery companies, 4% work for non-food delivery companies, 4% are self-employed, and the rest have other activities. Regarding weekly

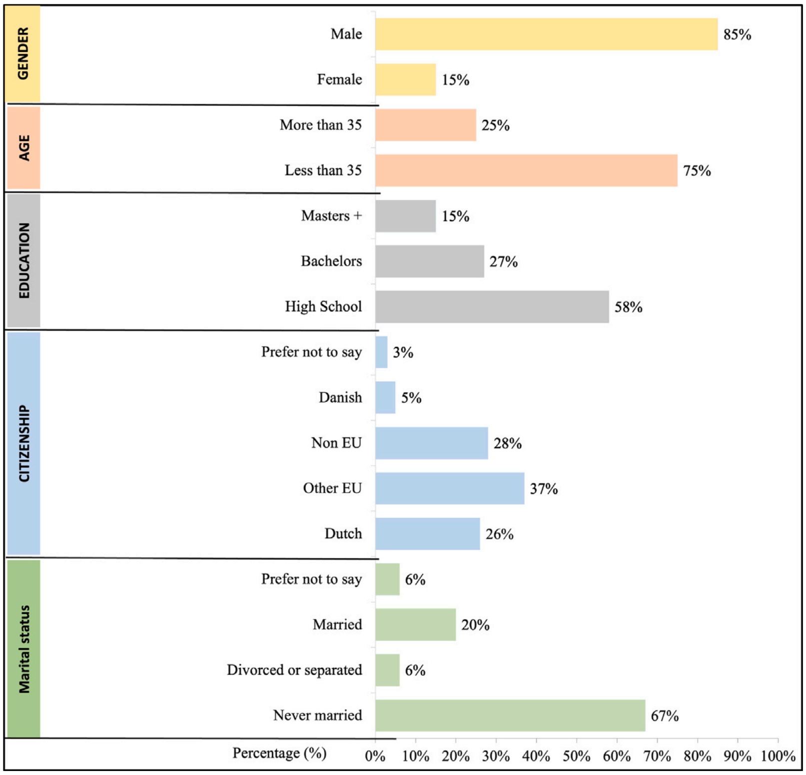


Fig. 3. Socio-demographics profile of riders.

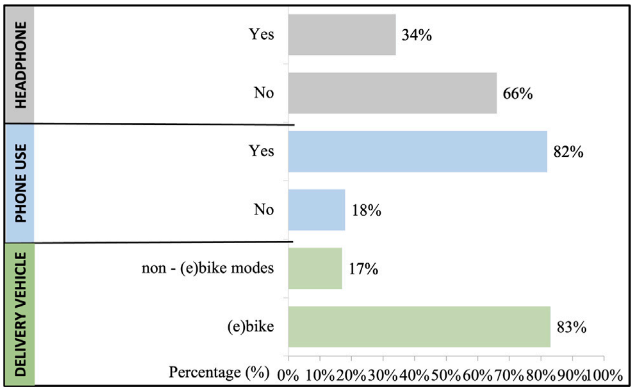


Fig. 4. Riding behavior summary.

work hours, 49% of riders work 16 h a week, while 26% work more than 32 h a week, reflecting the predominance of part-time employment in the sample. Most riders (52%) work 4 to 5 days a week. Concerning job tenure as a food delivery rider with the company, most riders (76%) have less than a year of experience.

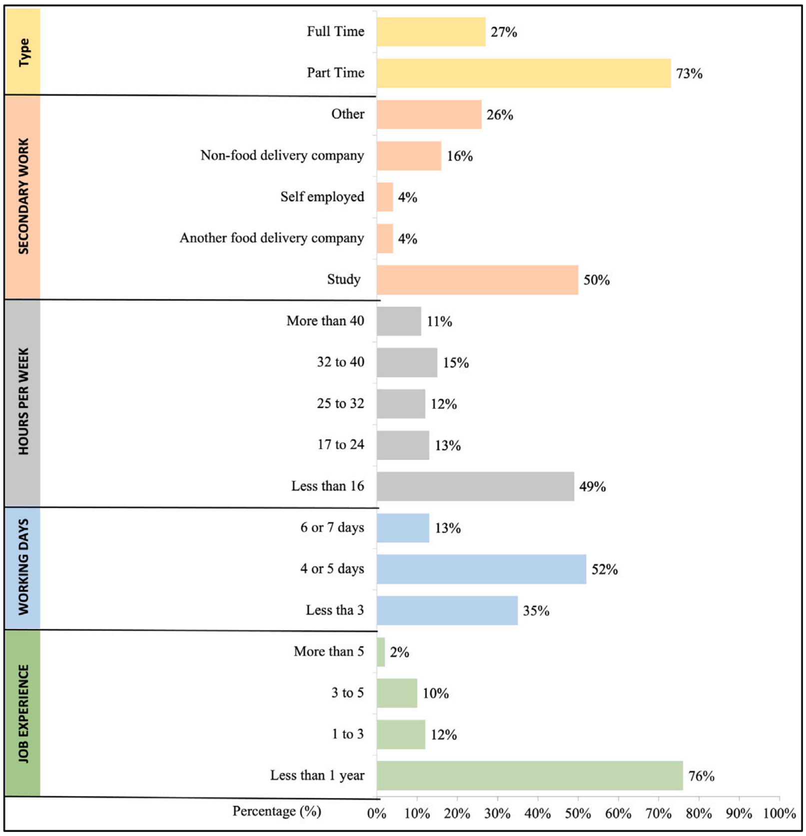


Fig. 5. Working arrangements descriptive statistics.

5. Methodology

5.1. Modeling framework

Riders' route choice preferences were analyzed, and the value of safety was estimated using a discrete choice model. Rooted in utility maximization theory, discrete choice models have long been a cornerstone in transportation research for understanding user behavior and preferences. Among these, mixed logit models offer a highly flexible structure, capable of approximating any discrete choice model by varying assumptions about random components and error terms (McFadden and Train, 2000; Train, 2009). This study employs an Error Component - Random Parameter Logit (EC-RPL) model, mathematically formulated to calculate the probability of choosing the alternative i by respondent n in task t, as given by Eqs. (1) and (2):

$$P_{i,n,t} = \iint_{\beta_n,\tau_n} \frac{\exp\left(V_{i,n,t} + \delta_i \tau_n\right)}{\sum_{j=1}^{J} \exp\left(V_{j,n,t} + \delta_j \tau_n\right)} f(\beta_n \mid \Omega)\, f(\tau_n)\, d\beta\, d\tau \tag{1}$$

$$V_{i,n,t} = \beta_f X^{f}_{i,n,t} + \beta_n X^{r}_{i,n,t} \tag{2}$$

where:

J represents the alternatives available in each choice task.

β_f is a vector of fixed taste parameters, assumed to be the same across all individuals.

β_n is a vector of individual-specific random taste parameters, capturing unobserved preference heterogeneity across individuals. These parameters are assumed to follow a distribution with density $f(\beta_n|\Omega)$.

$X^{f}_{i,n,t}$ is the vector of observed attributes associated with the fixed parameters for alternative i, individual n, and choice situation t.

$X^{r}_{i,n,t}$ is the vector of observed attributes associated with the random parameters.

τ_n is an individual-specific error component added only to the platform app route to capture persistent unobserved utility for that alternative. The error component follows a distribution with mean 0 and standard deviation σ_τ.

δ_i is a dummy variable equal to 1 if alternative i is the platform app route.

The joint probability of observing the sequence of choices made by individual n over T_n choice tasks is given by Eq. (3):

$$P_n = \iint_{\beta_n,\tau_n} \prod_{t=1}^{T_n} \prod_{i=1}^{J} \left(\frac{\exp\left(V_{i,n,t} + \delta_i \tau_n\right)}{\sum_{j=1}^{J} \exp\left(V_{j,n,t} + \delta_j \tau_n\right)} \right)^{y_{i,n,t}} f(\beta_n|\Omega)\, f(\tau_n)\, d\beta\, d\tau \tag{3}$$

where:

$y_{i,n,t}$ is an indicator variable equal to 1 if individual n chooses alternative i at time t, and 0 otherwise.

$f(\beta_n|\Omega)$ is the density function of the individual-specific taste parameters.

$f(\tau_n)$ is the density function of the individual-specific error component with mean 0 and standard deviation σ_τ.

The EC-RPL model simultaneously analyzes the effects of safety-focused strategies and unobserved variations. It treats the coefficients for travel time and strategies — safety information and monetary incentives — as random variables. Travel time follows a negative lognormal distribution, while strategies adopt a positive lognormal distribution. These assumptions align with behavioral expectations for the coefficients. A random error term captures the unobserved preference variations across alternatives (Bhat, 1995; Sasic and Habib, 2013). The utilities of both alternatives were specified as given in Eq. (4) and Eq. (5):

$$\begin{aligned} V^{\text{Platform}} = {} & \beta_{\text{tt},n} \times \text{TravelTime} + \beta_{\text{safety},n} \times \text{SafetyInfo} \\ & + \beta_{\text{money},n} \times \text{MonetaryIncentive} + \beta_{\text{citizen}} \times \text{NonEU} \\ & + \beta_{\text{age}} \times \text{AgeLessThan35} + \beta_{\text{timepressure}} \times \text{TimePressure} \\ & + \beta_{\text{experience}} \times \text{ExperienceLessThan1Year} + \sigma_\tau \times \tau_n \end{aligned} \tag{4}$$

$$V^{\text{Alternative}} = \beta_{\text{tt},n} \times \text{TravelTime} \tag{5}$$

The platform app route utility incorporates safety-improving interventions of safety information and monetary incentives, along with demographic (e.g., citizenship status, age) and work-related variables (e.g., time pressure, job experience). An individual-specific error component captures unobserved heterogeneity, with the alternative route's error term normalized to zero. In contrast, the alternative route's utility includes only the travel time attribute.

5.2. Estimation

The EC-RPL model was estimated using the Apollo package (Hess and Palma, 2019). Iterative forward estimation was employed to test different specifications, retaining only statistically significant variables in the final model. Model selection was based on comparisons of fit measures, including the Bayesian Information Criterion (BIC) and final log-likelihood values. The final model was estimated using simulated likelihood methods with 80,000 Halton draws, at which point the estimates had stabilized and showed no meaningful changes with additional draws, indicating convergence and stability. For models with a lognormal distribution, the parameters of the underlying normal distribution (c and s) were estimated. These parameters were transformed to derive the actual mean and standard deviation (μ and σ) of the lognormal distribution, calculated using Eq. (6) (Hess et al., 2005, 2006).

$$\mu = \exp(c + \frac{s^2}{2}) \qquad \sigma = \mu\sqrt{\exp(s^2 - 1)} \tag{6}$$

To further contextualize the model results, two indicators were calculated to illustrate the relative importance riders assign to safety during food deliveries. The first, the Value of Risk Reduction (VRR) (Eq. (7)), measures the additional travel time riders are willing to accept for a 10% reduction in crash probability. The second, the Willingness to Accept (WTA) (Eq. (8)), quantifies the expected monetary compensation for an additional travel time of 10 min.

$$VRR = \frac{\delta U/\delta(\text{safety info})}{\delta U/\delta(\text{travel time})} = \frac{\beta(\text{safety info})}{\beta(\text{Travel time})} \tag{7}$$

$$WTA = \frac{\delta U/\delta(\text{travel time})}{\delta U/\delta(\text{money})} = \frac{\beta(\text{travel time})}{\beta(\text{money})} \tag{8}$$

6. Results and discussions

Table 2 presents the final estimated model. A detailed interpretation of parameters and discussions about broader implications are provided in this section:

The factors influencing route choice can be broadly classified into three categories: socio-demographic characteristics, work-related attributes, and safety-oriented strategies. The following subsections discuss these factors in detail:

Table 2
Estimates of the coefficients for the platform suggested route.

	Estimate	t-ratio
Demographics and work-related variables		
ASC: Platform route	2.303	2.870***
Age: Less than 35	−1.891	−2.407**
Citizen: Non-EU country	1.646	2.533**
Time pressure: Yes	−1.393	−2.434**
Experience: Less than a year	1.128	1.662*
Route-related coefficients		
μ - Travel time (minute)	−0.40	–
σ - Travel time (minute)	0.506	–
μ - Monetary Incentive (Euros)	0.86	–
σ - Monetary Incentive (Euros)	0.867	–
μ - Safety Information	0.3	–
σ - Safety Information	0.30	–
Random parameters		
c – log (travel time)	−1.365	−6.571***
s – log (travel time)	−0.967	−4.937***
c – log (Safety information)	−1.566	−4.353***
s – log (Safety information)	−0.850	−1.620*
c – log (Monetary Incentive)	−0.797	−3.619***
s – log (Monetary Incentive)	1.144	3.619***
Error component (σ_τ)	2.162	4.115***
Model fit statistics		
Number of individuals	202	
Final Log Likelihood	−470.14	
BIC	1021.80	
Adjusted Rho-squared	0.218	

* 10% significance.
** 5% significance.
*** 1% significance.

6.1. Influence of individual characteristics and work-related attributes

The negative coefficient associated with age implies that individuals under 35 exhibit a decreased preference for selecting the platform application route. In contrast, their older counterparts prefer to follow the suggestion of the platform app. A similar influence of age was also reported in a study on route choice for car users on interurban roads in Chile (Rizzi and de Dios Ortúzar, 2006). Furthermore, riders who are non-EU citizens demonstrate a stronger inclination towards opting for the route recommended by the platform, as opposed to their EU citizen riders. Other socio-demographic variables such as education level, gender, income, and marital status were also tried in the model but were found to have no statistically significant impact on riders' route choices.

Regarding work-related attributes and their impact on route selection, various factors were investigated, including contract type (full-time/part-time), weekly working hours, earnings as a food delivery rider, time pressure during work, job experience, and job location. However, except for job experience and time pressure, none of the other variables showed a statistically significant effect on route choice. Riders with less than one year of experience in the food delivery business exhibit a greater preference for adhering to the route suggested by the platform. Conversely, riders with more experience tend to favor shorter routes with which they are already familiar. The riders who reported feeling pressure regarding being on time while making deliveries showed a preference for choosing their known route over the platform-suggested route. This result is intuitive as routes suggested by the platform are by default depicted longer in stated preference choice designs, and riders who feel time pressure during work opt for shorter known routes rather than longer and safer ones suggested by the platform. A similar influence of the time pressure on riders' safety has also been established by Dong et al. (2021).

Additionally, the model explicitly tested whether working in Amsterdam versus Copenhagen influenced route choice behavior. However, no significant differences were observed. A plausible explanation is that riders in both cities are employed by the same platform company, operating under similar organizational structures and work cultures. Moreover, both cities have comparable bike usage, possibly contributing to the uniformity in rider behavior across locations.

6.2. Influence of safety-focused strategies on route choice decisions

The safety-focused strategies encompassed two distinct interventions: safety information, which entailed presenting safety information regarding the reduction in the probability of crashes on the platform-suggested route, and monetary incentive, which involved offering an additional financial incentive for selecting the platform route. The positive coefficients for the mean associated with both nudging strategies indicate their effectiveness in influencing riders to opt for the platform route, which is safer. Specifically, as riders are shown higher values for reducing crash probability on the platform route, their preference for this route increases. Similarly, a higher monetary incentive increases preference for the platform route.

From a practical perspective, the results suggest that future mobile navigation applications could enhance safety by including an interface that indicates the safety levels of suggested routes, encouraging riders to choose safer paths. While offering monetary incentives for selecting safer routes may not always be feasible, such incentives could be introduced when the trade-off between safety and travel time is significantly high, potentially leading riders to choose shorter, riskier routes. Furthermore, the coefficient of travel time, which also emerges as statistically significant in the model, exhibits intuitively negative values. This suggests that survey respondents make a trade-off between selecting a safer route versus a shorter one. In essence, riders weigh the benefits of enhanced safety against the shorter travel time when making route decisions.

6.3. Value of safety

The estimates for the Value of Risk Reduction (VRR) and Willingness to Accept (WTA) were derived through simulations based on the estimated parameters of the random coefficients. A total of 10,000 random draws were generated, and the resulting distributions were summarized using their means and 95% confidence intervals around the mean. The mean values for VRR and WTA obtained were −1.85 and −1.80, respectively, indicating that, on average, riders are willing to travel an additional 1.85 min for every 10% reduction in the probability of crashes on the platform app-suggested route. Additionally, riders are willing to accept €1.80 for an additional 10 min of travel time on the platform-suggested route. The 95% confidence interval for mean VRR ranges from −1.37 to −2.33, while for WTA, it spans from −0.69 to −2.92. These confidence intervals provide a reference for the average effect, offering useful guidance for food delivery companies when planning the implementation of such interventions. Figs. 6 and 7 illustrate the full distributions of VRR and WTA.

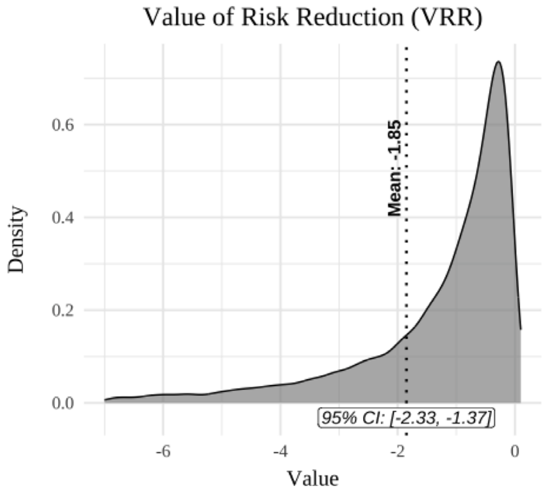


Fig. 6. VRR distribution.

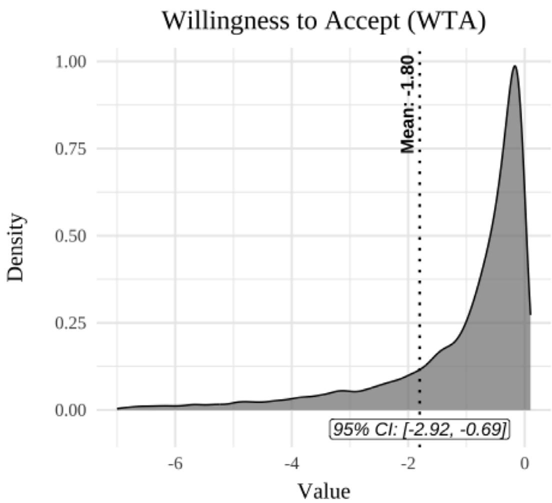


Fig. 7. WTA distribution.

A direct comparison of the estimated indicators is not feasible due to the lack of comparable studies in the existing literature. Nevertheless, the Willingness to Accept (WTA) estimate offers a meaningful interpretation in terms of the time value of money. Specifically, it can be compared to riders' actual hourly earnings, representing a revealed Value of Time in the context of food delivery work. Currently, riders earn approximately €15 per hour, whereas the average WTA value, when scaled to an hourly basis, is €11. This suggests that riders expect compensation that is relatively close to their current wage for choosing routes that require additional travel time but offer higher safety.

Building on these findings, the following two subsections discuss the practical implications from the perspectives of service providers and policymakers, and outline the key limitations of the study along with directions for future research.

6.4. Practical implications

The results highlight the empirical effectiveness of safety-focused strategies in reducing crash risks, but their practical implementation poses challenges for online food delivery companies. Integrating crash probability information into navigation applications would require significant backend efforts to modify the app interface, ensuring it remains easily comprehensible for riders. While technologically demanding, such a solution is feasible.

For riders less responsive to safety information, offering supplementary monetary incentives could motivate them to opt for safer routes. However, this approach would place additional financial burdens on food delivery platform companies already operating in a competitive market with limited profit margins. Nonetheless, the safety of riders and other road users is paramount, particularly given the rise in crashes involving riders—a concern for city authorities worldwide. A balanced approach is needed to enhance safety without compromising platform efficiency. One option is government-backed subsidies, similar to public welfare initiatives supporting eco-friendly products (Srivastava et al., 2022). Alternatively, a small surcharge on food orders could fund safety measures, similar to the environmental pricing strategies used in aviation, where lower-emission flights are labeled and priced higher to promote sustainable choices (Rotaris et al., 2020).

The current study focuses on a specific case within the online food delivery system; however, the findings may have broader implications for other same-day last-mile delivery services, such as those for groceries, commercial products, and medication. While these systems also involve delivery riders navigating urban environments, their operational models often differ. For example, food delivery services typically face more stringent timelines due to the freshness requirements of meals. Although directly applying these results to other quick-delivery contexts may be an overreach, the concept of nudging riders toward safer routes is transferable and holds significant potential for improving safety. However, adapting these findings requires careful consideration of the specific operational models of each delivery service to ensure their relevance and effectiveness.

6.5. Limitations and way forward

While this study provides valuable insights into the role of safety-focused strategies in influencing the route choices of food delivery riders, several limitations and future research avenues should be acknowledged. First, as the model is based on stated preference data, the alternative-specific constant (ASC) reflects the preferences of the sampled respondents under hypothetical scenarios. It may not align with real-world market shares and would need calibration using revealed preference (RP) data if the model were to be applied for prediction purposes. Second, while the study highlights the effectiveness of nudging strategies such as safety information and monetary incentives, it does not assess the long-term behavioral adaptation of riders. Future research could employ longitudinal studies to examine how riders adapt their route choice behavior after prolonged exposure to safety information. Finally, this study represents route safety as the probability of crashes or near-misses, shaped by various underlying factors such as infrastructure quality, traffic conditions, near-miss hotspots, and historical crash data. Independent of the current research, a compelling parallel research avenue could focus on developing a methodology to systematically integrate these factors to estimate the aggregate probability of crashes and near-misses on a given route.

7. Conclusions

This study examines the factors influencing the route choice behavior of food delivery riders and assesses the impact of two nudging strategies to encourage safer route selection. A stated preference experiment was conducted in Amsterdam and Copenhagen, where riders made a trade-off between the safety of the route and travel time, capturing the importance riders place on safety. The study introduces a novel approach for representing the aggregate safety level of a route in an SP experiment, which is easier to interpret and facilitates policy analysis. Descriptive findings reveal that the predominant demographic profile of riders is young, primarily male, European citizens with school-level education. Most riders work part-time, have less than a year of experience, and work 3 to 5 days a week. Riders predominantly use phones and wear helmets while riding, while headphone use is less common. Notably, nearly 40% of riders have been involved in major or minor crashes while working.

Estimates from the route choice model suggest that young riders and those under delivery time pressure are less likely to follow platform-recommended routes designed for safety. In contrast, non-European riders and riders with less than one year of experience tend to adhere to these routes. The findings highlight the effectiveness of nudging strategies, showing that providing safety information via navigation applications can influence riders to choose safer routes. Less safety-sensitive riders can be incentivized with monetary rewards to opt for safer routes. Two indicators that reflect the importance that riders put on safety were calculated: the Value of Risk Reduction (VRR) and the Willingness to Accept (WTA). VRR indicates riders are willing to travel 1.87 extra minutes for every 10% reduction in crash probability, while WTA shows they are willing to accept €1.74 for an additional 10 min of travel time. The paper concludes with a discussion on the practical implications of the results for operators and policymakers, along with a listing of the study's limitations and potential directions for future research.

CRediT authorship contribution statement

Kuldeep Kavta: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Shadi Sharif Azadeh:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Yousef Maknoon:** Writing – original draft, Validation, Supervision, Resources. **Yihong Wang:** Resources, Data curation, Conceptualization. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Conceptualization.

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Data availability

The data that has been used is confidential.

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