Modelling pedestrian crossing choice behaviour on Cape Town freeways: caught between a rock and a hard place?

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Mercy Dada

University of Cape Town

Centre for Transport Studies, Department of Civil Engineering
Faculty of Engineering and the Built Environment, Private Bag X3, Rondebosch 7701, SOUTH AFRICA

E-mail: mercidada@yahoo.com

Mark Zuidgeest

University of Cape Town

Centre for Transport Studies, Department of Civil Engineering
Faculty of Engineering and the Built Environment, Private Bag X3, Rondebosch 7701, SOUTH AFRICA

Tel: +27(0)216504756, E-mail: Mark.Zuidgeest@uct.ac.za

Stephane Hess

University of Leeds

Institute for Transport Studies (ITS)

34-40 University Road

Leeds LS2 9JT, UNITED KINGDOM

Tel: +44(0)113 34 36611, E-mail: s.hess@its.leeds.ac.uk

Abstract

Pedestrians and freeways are not supposed to coexist in any proximity to each other, yet in Cape Town, South Africa, the Freeway Management System (FMS) has recorded an alarming increase in pedestrian activity on its freeways in recent years, with a similar trend in (fatal) freeway pedestrian crashes. This paper reports on the development of a series of discrete choice models for pedestrian crossing decisions in a highly volatile and vulnerable freeway crossing environment. We hypothesize that freeway pedestrian crossing is driven by personal factors and the perceived risks associated with completing the crossing using a footbridge or (illegally) at-grade. We test this assumption by making use of stated choice and risk perception data collected from (adult) participants intercepted along three Cape Town freeways. Estimating mixed logit and hybrid choice models we look at the role of random heterogeneity and latent risk perception in the choice to cross at-grade or using a footbridge. The model estimates confirm that, as expected, crossing choice is largely influenced by a combination of built environment, vehicular and pedestrian traffic, next to some socio-demographic factors, but also risk perception. The study brings to light the seemingly opposite effect of some of the factors on risk perception and crossing choice. We also show that risk perception really only influences crossing choice in terms of the perception of at-grade crossing risk, where the impact is however non-trivial. Finally, we look at the implied relative sensitivities of the choice attributes within and between the crossing alternatives, as well between the three estimated models, amongst others demonstrating the power of the hybrid choice model over the other two. The results of the study can inform opportunities to counter the upward trend of fatalities and provide suggestions for policy-making that would lead to improved freeway crossing safety.

1. Introduction

Road fatalities have increasingly become a global health concern in road safety, even more so in developing countries. According to the International Transport Forum (ITF), South Africa had a road fatality rate of 25 persons for every 100,000 inhabitants in 2016 (ITF, 2017). This is far above the global average of 17 fatalities per 100,000 inhabitants, and slightly higher than the regional African average of 23 fatalities per 100,000 inhabitants. Vulnerable road users like pedestrians, cyclists and riders of motorized two – and three wheelers represent more than half (52%) of those killed, with pedestrians alone accounting for 38% in 2017 (RTMC, 2017), and children particularly being affected (ITF, 2017).

Over a 12-month period in 2017, a total of 14,050 fatal crashes have been recorded in South Africa (RTMC, 2017). In 2011, around 39% of all fatal pedestrian crashes occurred on freeways (RTMC, 2011). This is quite unique compared to other countries, particularly those in the Global North, as pedestrians and freeways are not expected to coexist in any proximity to each other, while traffic legislation internationally makes it clear that freeways are designed and intended for vehicular traffic only (Sinclair and Zuidgeest, 2016). In Cape Town alone, recorded monthly freeway pedestrian crash figures increased steadily from an average 3 to 16 between May 2010 and September 2016 (Cable, 2016). Each day an average of 1,065 pedestrians cross Cape Town freeways at-grade, based on a freeway system-wide pedestrian activity survey that was conducted in 2016 using closed-circuit television (CCTV) cameras of the Freeway Management System (FMS).

At-grade pedestrian crossing behaviour on freeways, even though illegal, cannot be looked at in isolation from a historical and contemporary context of poverty, inequality, spatial and social segregation, and crime. The legacy of apartheid, where between 1960 and 1983, an estimated 3.5 million 'non-white' people in Cape Town were forcibly removed from 'white' neighbourhoods and relocated to less desirable townships many kilometres away from the city centre without adequate infrastructure and services, continues until today. It created a situation of spatial and transport injustice whereby workers, job seekers, students and more, are highly reliant on walking long distances (inevitably having to cross a road) and/or using paratransit modes that frequently drop and pick-up passengers in the freeway road reserve to access opportunities that are mostly not located in the townships (Behrens et al, 2016). This situation, combined with world-class freeway infrastructure where speeds are high and where crime (harassment, mugging and even rape) are prevalent in and around available formal grade-separated crossing infrastructure (Sinclair and Zuidgeest, 2016), creates a context whereby many are caught between a rock and a hard place making an often inconvenient and uncomfortable choice between crossing at-grade and (where available) use grade-separated footbridges.

Whilst the vast majority of pedestrians use grade-separated infrastructure (footbridges and viaducts) to cross the freeway, a significant minority group of 'choice-crossers' make a choice between at-grade and grade-separated crossing options regularly. It goes without saying that the freeway can be placed on the highest scale for traffic – pedestrian crash impact (Tiwari, 2002), resulting in the local governments' and the South African National Roads Agency's (SANRAL) ambition to develop policies for improved freeway crossing conditions.

Earlier research by Behrens (2010) and Sinclair and Zuidgeest (2016) revealed that risk perception plays an important role in the decision to cross at-grade or not, i.e. making pedestrians consider crossing at-grade if they consider that risk to be inferior to say the risk of being mugged on a footbridge. This earlier research directly motivates the present paper, which seeks to investigate pedestrian crossing choice and the role of risk perception in a context of a highly fragile and volatile freeway crossing environment. Using hybrid choice models, we postulate that individuals presented with two freeway crossing alternatives consider the risks and other characteristics of both alternatives before responding with a visible action in the form of a choice that is at least in part influenced by that risk perception.

We first discuss literature on pedestrian crossing choice, in particular the literature that has looked at pedestrian crossing on higher-order roads. We then present the setup of a stated choice experiment in Cape Town, South Africa, before presenting our choice modelling framework for analysing the resulting data. This is followed by a presentation of the results, and a discussion of the key findings. The article ends with some policy recommendations and recommendations for further research.

2. Literature review

2.1. *Pedestrian crossing*

Most literature on pedestrian crossing starts from the premise that pedestrians confine themselves to types of infrastructure where they (in general) are welcome and for which the road design anticipates and accommodates pedestrians (Sinclair and Zuidgeest, 2016). This is not withstanding events where situational and behavioural factors may instigate illegal behaviour in this otherwise legal environment, for example when running red-light (Rosenbloom, 2009; Wu et al, 2012a; Cambon de Lavalette, 2009; Tom and Granié, 2011), or where traffic design and intersection control issues may bring about illegal behaviour in this otherwise legal environment (see for example Iasmin et al 2016; Osama and Sayed, 2017). Some research has looked into the type of users and their habitual behaviour. Kitaori and Yoshida (2004) for example find that first time crossers

are more likely to cross legally than routine crossers implying that the behaviour of surrounding people strongly predicts pedestrian crossing behaviour, while Rankavat and Tiwari (2016), in a study carried out in Delhi, India, observed that the use of footbridges, subways and other pedestrian structures reduces as compared to using zebra crossings with increasing age.

This is all true for legal, pedestrian controlled environments. The reality is however that in many developing countries pedestrians walk along and cross freeways at-grade as a matter of course. As discussed by Sinclair and Zuidgeest (2016), there are many reasons for this. First, crossing freeways at-grade often provides the most direct, quickest, route between suburbs and the city; second, freeways are barriers to the free movement of pedestrians wanting to access locations beyond them. This is especially true in the context of South Africa, where freeways have been used as tools of racial segregation; third, most pedestrians are captive walkers or want to access informal public transport vehicles that board and alight in the freeway road reserve; lastly, pedestrians may fear using footbridges because of crime.

Literature on pedestrian crossing on freeways is very limited, and indeed appears to be almost exclusive to a developing country/emerging economy context (with known research in Turkey, Colombia, Greece, China, Qatar and South Africa). Notably, Oviedo-Trespalacios and Scott-Parker (2017) explored factors of pedestrians' decisions, including attitudinal factors that influence high-volume highway crossing choice near footbridges in Barranquilla, Colombia. Also in Colombia, Bogotá, Cantillo et al (2015) looked at the role of factors, such as security/safety and attractiveness of the crossing facility in the choice to cross illegally or not. Räsänen et al (2007) studied habitual behaviour of pedestrians in the use and non-use of pedestrian facilities in Ankara, Turkey. Also in Turkey, Demiroz et al (2015) looked at gap acceptance and crossing times versus socio-demographics, such as age, in the decision to cross illegally in Izmir. In Greece, Papadimitriou et al. (2016a, 2016b) used revealed preference experimental data to study pedestrian crossing choice in Athens' CBD. In Xi'an, China, Wu et al. (2012b) investigated design and personal factors for crossing preferences over a major arterial to find that socio-demographic variables such as age, education level, driver's license etc. as well as distance to formal crossing infrastructure and the expected crossing time are major contributors to crossing choice decisions, whilst in Nanjing, China, Zhou et al. (2013) analysed four types of crossing behaviour at signalized intersections, specifically looking at subjective preferences explained through gender, age and income. Similarly, for Hefei, China, Zhang et al (2016) find that trip purpose, time of the day, being in a hurry and one's attitude towards the quality of the road crossing facility are key factors of illegal crossing choice. In Doha, Qatar, Shabaan et al. (2018) looked at crossing behaviour during the various stages (before, during,

after) of crossing a major divided arterial road using video observations and interacted these with socio-demographic variables. Finally, in Cape Town, South Africa, Behrens (2010) found that-grade-separated freeway crossing facility use is associated with a greater perceived risk associated with the greater speed differential on freeways, as well as other factors such as the illegality of, and the greater physical difficulty presented by, crossing freeways at-grade. Behrens also found a correlation between grade-separated crossing and a greater experience of urban life (referring to first generation residents who have migrated from the more rural districts to Cape Town), which by implication means a greater exposure to (urban) traffic risks.

Adding to these factors, the Michigan Department of Transport (MDoT, 2006) observed that for pedestrian crossing facilities to be considered by their users they need to be free from criminal elements and safety hazards, such as slippery surfaces, be protected from traffic and need to be accessible to all users, provide a convenient, direct and fast route; and provide comfortable gradients and an attractive crossing environment. Ribbens et al. (2008) furthermore observed that in the context of the Global South, and in particular in South Africa, footbridges, unless properly designed with appropriate ramps, smooth ground level access and hand railways, may actually prove disadvantageous to a significant part of the population that includes the sick, pregnant women, physically disabled, aged and even those with a fear of heights, and therefore instigate illegal crossing behaviour.

2.2. Modelling pedestrian crossing choice

Most of the previous examples use some kind of choice modelling in their approach and consider human factors (including risk attitudes). Papadimitriou et al (2016a, 2016b), in their study for Athens, developed an Integrated Choice and Latent Variable (ICLV), using principal component analysis to distinguish three different latent constructs of human factors to show that these human factors improve modelling results over and above road and traffic factors; as did Zhou et al. (2013) when incorporating safety, conformity, comfort, flexibility, and fastness as latent variables in their choice model for explaining crossing behaviour in Nanjing; Cantillo et al (2015) also developed an ICLV crossing choice model, to show that time taken to arrive at a safe footbridge crossing constitutes a critical factor in explaining pedestrian crossing behaviour in Bogotá. The other Colombian study by Oviedo-Trespalacios and Scott-Parker (2017) developed a logistic-regression model that includes perceptions around security and crime and distance to the footbridge. Both Demiroz et al (2015) and Räsänen et al (2007) used general statistical analysis techniques to study road crossing choice in Turkey, while Wu et al (2012b) as well as Zhang et al (2016) used binary logit models to study crossing choice.

Our paper specifically looks at pedestrian crossing in a (highly volatile African) freeway environment, with illegal at-grade crossing and the use of a footbridge as choice options, whereby neither option is perceived to be particularly "safe", with the footbridge crossing also having disadvantages beyond just access and effort. Cantillo et al (2015), yet similar to ours in their modelling and survey design, focus on urban roads and look at three legal crossing alternatives, including attitudinal statements. Oviedo-Trespalacios and Scott-Parker (2017)'s work, also looking at crossing choices in a high-traffic flow environment, including latent risk perception variables, use a stepwise logistic regression model and revealed choice data from a field experiment. We do not look at crossing choice near signalized intersections or compare crossing behaviour between different road classes as the other articles do.

2.3. Risk perception

A key component of existing research in transport studies has looked at the role of risk perception in crossing choice, driving behaviour and traffic safety (see for example Arbis et al. (2016), Fyhri and Backer-Grøndahl (2012), and - for a critical discussion on the use of risk perception as a reflective construct - Rundmo and Nordfjærn (2017)). Risk perception is defined here as a belief, whether rational or irrational, held by a respondent about the chance of occurrence of a crash when crossing at-grade or the chance of occurrence of a criminal attack when crossing using a footbridge, and is adapted from the more general definition of risk perception by Chambers (2004).

Risk ladders can be used to establish a linkage between an activity (e.g. a crossing decision) and the perceived risk associated with the activity in the context of assumedly known risks**.** Risk ladders have typically been developed to consistently measure relative judgments by respondents (Persoskie and Downs, 2015). It is believed that several factors account for risk among pedestrians when choosing to cross at any point. Ayres et al. (1998) for example find that people are often willing to accept an increased likelihood of severe injury in return for convenience. A pedestrian who has encountered traffic injury previously would be more inclined to use the footbridge rather than to cross the freeway. On the other hand, an individual with a history of harassment or worse on the footbridge would rather face the danger of traffic collision than relive the attack.

3. Methods

In our work and in line with the literature review, we hypothesize that freeway pedestrian crossing is driven by personal factors such as urban experience and situational factors of location, design, safety, crime and the perceived contribution thereof to the risks associated with the crossing, either at-grade or grade-separated.

We study these factors by means of a stated choice survey conducted along freeways in the city of Cape Town, data from which, alongside that from a risk ladder component, will be analysed by means of choice models.

3.1. Stated choice survey design

A stated choice survey was conducted at seven freeway sites known to be pedestrian activity hotspots, and by extension pedestrian crash hotspots, see Figure 1. These sites are all near townships and are typically situated along desire lines, being the shortest direct connection between formal and informal areas or between informal areas and public transport interchanges.

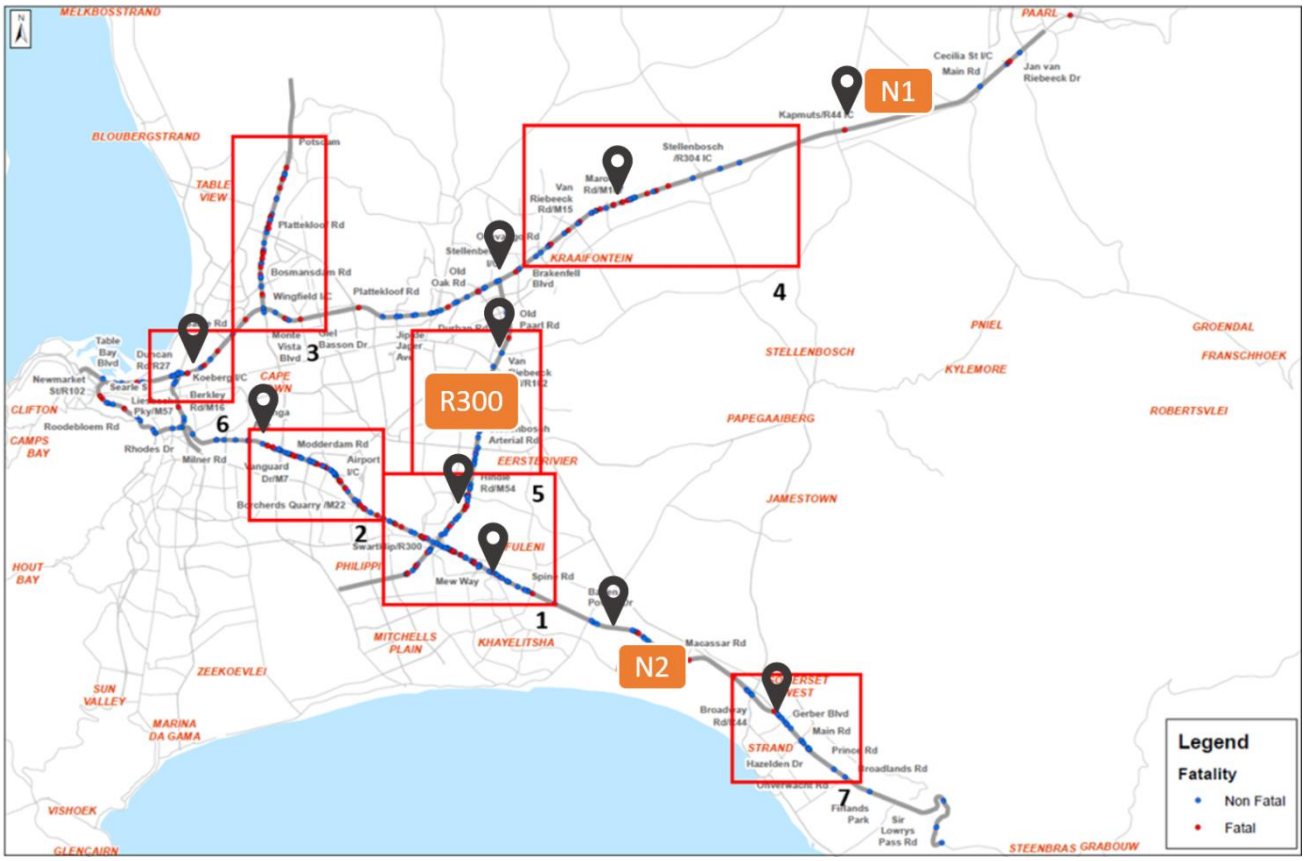

Figure 1. Pedestrian crossing hotspots (squares) (Cable, 2016) and survey locations along N1, N2 and R300

The stated choice survey presented pedestrians with a choice between at-grade crossing and crossing using a pedestrian footbridge. Based on the literature review, a long list of possible explanatory variables of freeway pedestrian crossing choice was established. These factors ranged from typical environmental conditions (infrastructure design, security), to personal factors (urban tenure, socio-demographics), as well as traffic

factors (traffic on the road, pedestrians on the bridge). In line with Abiiro et al (2014), attribute levels in this study were decided from the perspective of the characteristics of the respondent population. They were exhaustive, measurable and defined in a manner that gives room for trade-offs between the two alternatives. The list was then refined by eliminating factors not in line with our study objectives and research scope and through discussions with SANRAL, traffic police, informal discussions with pedestrians on-site as well as with those students of the University of Cape Town who are familiar with the use of the footbridges in South Africa, following recommendations on designing choice experiments in this kind of context by Mangham et al. (2009).

The final list and description of the selected attributes and assigned levels is shown in Table 1 below and includes at-grade crossing attributes, such as traffic density on freeways, presence of law enforcement agents (police), and physical features, such as fence and tall concrete barriers in the median (already used in several places in Cape Town). In addition, the footbridge attributes included pedestrian numbers on the footbridge, walking time to the footbridge, convenience and footbridge security.

A fractional factorial design (reduced from a full factorial design of 864 scenarios) was used with 18 scenarios spanning 8 attributes (3 attributes with 3 levels, and 5 attributes with 2 levels). The scenarios were presented to the respondents in 3 blocks of 6 choices, where in each choice task, the decision was between crossing at-grade or using the footbridge, alongside an indication of perceived risk of both crossing alternatives.

Table 1. Attributes and attribute levels

Attribute	Description	Attribute levels*
Roadway attributes		
Traffic density	Number of vehicles per lane on the freeway	• Low density represented as an average of 5 vehicles per lane (*base*) • Medium density represented as 15 vehicles per lane ($\beta_{t_{med}}$) • High density represented as 25 vehicles per lane ($\beta_{t_{high}}$)
Police personnel	Law enforcement on the freeway to prevent jaywalking	Two agents present or absent (β_p)
Median barrier	Elevated concrete barriers separating opposing flows of traffic	Median present or absent (β_m)
Fence	Barriers along the shoulders and sidewalk to restrict access into the freeway	Fences present or absent (β_f)
Footbridge attributes		
Crowd	Number of pedestrians on the footbridge at a particular time	• Low, represented as 2 pedestrians on the footbridge (*base*) • Medium, represented as 8 pedestrians on the footbridge ($\beta_{c_{med}}$) • High, represented as 15 pedestrians crossing the footbridge ($\beta_{c_{high}}$)
Travel time	Time taken to arrive at the nearest footbridge**	• Close distance, 2 minutes' walk to the footbridge (*base*) • Mid-level, 8 minutes' walk to the footbridge ($\beta_{d_{med}}$) • Far distance, 14 minutes' walk to the footbridge ($\beta_{d_{high}}$)
Efforts	Measure of exertion in walking up the footbridge	Stairs or ramp (β_s)
Footbridge Security	CCTV + Guard securing the footbridge	CCTV + Guard or none (β_e)

**Images with sketches were drawn to scale and correspond to the values highlighted in the table. See figure 2. Parameters and base values are explained in section 3.4.*

***For walking time, a 'time travelled' scale was estimated using the average walking speed/distance for an adult, 5.5 [km/h] following Parise et al (2004); Levine and Norenzayan (1999).*

Risk perception was measured using risk ladders set to a scale of 1 to 10 and broken down into health-related scenarios using rates of occurrence of generally known risks in contemporary South Africa (World Health Organization, 2014; Statistics South Africa, 2015), as shown in Table 2. These risk dialogues were included in the choice task to obtain information regarding the perceived levels of risk for each choice task. Indicators of safety and security were the motivating factors for the risk ladders.

Table 2. Characteristics of the risk variable

Risk ladder scales	Corresponding Likert –scale	Known risks	Odds
1	Not risky at all	Snake bites	1 in 100,000
2		Death by food poisoning	1 in 50,000
3	Somewhat risky		
4			
5	Risky	Residential fires	1 in 20,000
6			
7	Very risky	Contracting tuberculosis	1 in 10,000
8			
9	Extremely risky		
10		Injury from sharp objects	1 in 500

3.2. Choice task construction and additional survey components

Cognitive processes have been researched in psychology to understand the decision-making processes of individuals (Roch, 2000; Deck and Jahedi, 2015; Nicholson and O'Hare 2014; Arentze et al 2003). The impact of complexity in surveys on response rate and quality remains a relevant issue that is being debated in several fields, including environmental studies, transport and economics. Cognitive Load Theory (CLT) suggests that humans can absorb and retain information effectively only if it is provided in such a way that it does not "overload" their mental capacity (Pappas, 2014). Given the complexity of the choice tasks, some level of literacy restrictions of the target population and the volatile survey environment, choice tasks in this experiment incorporated sketches to graphically represent the choices as seen in Figure 2. In doing so, we exaggerated changing attributes and their attribute levels by not drawing them to scale (other than traffic and pedestrian levels) as the pilot testing revealed that respondents didn't attend to some attributes, like CCTV cameras and a security guard on the footbridge, when drawn to scale. To further reduce the cognitive burden on respondents, we used a generic presentation across all scenarios with a two-lane highway.

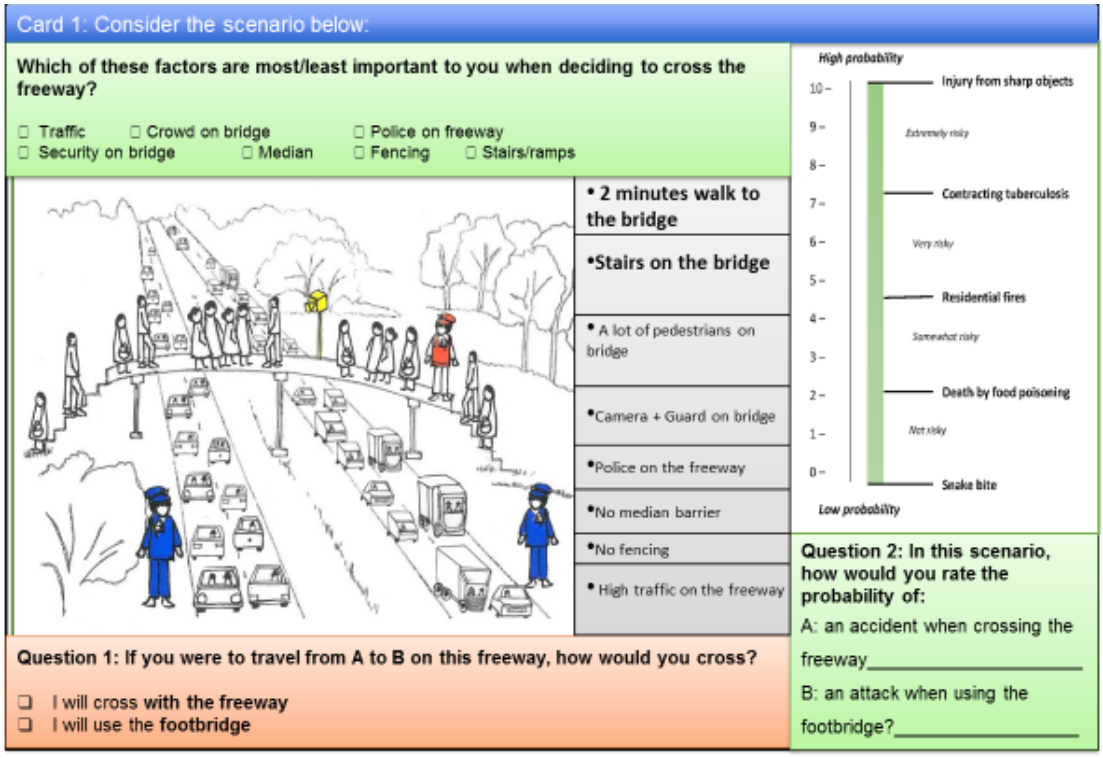

Figure 2. An example choice task

The questionnaire was further divided into three sections covering socio-demographic details, recent trip information, and six separate crossing choices with associated risk ladders. The socio-demographic section included questions about gender, age, employment status, how long the respondent has lived in Cape Town (urban tenure) and whether the respondent has children or not.

3.3. Pilot survey and main data collection

The questionnaire was initially tested for understanding, ease of task, time to complete and engagement of respondents in a focus group setting with University of Cape Town staff and students, as well as a number of transport professionals from Cape Town to ascertain the best approach for ordering and structuring the questionnaire. A first field pilot testing was carried out in July 2016 to test the survey in the field and to ensure that the information obtained was adequate to fulfil the purpose of the study (cf. Coast and Horrocks, 2007). The initial number of nine treatments per respondent appeared to be too burdensome for most respondents. We therefore decided to use six treatments instead.

The University of Cape Town, Faculty of Engineering and the Built Environment (EBE), EBE Ethics in Research Committee required that all subjects for the research must be 18 years or older at the time of the survey. This poses a limitation to the research as a good number of pedestrians walking along and crossing the freeway are teenagers (Bhole, 2015). Hence, qualifying respondents were those moving alongside and/or crossing the freeway near the survey sites, and who are older than 17 years as well as have experience in crossing the freeway illegally at least once (making them choice crossers). An intercept survey process elicited a total number of 300 randomly selected and qualifying respondents at the time of the survey. This is equivalent to 1,800 choice observations.

The language barrier was reduced to a minimum with the utilization of English, IsiXhosa and Afrikaans speaking interviewers. The fieldworkers were recruited and trained adequately ahead of the main survey which took place in September 2016. The main survey was carried out in two phases and at peak periods of the day – morning between 6am and 9am, afternoon at 12 noon and evening between 4pm and 7pm, at ten sites within proximity of existing footbridges along the N1, N2 and R300 freeways (see Figure 1). These areas are known to be hotspots for (fatal) pedestrian crashes.

Before respondents were interviewed, they were briefed on what the attributes and levels meant and how they were to respond to the choice tasks presented to them. Considering the nature of the choice design, they were informed on what to look out for in the sketches (i.e. those attributes also shown in text) and what elements were irrelevant to the experiment (such as trees).

3.4. Modelling

Our analysis makes use of three different models, a Binary Logit model, a Mixed Binary Logit model allowing for random heterogeneity in crossing-type preference, and a Hybrid Choice model additionally incorporating the role of latent risk perception. Especially Binary and Mixed Logit models are standard tools in travel behaviour work, and we refer readers from other fields to Train (2009).

Binary Logit model

The binary logit model is used to explain the role of environmental, traffic and personal characteristics in the choice of crossing at-grade and using a footbridge. In a random utility context, we have that:

$$U_{jnt} = V_{jnt} + \varepsilon_{jnt} \tag{1}$$

where U_{jnt} is the utility of respondent *n* in choice situation *t* for crossing alternative *j*, which is made up of a deterministic component, V_{jnt}, and a random component or error term, ε_{jnt}. This utility characterises the appeal of this crossing type *j* as a function of the estimated sensitivities and observed characteristics of the respondent and the attributes of the two crossing options, as faced by respondent *n* in choice situation *t*.

The deterministic part of the utility (V_{jnt}) for the at-grade crossing alternative (*j*=1) for respondent *n* in choice situation *t* is shown in Equation 2, while for the footbridge crossing choice (*j*=2), it is shown in equation 3. The utility is thus influenced by the levels taken by the different attributes (see table 1), where for traffic, crowding and distance, the lowest level is used as the base, while for fence, median, police and security, an absence of these measures is used as the base. Finally, we estimate the effect of stairs relative to the base level of a ramp design. The vector of crossing attribute specific marginal utility coefficients β is to be estimated. In addition, the parameter $\delta_{\text{at-grade,n}}$ relates to the crossing type and captures a baseline desire or dislike for at-grade crossing relative to the footbridge option, at the base levels of the different crossing-specific attributes:

$$V_{\text{at-grade},nt} = \delta_{\text{at-grade,n}} + \beta_{t_{med}}\text{Traffic}_{\text{med},nt} + \beta_{t_{high}}\text{Traffic}_{\text{high},nt} + \beta_f\text{Fence}_{nt} + \beta_m\text{Median}_{nt} + \beta_p\text{Police}_{nt} \tag{2}$$

$$V_{\text{footbridge},nt} = \beta_{d_{med}}\text{Distance}_{\text{med},nt} + \beta_{d_{high}}\text{Distance}_{\text{high},nt} + \beta_{c_{med}}\text{Crowd}_{\text{med},nt} + \beta_{c_{high}}\text{Crowd}_{\text{high},nt} + \beta_s\text{Security}_{nt} + \beta_e\text{Stairs}_{nt} \tag{3}$$

In our specification of the model, we allow for variations in this baseline preference ($\delta_{\text{at-grade,n}}$) as a function of the characteristics of the respondent, allowing us to understand how different types of respondents react differently to the various attributes and have different baseline preferences for the two crossing types. This means that $\delta_{\text{at-grade,n}}$ is allowed to vary across different types of respondents. Specifically, we have that:

$$\delta_{\text{at-grade,n}} = \mu_{\text{at-grade}} + \Delta z_n \tag{4}$$

where $\mu_{\text{at-grade}}$ represents a base value while Δ is a vector of *shift* parameters that capture deviations from this base value for respondents with specific socio-demographic characteristics captured in z_n. The specific characteristics used are discussed in the results section. Assuming that the error terms ε_{jnt} are distributed independently and identically across individuals, choices and alternatives using a *type I* extreme value distribution, the probability of respondent *n* choosing crossing type *i* in choice situation *t* is given by:

$$P_{int}(\beta, \delta) = \frac{\exp(V_{int})}{\sum_j \exp(V_{jnt})} \tag{5}$$

which is a function of the estimated baseline preference δ (for at-grade crossing) and the vector of marginal utility coefficients β for the different attributes. The likelihood of the sequence of choices for respondent *n* is then given by:

$$L_n = \prod_{t=1}^{6} P_{j^*_{nt}nt}(\beta, \delta) \tag{6}$$

where j^*_{nt} represents the alternative (either at-grade or footbridge) chosen by respondent *n* in choice situation *t* (out of 6 choice situations).

Mixed Logit model

In a mixed logit version of the model, we incorporate random heterogeneity in the baseline sensitivity for at-grade crossing, $\delta_{\text{at-grade}}$, allowing us to capture additional differences across respondents not captured by the socio-demographic interactions (Δ). We now write:

$$\delta_{\text{at-grade,n}} = \mu_{\text{at-grade}} + \Delta z_n + \sigma_{\text{at-grade}}\xi_n \tag{7}$$

where ξ_n follows a standard Normal distribution across individuals but held constant across choice situations *t*, meaning that the estimates of $\mu_{\text{at-grade}}$ and $\sigma_{\text{at-grade}}$ now provide the mean and standard deviation, respectively, of the baseline preference for at-grade crossing. With the presence of such random heterogeneity, the likelihood in Equation (6) is now replaced by an integral over the distribution of ξ, i.e:

$$L_n = \int_{\xi} \prod_{t=1}^{6} P_{j^*_{nt}nt}(\beta, \Omega_\delta)\phi(\xi)\mathrm{d}\xi \tag{8}$$

where $\phi(\xi)$ is the standard Normal density function and where $\Omega_\delta =< \mu_{\text{at-grade}}, \sigma_{\text{at-grade}} >$, i.e. the parameters of the distribution of the at-grade crossing parameter. This model no longer has a closed form solution for the likelihood function, hence a simulation-based estimation is required (cf. Train, 2009).

Hybrid Choice model

The incorporation of random heterogeneity as done in the Mixed Logit model above generally leads to important gains in model fit and highlights the presence of extensive amounts of unexplained variation in preferences across respondents. Over the last decade especially, there have been increasing attempts to link at least part of this variation to psychometric factors, such as attitudes and perceptions. This has led to the development of a very flexible modelling framework, commonly referred to as either the integrated choice and latent variable (ICLV) structure or more broadly hybrid choice models (Ben-Akiva et al., 1999a; Ashok et al., 2002; Ben-Akiva et al., 2002; Bolduc et al., 2005).

A hybrid choice model recognises that attitudes or perceptions themselves are not observed and that an analyst only witnesses manifestations of these psychometric factors in the form of indicators, such as answers to attitudinal questions or in our case risk ladders. These attitudes or perceptions themselves are treated as latent (unobserved) variables, which are used to explain both the values of these observed indicators (through the measurement model) and part of the heterogeneity in the choice model component of the hybrid structure.

Hybrid choice models have been used across different disciplines to study the role of a wide variety of attitudes, ranging from privacy and security concerns (Daly et al., 2012) to environmental considerations (Kim et al., 2012). In a transport context, they have been used for example in the study of decisions around vehicle type (Glerum et al., 2013), mode choice (Atasoy et al., 2013; Kamargianni et al., 2014), route choice (Prato et al., 2012), departure time choice (Thorhauge et al., 2016) and indeed pedestrian crossing choice (Papadimitriu et al., 2016; Cantillo et al., 2015). Alongside numerous empirical applications, further refinements of the modelling framework have taken place, looking at the specification of the measurement model (Daly et al., 2012), how and where to incorporate the latent variables into the choice model (Bahamonde-Birke et al., 2017) and testing for non-linearity and distributional assumptions (Kim et al., 2016). For a fuller overview of the development and applications of hybrid choice models, see Abou-Zeid and Ben-Akiva (2014).

An important misperception in many early applications of hybrid choice models was that they could lead to further improvements in model fit compared to for example a mixed logit model. This is mathematically not possible, a point first discussed by Vij & Walker (2016). Indeed, a hybrid choice model needs to explain both the choices as well as the answers to attitudinal questions. Aside from the fact that the overall likelihood will clearly be more negative (by having a larger set of dependent variables), the part of the log-likelihood related to the choices alone cannot by definition be better than that of a suitably specified model which only needs

to explain the choices. Furthermore, if that model uses the same level and detail of deterministic and random heterogeneity as the hybrid choice model, it is given the same flexibility but only needs to explain the choices alone. Vij & Walker (2016) refer to such a model as a "reduced form" model, which will generally be a mixed logit model. While a hybrid choice model thus cannot offer a better mathematical explanation of the choice behaviour, it can offer gains in efficiency (i.e. lower standard errors) through making use of more data. Additionally, it can provide further behavioural insights by linking heterogeneity to underlying attitudes and allowing an analyst to explain what part of the heterogeneity can in fact be linked to these attitudinal constructs. For detailed discussions about this final point, see also Hess et al. (2018).

The data collected for this study contains three different sets of response variables, namely the stated choices themselves, the choice task specific risk perception for the footbridge crossing and the choice task specific risk perception for at-grade crossing. In our hybrid choice model, we use the answers to the risk ladders as indicators of latent risk perceptions that then also help to explain the answers in the stated choice scenarios.

Specifically, we define two latent variables, one for the risk perception towards at-grade crossing, and one for footbridge crossing. Either of them is a function of the characteristics of the respondents (which are invariant across choices) and attributes of the alternative in question (which change across choices). In addition, there is random variation across respondents. We now have a structural equation for the latent variable α_{jnt} with alternative *j* for respondent *n* in choice situation *t*:

$$\alpha_{jnt} = \lambda_j X_{jnt} + \gamma_j z_n + \eta_{jn} \tag{9}$$

where λ_j is a vector of estimated parameters, measuring the impact of the attributes of alternative *j* in choice situation *t* for respondent *n* on the risk perception towards that alternative, for the specific respondent and choice situation. The risk perception is also driven by respondent characteristics z_n (which are constant across choice scenarios *t*), again with a vector of estimated parameters γ_j. Finally, η_{jn} is a standard Normal disturbance, which varies across the two risk perceptions and across respondents, but is constant across choice situations for the same respondent. The motivation for making the error terms invariant across choices was to make the risk attitudes person specific in terms of their random variation, while allowing for shifts in the risk attitudes as a function of the characteristics of the crossing, which vary across choice tasks. While it would have been possible to add additional variation across choice tasks, this would have led to the presence of an additional layer of integration at the observation level in equation 12, with substantial increases in computational complexity. An alternative would have been to make the λ parameters vary across individuals,

thus allowing for variation across individuals in the impact of the choice task specific characteristics, but we again decided against such an increase in complexity.

We now rewrite Equation (7) as:

$$\delta_{\text{at-grade,nt}} = \mu_{\text{at-grade}} + \Delta z_n + \sigma_{\text{at-grade}}\xi_n + \tau_{\text{at-grade}}\alpha_{1\text{nt}} + \tau_{\text{footbridge}}\alpha_{2\text{nt}} \tag{10}$$

The two additional parameters $\tau_{\text{at-grade}}$ and $\tau_{\text{footbridge}}$ capture the impact of the latent risk perception towards the two crossing types on the baseline preference for at-grade crossing.

The two latent variables are used in the measurement model component of our overall framework to explain the responses to the risk ladders in each choice task. These ladders used a 10-level scale, and, with I_{jnt} referring to the response by respondent *n* to the risk ladder for alternative *j* in choice task *t*, we can use an ordered logit model (cf. Train, 2009) to explain the likelihood of the actual observed value of I_{jnt} as LI_{jnt}:

$$LI_{jnt}(\alpha_{jnt}, \zeta_j) = \sum_{p=1}^{10} x_{I_{jnt},p} \left(\frac{e^{t_{I_j,p} - \zeta_j \alpha_{jnt}}}{1 + e^{t_{I_j,p} - \zeta_j \alpha_{jnt}}} - \frac{e^{t_{I_j,p-1} - \zeta_j \alpha_{jnt}}}{1 + e^{t_{\text{j},p-1} - \zeta_j \alpha_{jnt}}} \right) \tag{11}$$

where $x_{I_{jnt},p}$=1 if and only if respondent *n* chooses answer *p* for the risk ladder for alternative *j* in choice situation *t*. The $t_{I_j,p}$ parameters are thresholds that are to be estimated, with the normalisation that $t_{I_j,0} = -\infty$ and $t_{I_j,10} = +\infty$. The estimated parameter ζ_j measures the impact of the latent variable α_{jnt} on I_{jnt}, where a significant estimate for ζ_j shows us that the latent risk perception has a statistically significant impact on the answers provided to the risk ladder.

The combined utility specification now includes three components:

1. the impacts of the explanatory variables, which are interacted with respondent characteristics;
2. the baseline parameter for at-grade crossing, which is interacted with respondent characteristics and includes a random part;
3. an impact on the baseline at-grade crossing sensitivity by the two latent variables, which again include a deterministic and random component, where the latter depends on respondent as well as crossing characteristics.

All respondent and trip characteristics included in the deterministic component of the latent variables have also been included directly in the utility function, thus avoiding a situation where a sociodemographic or crossing characteristic effect is erroneously captured as relating to risk perception when it may just relate to underlying crossing type preferences, or vice versa (cf. Vij and Walker, 2016). In a standard choice model, this would be an overspecification, with two parameters capturing the same effect. However, what allows us to separately identify the two components is that one of them, namely the latent variable component, is also used in a separate measurement model.

Our estimation now jointly maximises the probability of the observed choices and answers to risk ladders, with:

$$L_n = \int_{\eta} \int_{\xi} \prod_{t=1}^{6} P_{j^*_{nt}nt}(\beta, \Omega_\delta, \Omega_\alpha, \tau_1, \tau_2) \cdot \prod_{j=1}^{2} LI_{jnt}(\alpha_{jnt}, \zeta_j)\, \phi(\xi)\phi(\eta_1)\phi(\eta_2)\mathrm{d}\xi\mathrm{d}\eta_1\mathrm{d}\eta_2 \qquad (12)$$

where Ω_α= <$\lambda_1, \lambda_2, \gamma_1, \gamma_2$>.

All models coded in *R* using the Choice Modelling Centre (CMC) estimation package[1] and estimated using 500 Halton draws in simulation-based estimation (Halton, 1960).

4. Results

4.1. Sample statistics

From the 300 qualifying interviews (completed and consented interviews with adult choice crossers only) the overwhelming majority was male (90%). The average age of the respondents was 34 years (those 17 years or younger were excluded but constitute a significant group of choice crossers we observed), the oldest (man) being 65 years of age. Almost 91% of the intercepted trips could be classified as Home – Based Work (HBW) trips, which matches the 90% employment rate (including self-employed) among the randomly selected participants. More than 67% of respondents indicated that they have children, which suggests that most have family responsibilities (in terms of income and family care).

In terms of 'urban tenure' it was revealed that about 45% of the respondents had lived in Cape Town for less than 5 years at the time of the interview, while 46% had lived in the area for more than 16 years. Behrens

[1] http://www.cmc.leeds.ac.uk/resources/software/

(2005; 2010) already showed that short tenure in the city can be associated with risky crossing behaviour. Furthermore, the majority of respondents (55%) indicated that they alight or board (informal) public transport before or after crossing the freeway.

Respondents were asked to indicate their perceiped risk levels for each of the six choice scenarios that were presented to them. At-grade crossing is seen as risky on average and footbridge crossing is perceived as somewhat risky on average. These risk perception levels vary between socio-demographic groupings based on age, urban tenure and family responsibility, as seen in Table 3.

Table 3. Choice task specific risk perception levels of at-grade crossing and footbridge crossing

In-choice risk **[not risky (1) … (10) extremely risky]**	**Mean at-grade risk***	**Mean footbridge risk***	**SD traffic risk**	**SD footbridge risk**	**N**
all	7.03	4.57	2.98	3.46	1,800
age below / equal 35	7.14	4.61	2.92	3.46	1,116
age above 35	6.86	4.51	3.07	3.40	684
in Cape Town less than 15 years	6.94	4.53	2.97	3.46	1,001
in Cape Town more than 15 years	7.15	4.62	2.98	3.48	799
Children	6.91	4.46	2.95	3.46	1,205
no children	7.28	4.78	3.04	3.58	595

* the difference in means are statistically significant with $p < 0.0001$.

Out of 1,800 choice tasks, the at-grade crossing alternative is chosen 785 times (44%), which shows that there is not a dominant alternative. Looking for possible forcing attributes we find that roadway attributes, such as fences and the presence of police personnel, are as expected reducing the choice frequency for at-grade crossing, yet in 42% of such scenarios the at-grade alternative is still chosen. The fact that people still choose to cross at-grade even in the presence of fences and police may seem surprising in some areas, but is unfortunately a reality in South Africa.

4.2. Model results

Choice model component

We start our study of the results by looking at the estimation of the choice model component, which is only a subset of the overall hybrid model. These results are presented in Table 4. We see that the Mixed Logit model offers a substantial improvement in model fit over the binary logit model, with an increase in log-likelihood by 36.23 units, for only one additional parameter ($\sigma_{\text{at-grade}}$). This improvement gives us a likelihood ratio test value of 72.46 units, where the corresponding 99% percent critical value with one degree of freedom is only 6.64. The combined log-likelihood of the hybrid choice model is, at -7,543.62, of course substantially more negative given that this model explains both the choices as well as the answers to the risk ladders, while the log-likelihood for the choice model component alone is no different (except for simulation noise) compared to the Mixed Logit model, in line with the theoretical points made in Vij and Walker (2016), and our earlier discussions in Section 3.4.

We next turn to the parameter estimates. We see that in all three models, the mean estimate for the baseline at-grade crossing parameter is negative, showing that, at the base levels for all attributes, respondents in the base group prefer the footbridge crossing. This estimate is however not significantly different from zero at usual levels of confidence. More interestingly, in the mixed logit and hybrid model, there is extensive heterogeneity around this mean value, as shown by the estimated standard deviation ($\sigma_{\text{at-grade}}$). Further heterogeneity arises in the hybrid model through the impact of the latent variables, a point we return to below. We also see differences across socio-demographic segments in the baseline preferences. Specifically, we see increased utility for at-grade crossing, depicted as shifts from the mean baseline at-grade crossing preference (see equation 4), for respondents who are not in employment, who don't have children, or who are aged either under 30 years or over 40 years of age. The fact that those over 40 years seem less risk averse contradicts Cantillo et al. (2015). However, the same study of Cantillo et al. also found that those with increased responsibility, for example when crossing with a minor, take less risks when crossing a road, which may speak to those aged between 30 and 40 more than to the older ones. Rankavat and Tiwari (2016) also found increased usage of the at-grade crossing option with age (in their case a legal zebra crossing option!) for reasons of crossing convenience. The utility for at-grade crossing decreases even further for respondents who have been resident in Cape Town for more than 16 years, in line with findings of Behrens (2005; 2010).

These socio-demographic impacts are consistent in sign across the three models, albeit with some changes in magnitude and significant, a point we return to below as well.

Table 4. Estimation results for choice model components

		BINARY LOGIT		MIXED LOGIT		HYBRID	
	LL total	-978.62		-942.39		-7543.62	
	LL choice	-978.62		-942.39		-942.51	
		estimate	*robust t-ratio*	*estimate*	*robust t-ratio*	*estimate*	*robust t-ratio*
baseline preferences for at-grade crossing in choice model	mean baseline ($\mu_{\text{at-grade}}$)	-0.2297	-1.13	-0.1998	-0.83	-0.1825	-0.76
	standard deviation ($\sigma_{\text{at-grade}}$)			-1.0794	-9.13	-1.0069	-8.69
	shift for unemployed respondents	0.4868	2.22	0.5934	2.28	0.5058	1.84
	shift if resident in Cape Town for over 16 years	-0.3007	-1.94	-0.344	-1.86	-0.3057	-1.68
	shift for respondents without children	0.2749	1.8	0.3001	1.63	0.3862	2.12
	shift for respondents aged under 30	0.1374	0.89	0.1738	0.94	0.2745	1.45
	shift for respondents aged over 40	0.6496	3.01	0.7992	3	0.8849	3.41
impact of at-grade attributes on utility of at-grade crossing in choice model	medium traffic (vs low)	-0.3180	-2.14	-0.4242	-2.53	-0.1992	-1.13
	high traffic (vs low)	-0.9491	-6.09	-1.1617	-6.28	-0.4962	-2
	fence (vs no fence)	-0.4589	-4.43	-0.5227	-4.23	-0.5935	-4.92
	road median (vs none)	0	NA	0	NA	0	NA
	police present (vs none)	-0.0113	-0.09	0.0082	0.06	-0.1778	-1.2
impact of footbridge attributes on utility of footbridge crossing in choice model	medium distance (vs low)	-1.6220	-9.96	-1.8189	-9	-1.7691	-8.89
	high distance (vs low)	-2.0587	-10.17	-2.4478	-10.1	-2.4762	-10.11
	medium crowd (vs low)	0	NA	0	NA	0	NA
	high crowd (vs low)	0.3160	2.34	0.3783	2.47	0.3712	2.44
	security present (vs none)	0.9015	7.13	1.0942	7.16	1.0881	7.18
	stairs (vs ramp)	-0.1734	-1.68	-0.1451	-1.22	-0.1173	-0.98
influence of latent risk attitude towards at-grade on at-grade utility in choice model ($\tau_{\text{at-grade}}$)						-0.4282	-3.5
influence of latent risk attitude towards footbridge on at-grade utility in choice model ($\tau_{\text{footbridge}}$)						0	NA

Looking at the characteristics of the at-grade alternative, we see that the utility of this option decreases with increasing traffic, as well as in the presence of a fence. There is no impact on the utility whether or not a median is present, while the presence of police has a negative impact only in the hybrid model, where even in this model, the significance level of this impact is small. Turning to the characteristics of the footbridge option, we see greater distance to the footbridge reduces the appeal of this option, as expected and in line with findings by Cantillo et al. (2015) and Oviedo-Trespalacios and Scott-Parker (2017). The presence of more people on the footbridge only has an impact with high levels of crowding, where this impact is positive. If a footbridge is equipped with CCTV cameras and guards, this leads to a substantial increase in utility, while the presence of stairs as opposed to a ramp has a negative impact, which however becomes less significant in the more advanced models. The latter finding is again in line with Cantillo et al. (2015) who showed that pedestrian comfort is positively associated with the decision to cross using a footbridge.

Finally, the role of the latent risk perception in the choice model is captured by $\tau_{\text{at-grade}}$ and $\tau_{\text{footbridge}}$, where our estimation work revealed that only the former has a significant impact on utility, with increases in the latent risk perception for the at-grade option leading to a reduction in the utility for at-grade crossing. Interestingly, Oviedo-Trespalacios and Scott-Parker (2017) conclude that a high perception of footbridge safety isn't necessarily associated with an increased likelihood of using the footbridge. We'll observe the same when comparing baseline preferences and risk perception in the next section. We believe that our results show that, while respondents perceive differences in risk for the footbridge for different settings, and reflect this in their answers to the stated risk question (as seen in table 3), this does not vary strongly enough to influence the actual choice. The same is not the case for the at-grade risk, which clearly has more substantial consequences. This result could of course be specific to our application.

Structural equation for latent risk perception

Table 5 shows the results for the structural equations for the latent risk perception. Here, we see that respondents who are not employed have a reduced risk perception for the at-grade crossing alternative, which is in line with the finding in the choice model too, where they have an increased utility for this option compared to the footbridge option. However, for respondents without children, as well as those aged under 30 or over 40, the latent risk perception is now increased, which is contrary to the finding in the choice model. This is a first indication of differences between risk perceptions and choice behaviour. For the latent risk perception

for the footbridge crossing, the only socio-demographic effect we observe is a reduced risk perception for those aged under 30, where this is however only weakly significant.

Turning to the impacts of the characteristics of the crossing type, we see that the perceived risk for at-grade crossing increases with the level of traffic, which is in line with the findings in the choice model. However, the perceived risk level reduces in the presence of a fence or police, contrary to the findings in the choice model. This is an indication that the presence of a fence or police may have beneficial impacts on perceived risk of crossing at-grade, but reduces the likelihood of crossing at-grade due to greater effort required or the deterrence effect of police being present.

For the characteristics of the footbridge option, we see that increasing distance leads to increased risk perception, as expected, and is in line with the findings from the choice model. In terms of crowding, only low footbridge pedestrian numbers lead to increased risk perception (as compared to medium and high crowding), a finding in line with the choice model, as is the reduced risk perception in the presence of security. The presence of stairs as opposed to a ramp reduces the perceived risk level, which is contrary to the findings in the choice model, which could explain that the latter is due more to increased physical effort rather than safety considerations.

Table 5. Estimation results for structural equations for latent risk perception in hybrid model

		estimate	*robust t-ratio*
influence of socio-demographics on latent risk attitude towards at-grade crossing	unemployed respondents	-0.2723	-1.97
	respondents without children	0.246	1.83
	respondents aged under 30	0.2774	2.01
	respondents aged over 40	0.2062	1.17
influence of socio-demographics on latent risk attitude towards footbridge crossing	respondents aged under 30	-0.2628	-1.1
influence of attributes on latent risk attitude towards at-grade	medium traffic	0.5778	6.51
	high traffic	1.5455	9.42
	fence	-0.1552	-3.1
	police present	-0.4463	-6.17
influence of attributes on latent risk attitude towards footbridge	high distance	0.8284	2.3
	low crowd	1.2171	2.66
	security present	-6.5003	-2.95
	stairs	-0.3889	-1.66

Measurement model for latent risk perception

The final component of the hybrid choice model is the measurement model for the risk perception ladders, with results shown in Table 6. We see that increased latent risk perception has a positive impact in the ordered logit models, i.e. increased latent risk perception for a crossing type increases the likelihood of a higher stated risk on the risk ladders for that crossing type. The threshold parameters $t_{I_j,p}$ reflect the distribution of the risk ladder responses in the data.

Table 6. Estimation results for measurement model component of hybrid model

		estimate	*robust t-ratio*
influence of latent risk attitude in measurement model:			
• **for risk response towards at-grade (ζ_1)**		1.5635	12.25
• **for risk response towards footbridge (ζ_2)**		0.4115	3.01
Threshold parameters for measurement model for risk response towards at-grade crossing	$t_{I_1,1}$	-2.635	-12.05
	$t_{I_1,2}$	-1.7846	-8.81
	$t_{I_1,3}$	-1.4802	-7.22
	$t_{I_1,4}$	-0.521	-2.58
	$t_{I_1,5}$	-0.4055	-2.01
	$t_{I_1,6}$	0.3156	1.57
	$t_{I_1,7}$	0.8533	4.36
	$t_{I_1,8}$	1.2402	6.28
	$t_{I_1,9}$	2.5198	12.88
Threshold parameters for measurement model for risk response towards footbridge crossing	$t_{I_2,1}$	-2.5864	-18.97
	$t_{I_2,2}$	-1.9195	-15.22
	$t_{I_2,3}$	-1.3263	-11.11
	$t_{I_2,4}$	-0.7408	-6.34
	$t_{I_2,5}$	-0.4443	-3.78
	$t_{I_2,6}$	-0.1727	-1.42
	$t_{I_2,7}$	0.0278	0.22
	$t_{I_2,8}$	0.3018	2.34
	$t_{I_2,9}$	1.0069	7.53

Interpretation of results

As discussed in the theory section (3.4), one advantage of a hybrid choice model is that it allows us to understand the sources of heterogeneity better than a simple Mixed Logit model through studying what part of the heterogeneity can be linked to the latent constructs. We have already alluded to the fact that some of the socio-demographics as well as some of the crossing characteristics have opposite effects in the formation of the risk perception and in the choice model specific utility function. We will now look at these in more detail, where, given that the risk perception for the footbridge crossing does not have an influence in the choice model, we focus on the risk perception for at-grade crossing. The results of this comparison are summarised in Table 7. For the baseline preferences, given that $\tau_{\text{footbridge}}$came out as zero, we now have that the overall contribution to the utility (equation 10) is given by: $\mu_{\text{at-grade}} + \Delta z_n + \sigma_{\text{at-grade}}\xi_n + \tau_{\text{at-grade}}\alpha_{\text{1nt}}$. From this, we see that the pure random effect is given by $\sigma_{\text{at-grade}}\xi_n$, while randomness also enters through the latent variable, with the $\tau_{\text{at-grade}}\eta_{at-grade,n}$ subcomponent of $\tau_{\text{at-grade}}\alpha_{\text{1nt}}$ (see equation 9). The overall socio-demographic contribution to the utility is composed both of a *direct* effect, namely Δz_n from equation 7, and an effect via the latent variable, namely $\tau_{\text{at-grade}}\gamma_{\tau_{\text{at-grade}}}z_n$ (see equation 9). Finally, for the characteristics of the crossing itself, the *direct* contribution comes via the β parameters in equation 2, while they also have an impact through the latent variable, namely $\tau_{\text{at-grade}}\lambda_{\text{at-grade}}X_{\text{at-grade},nt}$.

In line with theory, the values in the first column of Table 7, which combine the *direct* effect with that through the latent variable, are nearly identical to those from the reduced form mixed logit model in Table 5, i.e. the reduced form model. With the constant for the latent variables fixed at zero for normalisation, the baseline negative value for at-grade crossing stems entirely from the direct effect. In addition, the majority (84.7%) of the random heterogeneity across respondents in their preference or dislike for at-grade crossing is attributed to factors other than the latent risk perception. In terms of socio-demographic characteristics, the most interesting findings relate to respondents without children, and those aged either under 30 or over 40. In all three groups, there is a heightened baseline preference for at-grade crossing, but this is reduced by the increased risk perception for at-grade crossing for these respondents. For the crossing characteristics, the most interesting effects also again relate to those where the risk perception and baseline preference go in opposite direction. We see that the presence of a fence or police reduces the perceived risk and this counterbalances the negative impact these characteristics have in the utility function itself, nearly completely so in the case of police presence.

88 **Table 7. Role of latent risk perception in preference for at-grade crossing**

		Overall effect	Direct effect in choice model	Effect linked to at-grade risk perception
baseline preferences for at-grade crossing in choice model	mean baseline	-0.1825	-0.1825	0
	standard deviation	1.09	84.68%	15.32%
	shift for unemployed respondents	0.62	0.51	0.12
	shift for respondents resident in Cape Town for over 16 years	-0.31	-0.31	0
	shift for respondents without children	0.28	0.39	-0.11
	shift for respondents aged under 30	0.16	0.27	-0.12
	shift for respondents aged over 40	0.80	0.88	-0.09
impact of road attributes on utility of at-grade crossing in choice model	medium traffic	-0.45	-0.20	-0.25
	high traffic	-1.16	-0.50	-0.66
	Fence	-0.52	-0.59	0.07
	road median	0	0	0
	police present	0.01	-0.18	0.19

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As a final step in our analysis, we now look at a number of implied relative sensitivities, i.e. trade-offs between different components. These are reported in Table 8. We start by exploring the importance of the increased utility that specific segments of respondents have for at-grade crossing, as reported earlier in Table 4 and Table 5. We compare that increased utility (over the footbridge option) with the reduction in utility resulting from increasing traffic. For the reasons outlined earlier, our survey made use of a graphical presentation of the key attributes. We acknowledge that transforming graphical attributes into numbers in this way makes strong assumptions about how respondents perceive the graphical presentation[2]. Furthermore, the presence of a non-linear coding for the traffic attribute complicates matters, and we make the assumption that the change in utility is linear between the different levels. However, we feel that we obtain reasonable and interesting insights and thus, with some caveats attached, report such findings. In addition, this clearly offers some validation of the use of the graphical presentation and suggests reasonable understanding/interpretation by the respondents. Finally, the computation of these values allows us to compare the results across models, which is not possible using the individual parameter results in Table 5 given scale differences between models.

As an example, we would assume that the estimate of -0.318 for medium traffic in the base model implies that each additional vehicle going from 5 to 15 vehicles accounts for a reduction in utility by 0.0318. We apply the same logic to the change in utility from the middle to the higher level, and for the crowding attribute. We see that a substantial increase in traffic over the base level of 5 vehicles per lane is needed to make at-grade crossing as unattractive as footbridge crossing for respondents who are not in employment, where this number is higher in the Mixed Logit and hybrid choice models. A much lower trade-off arises for respondents without children, while for respondents aged over 40, the highest trade-offs are observed, with the two crossing types only becoming equivalent with an increase by 12.35 vehicles in the hybrid model.

We finally look at trade-offs between the different at-grade and footbridge characteristics. We see that the presence of a fence is as strong a deterrent to at-grade crossing as an increase in traffic by 11.13 vehicles per lane in the hybrid model. For footbridge crossing, we evaluate the trade-offs relative to walking time and crowding on the footbridge. Here, we see that respondents have a very low willingness to walk further. As an example, an increase to the highest level of crowding (from 2 to 15 people) only compensates for around 1 minute in additional walk time, while the willingness to walk further to a footbridge with security measures is higher, but still low, at 3.69 minutes in the hybrid model. This shows a strong need to position footbridge

[2] We use levels of 5, 15 and 25 vehicles for low, medium and high traffic, 2, 8 and 14 minutes for low, medium and high distance, and 2, 8 and 15 pedestrians for low, medium and high crowding.

crossings closer to each other, as suggested in MDoT (2006); Ribbens et al. (2008). Our final trade-off highlights major differences between the three models, showing that the Binary Logit model and to a lesser extent the Mixed Logit model, overstate the dislike of stairs, showing that a substantial increase in people on the footbridge would be needed to compensate for the presence of stairs instead of a ramp, where this is much lower in the hybrid model. This highlights clear differences across the model structures.

Table 8. Implied trade-offs

	Binary Logit	Mixed Logit	Hybrid
additional vehicles needed per lane (over 5) to make road as unattractive as footbridge for those not in employment	8.08 veh	9.28 veh	9.85 veh
additional vehicles needed per lane (over 5) to make road as unattractive as footbridge for those without children	1.42 veh	2.36 veh	2.20 veh
additional vehicles needed per lane (over 5) to make road as unattractive as footbridge for those aged over 40	11.61 veh	12.38 veh	12.35 veh
impact of fence as a deterrent to at-grade crossing evaluated in terms of vehicle increase from 5	12.23 veh	11.34 veh	11.13 veh
willingness in minutes to walk further to a footbridge in return for increase from 2 to 15 pedestrians	1.17 min	1.25 min	1.26 min
willingness in minutes to walk further to a footbridge in return for security measures	3.33 min	3.61 min	3.69 min
additional pedestrians (over 2) needed on footbridge to make stairs as attractive as a ramp	7.13 ped	4.99 ped	4.11 ped

5. Conclusions

The context of high risk crossing environments appears to polarise crossing choices for pedestrians in cities like Cape Town, South Africa. As a consequence, authorities see an alarming increase in pedestrian activity on its freeways in recent years, with a similar trend in (fatal) freeway pedestrian crashes. Even though still in a minority, freeway crossing poses a great concern to city authorities, the communities and vehicle traffic. This study therefore explored factors of freeway pedestrian crossing choice and the role of risk perception therein. Using a 300 participants' stated choice survey in seven known pedestrian activity zones along Cape Town's freeways, three sets of response variables were collected, namely stated choices around crossing the freeway at-grade or using a footbridge, a choice task specific risk perception for the footbridge crossing and a choice task specific risk perception for at-grade crossing. Information on the risk perceptions were captured using risk ladders showing a range of assumedly known risks. The attributes for the choices varied from typical environmental variables related to the built environment (design, distances, security etc.), traffic (traffic volume and pedestrian volume on the footbridge), next to socio-demographic variables related to age, urban

tenure and responsibility (e.g. having children or not). We used these data to estimate Binary Logit and Mixed Logit models, as well as a Hybrid Choice model, which incorporates a latent risk perception component to explain the answers to the risk ladders and test the influence of this risk perception on the stated choices.

The model estimates confirm that, as expected, crossing choice is largely influenced by a combination of built environment, vehicular and pedestrian traffic, next to some socio-demographic factors. For example, a small crowd of pedestrians on a footbridge reduces the probability of choosing the footbridge option over the at-grade option, while increased traffic on the road reduces the probability of choosing the at-grade crossing option. Differences exist across individual respondents in their baseline preferences too. Some of this can be linked to socio-demographic characteristics (e.g. reduced aversion to at-grade crossing for unemployed, with increased aversion for those resident in Cape Town for longer) while a large share of the heterogeneity is random, i.e. down to idiosyncratic differences across people, a finding leading to important gains in the Mixed Logit model.

Given the complex spatial and social context in which the (mostly) urban poor residents are making their crossing decisions it is not surprising to see that both types of crossing are seen as risky activities, justifying the question of how these risk perceptions influence stated crossing behaviour. The hybrid model addresses this by incorporating a latent risk perception component. The model shows that this plays a role in explaining the crossing choice, but also highlights that only the risk perception towards at-grade crossing influences that choice. This is likely due to the very different nature of the two crossing tasks, despite both taking place in highly volatile environments. The hybrid model also shows the seemingly opposite effect of some of the factors on risk perception and crossing choice, for example when looking at the presence of a fence or policing in the case of at-grade crossing. Even though the perceived risk level for at-grade crossing reduces in both these cases, the probability of an at-grade crossing decreases. It feels safer to cross, yet the outlook of crossing a fence or being caught by a police officer deters. Results could of course be different in other areas.

An analysis of the implied relative sensitivities of the choice attributes within and between the crossing alternatives, as well between the three estimated models, finally shows us the value of including heterogeneity and latent risk perception into the models. Further work will have to concentrate on further analysis of the behavioural model and use those insights to inform opportunities, for example for the location-allocation and design of footbridges, to hopefully counter the upward trend of fatalities on South Africa's freeways. In addition, further research may provide suggestions for more general policy-making, freeway interventions and safety campaigns that would lead to improved freeway crossing safety. The work in this

article will have to be extended to other areas of South Africa, as this is a national problem, also including minors in the survey who constitute a significant part of the at-grade crossing population. Minors also tend to cross at-grade in groups, possibly because of group pressure, something we might want to include as well. Future work should also make use of a larger and more heterogeneous sample, which would also help with statistical significance. However, the circumstances of data collection may make the use of a larger sample challenging.

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