WHY DO YOU CYCLE ON THAT ROUTE?

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ABSTACT

Safe cycling has become a priority in many New Zealand cities and a large investment in cycleways is underway. To maximize the benefit, it is important to have insight into cyclists' preferences and factors influencing cyclist route choice. Previous, studies about preferences were typically done by asking respondents to rank/rate factors important to them, without linking those ranked/rated factors with respondents' choices. Thus, such an approach cannot assess the changes in preferences and choices when there is interaction between factors. For example, cyclists' route choices may change depending upon combinations of 'levels/states' of the 'bicycle lane' and 'road hierarchy' factors. Furthermore, when designing cycle networks/routes, it is not always possible to optimise them with respect to all factors. The stated preference method, used in this study, presented respondents with pairs of scenarios, involving different combinations of factor 'levels', and asked which were preferred, highlighting 'trade-off' between factors. In this study, the factors of travel time, road hierarchy, on-street car parking and bicycle lanes were investigated. The responses were used to estimate choice models, indicating the relative importance of those factors. Ultimately, these results can be used to assist in the design of better cycle routes, hence, increasing cycle route use.

INTRODUCTION

This study aimed to systematically investigate New Zealanders' preferences over factors that influence their route choice when commuting by bicycle, using Christchurch as a case study. Christchurch was selected due to its unique situation caused by the rapidly evolving nature of the city after the earthquakes in 2010 and 2011 and the City Council's ambitious plans to develop its cycle networks. These make the investigation of cyclists' behaviour in Christchurch essential, as results of such a study can be used to assist better design to increase cycle route use.

Given the research objective described above, several methods to elicit preferences were investigated. In the past years, ranking and rating methods were the two common methods used to reveal people's preferences. In traditional surveys, respondents were often asked to rank or rate a number of preselected factors in their order of importance. By such a means, the relative importance of individual factors was captured. However, such methods do not link people's preferences over factors with choices that they make. People tend to make different choices in different circumstances, which are created by different combinations of states/levels of considered factors. For instance, with regard to route choices, cyclists' preferred/selected routes may depend upon the factors of 'bicycle lane' and 'road hierarchy'. Road hierarchy categorizes roads according to their functions and capacities. Cyclists may choose a route that passes through major arterial roads if there are bike lanes on the roads, otherwise, in the absence of bicycle lanes, cyclists may only choose a route that passes through roads of a more minor nature, for example residential roads.

Given the above descriptions and the research objective, choice modelling was considered the most appropriate method to be used in this study. Choice modelling is an analytical method which attempts to identify the sources of preferences or reasons behind individuals' choice behaviour (Hensher et al., 2005). It involves specifying and estimating choice models, and thus deriving the relative weights (or importance) of factors in specified models. This will further be explained in the subsequent section.

To obtain data needed to develop choice models and thus, to capture underlying preferences that trigger behavioural responses, two surveying techniques were considered: the revealed preference (RP) and stated preference (SP) methods. These methods, including their strengths and weaknesses, have been widely discussed in research literature (e.g. Hensher et al., 2005; Louviere et al., 2000). In brief, in an RP survey, respondents are asked to reveal their current or past behaviour or to indicate choices that they had made, leading to one observation per respondent. For instance, respondents are asked to draw, on a map, the route they took when commuting to work this morning. Because RP data represent real-life choices (also known as 'market' data), they tend to have higher reliability and face validity.

However, despite the strengths mentioned above, the RP method is constrained by the alternatives currently available. It cannot be used to assess people's preferences when a new alternative is to be introduced. In addition, because researchers cannot control the relationships amongst factors, data related to non-chosen alternatives are often cannot be collected.

The SP method involves presenting respondents with a number of hypothetical situations or scenarios and asking respondents to make a choice on each one of them, allowing the 'trade-off' between factors (Hensher, 1994). Factors represent the various characteristics of the alternatives (or choice options). A factor can then be subdivided into levels, defining its values. For example, when commuting to work, there are two routes that cyclists can take (and thus, two choice options/alternatives). These routes are different with regard to the following factors (and levels): commuting time ('20 minutes' and '30 minutes'); road hierarchy ('arterial' and 'residential roads'); and bicycle lane ('absence' and 'presence'). Hypothetical scenarios are created by varying the 'levels' of preselected factors (or independent variables), leading to multiple observations of the response (or dependent variable) per respondent. For the example above, the numbers of factors and levels create eight possible hypothetical scenarios, leading to eight observations per respondent. Because researchers select factors and levels to be included in their study, they have more control over the research design and thus, they can minimise confounding effects of factors not included in their study. Furthermore, as hypothetical scenarios are used to elicit people's preferences, an SP study can include alternatives not currently available in the market.

There are two main weaknesses of the SP method. As previously mentioned, in an SP study, more observations are required per respondent. This can mean that respondents may experience higher mental workload. Furthermore, respondents may not be able to understand hypothetical scenarios presented to them, possibly affecting the reliability of research outcomes. These weaknesses' are addressed by carefully selecting factors and levels to be included in a study, examining the realism of combinations of levels in hypothetical scenarios and conducting pilot surveys. Thus, the clarity and readability of hypothetical scenarios can be improved and ambiguity can be minimized.

Considering the strengths and weaknesses of both RP and SP methods, as summarized above, it was decided to use the SP method. Note that in an SP study, the number of hypothetical scenarios, which need to be assessed by respondents, increases with the increase in the number of factors and levels. Therefore, it may become unfeasible to ask respondents to assess all possible hypothetical scenarios. For instance, a study that investigates four factors, each having three levels, requires 81 possible hypothetical scenarios. To reduce the burden of respondents, it becomes necessary to limit the number of factors and levels to be investigated and to select, amongst all possible scenarios, the ones to be presented to respondents.

In order to select hypothetical scenarios, two experimental design approaches were considered: orthogonal and efficient design. The orthogonal design approach is the most well-known and widely used approach. However, results of existing studies (e.g. Bliemer et al., 2009; Huber and Zwerina, 1996; Kessels et al., 2011; Sándor and Wedel, 2002) have highlighted the difficulty of maintaining orthogonality in a design generated by the orthogonal design approach, in particular, when such a design is used in a choice modelling study. Therefore, it was decided to apply the efficient design method. This method will be described in the *Model Specification* section.

Any SP study requires a comprehensive process, involving multiple steps: 1) deciding upon the choice modelling type; 2) refining all stimuli, such as factors and levels; 3) specifying models to be estimated; 4) generating a design using the selected experimental design method (e.g. efficient design); and 5) creating a survey. These stages will in turn be described in the subsequent sections. The modelling outcomes and conclusion will be presented in the end of this paper.

CHOICE MODELLING

In choice modelling, each alternative (e.g. a route that cyclists can take) is considered to give a certain amount of utility (or net benefits) to people. Furthermore, the overall utility associated with alternative *i* (U_i) has two components. The first one is referred to as the representative utility (denoted by V_i), and it represents the utility that can be observed by researchers based on the selected factors and levels of the alternative. The second component, often referred to as the random error component (denoted by ε_i), represents the utility associated with factors unobserved by researchers, such as variations in taste amongst individuals and other factors excluded from a study. Accordingly, the overall utility associated with alternative *i* (Eq. 1) and the representative utility (Eq. 2) can be written as:

$$U_i = V_i + \varepsilon_i \qquad \text{Eq. 1}$$

$$V_i = \beta_{0i} + \beta_{1i}X_{1i} + \beta_{2i}X_{2i} + \cdots + \beta_{Ki}X_{Ki} \qquad \text{Eq. 2}$$

where β_{0i} is an alternative-specific constant (ASC), representing the average role of all unobserved components of utility, and β_{Ki} is the estimated parameter (or the weight) associated with factor X_K of alternative *i*.

Eq. 2 shows that choice modelling provides an estimate of the weight for each factor, indicating the relative importance of the factor affecting the representative utility. The statistical significance of each weight is also identified. Furthermore, assuming that an individual makes a rational decision, an alternative with the highest utility is chosen.

In this study, the multinomial logit (MNL) modelling technique, a particular type of choice modelling, was used. The MNL model makes rigorous assumptions about the unobserved components of utility: they are independent and identically distributed (IID) across alternatives and observations, and they are distributed according to the extreme value type-1 (EV1) distribution. Note that there are other choice modelling types which relax these assumptions, such as the mixed logit model, the scale heterogeneity model and the generalized mixed logit model (see Ben-Akiva and Lerman, 1985; Fiebig et al., 2010; Hensher et al., 2005; Louviere et al., 2000; Train, 2009). However, they are not discussed here. The MNL model was selected because it is simpler and it can be used to calculate analytically the values of probability of choosing alternative i ($Prob_i$) using the following equation (Eq. 3).

$$Prob_i = \frac{expV_i}{\sum_{j=1}^{J} exp\, V_j} \qquad \text{Eq. 3}$$

STIMULI REFINEMENT

To select factors to be included in the study (or X_K in Eq. 2), a literature study was conducted. This study predominately focused on international papers due to the limited number of New Zealand publications researching cyclists' route choice. During the literature study, many factors were identified to influence route choices, as summarized below.

- **Topography**
  Topography, especially the hilliness of an area, has previously been identified as a substantial influencing factor in cycling. This empirical basis was investigated, in an attempt to quantify it. It was suggested that 1 meter vertical travel on a bicycle could be considered to be equivalent to approximately 8 meters horizontal travel (Scarf and Grehan, 2005). The results of a study of cycling in Zurich (Switzerland) (Menghini et al., 2010) also found that road gradient is an influential factor.
- **Bicycle infrastructure**
  Bicycle infrastructure is a powerful factor that affects cyclists' route preference, with the presence of bicycle lanes, trails and paths influencing individuals' decisions (Akar and Clifton, 2009). This sentiment appears particularly true for the older generation, who appreciate cycle paths more than the youth (Bernhoft and Carstensen, 2008). However, the results of another study (Broach et al., 2012) show that bike lanes have been found to be no more or less attractive than a basic low traffic volume street. While in certain situations, the construction of a bike lane is unwarranted, in other situations, such construction is essential.
- **Cyclists' experience**
  As a level of cyclists' experience increases with cycling times on roadways, cycling tends to gradually become less onerous (Hunt and Abraham, 2006). Thus, cyclists may modify routes as their skill level and confidence increases.
- **Road hierarchy/traffic volume and the number of intersections**
  These are important factors. Cyclists commonly use routes significantly longer than the most direct ones, actively diverting to avoid main roads and crossings (Krenn et al., 2014). If the infrastructure was designed in such a way that it took into account route directness for cyclists, travel distances could be notably reduced. Distance is a crucial factor as demonstrated in a study of cycling in Zurich (Switzerland) (Menghini et al., 2010).
- **On-street car parking**
  The results of a study conducted in Texas (the USA) indicate that on-street car parking is another important factor (Sener et al., 2009). All cyclists participated in their study preferred a route without any on-street parking as parking may hinder bicycle movement and it causes a safety threat.
- **Other factors**
  Besides the factors listed above (i.e. topography/gradient, bicycle lane/path, cyclist's experience, road hierarchy/traffic volume, the number of intersections, travel distance/time and on-street car parking), other factors were also found to affect route choices, such as pavement-surface condition (Landis et al., 1997), traffic speed, street width, the number of roundabouts, the number of stop signs, street lightning (Segadilha and Sanches, 2014),

traffic calming (Winters et al., 2010), the number of traffic lights (Krenn et al., 2014) and speed limit (Sener et al., 2009).

In order to limit the number of hypothetical scenarios, the number of factors to be included in this SP study must be limited. The research objective, the findings from the literature review and the specific conditions of Christchurch were considered when selecting the most relevant factors. Furthermore, the selected factors should also be relevant to the policy development in Christchurch. Accordingly, the following four factors were chosen: 1) on-street parking, 2) bicycle lanes, 3) road hierarchy and 4) travel time. These factors were also considered to be easily defined, meaning less attribute ambiguity. This aided in the clarity of the hypothetical scenarios.

Once the factors were determined, it was necessary to set the levels for each of them. The levels of the bicycle lanes and on-street parking factors were either present or absent, implying that two levels were assigned to each of these factors. The road hierarchy were determined by the road types around Christchurch and roads that cyclists are allowed to travel on (hence no motorways or sidewalks). Initially, two levels were assigned to this factor: minor and major arterial roads. Furthermore, the following three levels were initially assigned to the travel time factor: 20, 25 and 30 minutes.

A pilot SP survey was generated using the above factors and levels. The aim of this pilot survey was to check the clarity and readability of the survey and to conduct a primary analysis to check whether or not the selected factors and levels would yield statistically significant parameter coefficients. The NGENE software, specialized in the experimental design generation, was used to generate the design. The resulted design was converted into a pilot survey and was distributed to seven respondents. The data were analysed using the NLOGIT software, specialized in the choice modelling analysis.

The results of the preliminary analysis show that the coefficient of the travel time factor was not statistically significant. This had not been expected, as the results of existing studies (mentioned above) show a strong influence of this factor in the route choice decision. It was suspected that this result was caused by the relative closeness of the selected levels, making the respondents underestimate the factor. Therefore, it was decided to change the levels to 20, 30 and 40 minutes. Furthermore, after contemplating on the preliminary design, an extra level was added to the road hierarchy factor and thus, the levels of this factor became: residential, minor arterial and major arterial roads. Feedback from the respondents also highlighted concerns over the interpretation of the road hierarchy. The solution for this was to provide visual aids in the form of photographs for the final survey. This will further be explained in the *Survey Generation* section.

MODEL SPECIFICATION

Before listing the utility functions to be estimated, it should be noted at this point that in general, two types of effects can be estimated: main and interaction effects. However, in this study, only the main effects were to be estimated.

The main effect can take two forms: linear and non-linear. In a model that estimates linear main effects, a unit increase in a level of a factor is assumed to influence the utility (or dependent variable) in a linear way. Two types of coding can be used for this purpose: the design coding (e.g. three levels of a factor are coded as 0, 1, 2) and the orthogonal coding (e.g. three levels of a factor are coded as -1, 0, 1). In a model that estimates non-linear main effects of factors, either dummy or effects coding can be used to code the levels of factors. Both coding methods work by creating 'new variables' for each factor. The number of those new variables is equivalent to the number of levels minus one. For example, the factor of 'road hierarchy' had three levels (i.e. residential, minor arterial and major arterial roads). If non-linear effects were to be estimated for this factor, two variables must be created (3 levels-1), e.g. RH1 and RH2. If a route passes residential roads, RH1=1 and RH2=0. If a route passes minor arterial roads, RH1=0 and RH2=1. If a route passes major arterial roads, RH1=0 (dummy coding) or -1 (effects coding) and RH2=0 (dummy coding) or -1 (effects coding). Further descriptions of the above coding methods can be seen in Hensher et al. (2005).

Given the final selection of factors and levels, the following four models were specified. The parameters (β_x) of each model were to be estimated using the data obtained from the final SP survey (to be discussed in the *Survey Generation* section). Note that models with non-linear effects were also specified (i.e. Models 2 to 4). However, a model with non-linear effects could be estimated only when a factor has at least three levels. Thus, in this study, the non-linear effects were estimated only for the road hierarchy and travel time factors.

Model 1 (the model with linear main effects only):

$$V_{RouteA} = \beta_{RouteA} + \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH}RH + \beta_{TT}TT$$
$$V_{RouteB} = \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH}RH + \beta_{TT}TT \qquad \text{Eq. } 4$$

Model 2 (the model with non-linear main effects on the road hierarchy factor):

$$V_{RouteA} = \beta_{RouteA} + \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH1}RH1 + \beta_{RH2}RH2 + \beta_{TT}TT$$
$$V_{RouteA} = \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH1}RH1 + \beta_{RH2}RH2 + \beta_{TT}TT \qquad \text{Eq. } 5$$

Model 3 (the model with non-linear main effects on the travel time factor):

$$V_{RouteA} = \beta_{RouteA} + \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH}RH + \beta_{TT1}TT1 + \beta_{TT2}TT2$$
$$V_{RouteA} = \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH}RH + \beta_{TT1}TT1 + \beta_{TT2}TT2 \qquad \text{Eq. } 6$$

Model 4 (the model with non-linear main effects on the road hierarchy and travel time factors):

$$V_{RouteA} = \beta_{RouteA} + \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH1}RH1 + \beta_{RH2}RH2 + \beta_{TT1}TT1 + \beta_{TT2}TT2$$
$$V_{RouteA} = \beta_{PARK}PARK + \beta_{BLANE}BLANE + \beta_{RH1}RH1 + \beta_{RH2}RH2 + \beta_{TT1}TT1 + \beta_{TT2}TT2 \qquad \text{Eq. } 7$$

where *PARK* = on-street parking; *BLANE* = bicycle lanes; *RH* = road hierarchy; *RH1* and *RH2* = new variables to estimate non-linear effects of residential road; *TT* = travel time; *TT1* and *TT2* = new variables to estimate non-linear effects of travel time; β_x = parameters to be estimated using data from the final survey and β_{RouteB} = 0 (i.e. the reference alternative). Note that the design coding (e.g. 0,1,2) was used in the analysis to code the two-level factors while the effects coding was used to code the three-level factors.

EXPERIMENTAL DESIGN GENERATION

It has been previously mentioned that the efficient design was used to generate the experimental design for the survey. The efficient design method seeks to obtain more reliable estimates (i.e. parameters with small standard errors). To do this, the efficient design requires some prior information about estimates of factors, which can be obtained, for instance, using results from a pilot study. These prior estimates are used to determine an asymptotic variance-covariance (AVC) matrix, through which the asymptotic standard errors are obtained (Bliemer and Rose, 2009a). Huber and Zwerina (1996) found that designs that minimize asymptotic standard errors of parameter estimates are able to produce more reliable estimates with smaller sample sizes. Furthermore, the results of a study done by Bliemer and Rose (2009a) suggest that the standard error of an estimate improves as the sample size gets larger. However, the reduction of the standard error caused by the increase in sample size is still much smaller than the reduction caused by using a more efficient design.

Two types of 'error' indices, called D-error and A-error, are commonly used to measure efficiency, or precisely inefficiency, and they are derived from an AVC matrix. Without going into technical detail, D-error is calculated using the determinant of an AVC matrix while A-error is calculated using the trace of an AVC matrix. A design with low D-error and A-error values is considered to be more efficient (and thus, it is more likely to produce statistically significant parameter estimates) than a design with high D-error and A-error values. Accordingly, the goal of researchers is to obtain a design that can minimize these error indices. Furthermore, D-error is often preferred over A-error because the latter often gives some scaling problems (Bliemer and Rose, 2009a). In addition to the above indices, S-estimate, calculated using the information obtained through prior estimates, is used to give an indication of the minimum sample size required to obtain significant parameter estimates (Bliemer and Rose, 2009b).

Thus, considering the above, a second pilot survey was conducted. The main purpose was to obtain the prior estimates used to generate the final survey design. The NGENE software was used to generate a starting up design that consisted of 36 hypothetical choice scenarios. This rather large number of hypothetical scenarios was used to compensate for a small number of respondents targeted in the second pilot survey. The resulted design was distributed to 14 respondents who all completed the survey. Similar to the first pilot survey, the data were again analysed using the NLOGIT software and the resulted estimates were used as the prior estimates to generate the efficient design for the final survey.

SURVEY GENERATION

The final SP design was generated using the NGENE software. NGENE is software specialized in generating an experimental design. The advantage of using such software is its ability to assess a large number of designs in a shorter period of time. The final design was obtained after evaluating over one million designs. It took around 24 hours to assess that large number of designs. For each design, D-error, A-error and S-estimate values were computed. The final design was selected because, compared to other designs, it had the lowest D-error value (i.e. 0.319491) and a sufficiently low A-error value (i.e. 0.497597). Furthermore, it has a manageable sample size indicated by the S-estimate value (i.e. 16.150781). Note that in practice, a design with the lowest possible D-error value (or global optimum) is hard to find and thus, a design with a considerably low D-error value (or local optimum) is considered sufficient. Moreover, there is no exact indication of acceptable D-error values. For some studies, the D-error of 0.32 may be considered as acceptable while for others, it is not.

Choice scenario	Route A				Route B			
	Travel time	Road hierarchy	Bike lane	On-street parking	Travel time	Road hierarchy	Bike lane	On-street parking
1	40 mins	residential	yes	yes	20 mins	minor	no	no
2	40 mins	major	yes	no	20 mins	residential	no	yes
3	20 mins	residential	no	no	40 mins	minor	yes	yes
4	20 mins	minor	no	yes	40 mins	residential	yes	no
5	30 mins	residential	no	yes	30 mins	major	yes	no
6	40 mins	minor	yes	no	20 mins	major	no	yes
7	30 mins	residential	no	no	30 mins	major	yes	yes
8	20 mins	major	yes	yes	40 mins	minor	no	no
9	30 mins	major	no	no	30 mins	minor	yes	yes
10	30 mins	minor	no	no	30 mins	residential	yes	yes
11	40 mins	minor	yes	yes	20 mins	major	no	no
12	20 mins	major	yes	yes	40 mins	residential	no	no

Table 1 The efficient design used in the final SP survey

The final survey was administered online using Qualtrics, an online survey development and management tool. Thus, the final SP design (Table 1) was converted into an online survey and each hypothetical scenario was visualized using photographs, taken from the Google Street View, as shown in Figure 1. Several other questions, inquiring about the respondents' socio-demographic characteristics and cycling behaviour, were added into the survey (see Table 2).

Figure 1 An example of a hypothetical scenario presented to the respondents in the survey

SAMPLE

A link to the survey was published on various Facebook pages and was shared amongst colleagues in the University of Canterbury in the middle of 2015. Once launched, the survey remained active for approximately 2 weeks. Within this time period a total of 53 respondents started the survey. However, only 42 completed the survey in its entirety and hence, only their data were used in the analysis. This sample size surpassed the minimum required sample of 17 respondents suggested by the S-estimate (see the *Survey Generation* section). The socio-demographic characterises of the respondents along with their travel/cycling behaviour are presented in Table 2.

Socio-demographic characteristics & mode choice/cycling behaviour	Sample (N=42)
Gender	female: 38%; male: 52%
Age	18-20 years old: 22%; 21-25 years old: 37%; 26-30 years old: 19%; 31-40 years old: 15%; 41-67 years old: 7%
Usual modes for commuting	car: 22%; motorbike: 1%; bike: 46%; bus: 7%; walk: 22%; skateboard: 2%
Accessibility to bicycle	never: 9%; rarely: 10%; sometimes: 5%; always: 76%
Commuting distance	1km: 21%; 2km: 14%; 3km: 14%; 4km: 5%; 5km: 3%; 6km: 7%; 7km: 7%; 8km: 5%; 9km: 7%; 10+km: 17%
Annual cycling habit	never: 12%; rarely: 9%; sometimes: 17%; often: 14%; daily: 48%
Relations with the University of Canterbury	full-time student: 67%; full-time staff: 14%; part-time student: 12%; visitor: 5%; other: 2%

Table 2 The respondents' socio-demographic characteristics and mode choice/cycling behaviour

RESULTS AND DISCUSSION

The MNL models, i.e. Models 1 (Eq. 4) to 4 (Eq. 7), were estimated using the NLOGIT software. However, because Models 3 and 4 produced fewer statistically significant parameter estimates, it was decided to proceed with Models 1 and 2 (see Table 3).

The modelling results show that all parameter coefficients were statistically significant at 1%, except for β_{RouteA} which is the alternative specific constant of Route A. This is a good result as this means that the average influence of all factors excluded in the models was not significantly different than zero. Furthermore, the results of the other estimates of both models were intuitive: 1) the presence of on-street car parking negatively affects (or reduces) the utility of taking a certain route, i.e. -0.89264 in Model 1 and -0.96500 in Model 2; 2) the presence of bicycle lane positively affects (or increases) the utility of taking a certain route, i.e. 1.04740 in Model 1 and 1.16289 in Model 2; 3) the increase in travel time negatively affects the utility, i.e. -0.92176 in Model 1 and -

1.01759 in Model 2; and 4) the increase in road hierarchy negatively affects the utility. In the linear model (Model 1), its coefficient was -0.58669. In the non-linear model (Model 2), the RH1 and RH2 variables positively affect the utility. This means, the presence of residential roads positively affects the utility (i.e. 0.47966×1+0.31306×0=0.47966) and the presence of minor arterial roads positively affects the utility as well (i.e. 0.47966×0+0.31306×1=0.31306). However, the magnitude of influence of minor arterial roads on the utility was found to be smaller than residential roads. Furthermore, as the effects coding was used (see the *Model Specification* section for further explanation), the presence of major arterial roads negatively affects the utility (i.e. 0.47966×-1+0.31306×-1=-0.79272). These imply that the respondents much preferred to cycle either on residential roads or minor arterial roads than on major arterial roads, with residential roads being slightly preferred over minor arterial roads. These results were in line with the results of Model 1 (i.e. showing the negative influence of the increase of road hierarchy on the utility).

Parameter[1]	Model 1[1]		Model 2[1]	
	Coefficient[2]	Standard Error	Coefficient[2]	Standard Error
β_{RouteA}	0.11323	0.10294	0.07532	0.10478
β_{PARK}	-0.89264***	0.12897	-0.96500***	0.13287
β_{BLANE}	1.04740***	0.14326	1.16289***	0.14999
β_{RH}	-0.58669***	0.08971	NA	NA
β_{RH1}	NA	NA	0.47966***	0.09409
β_{RH2}	NA	NA	0.31306***	0.09151
β_{TT}	-0.92176***	0.09748	-1.01759***	0.10093
[1] See the Model Specification section for the definitions of the parameters 2 ***, **, * in turn mean significance at 1%, 5%, 10%				

Table 3 MNL results of Models 1 and 2

The results of both models show the order of relative importance of factors: bicycle lane appeared to be the most influential factor, followed by travel time, on-street parking, and road hierarchy. The results also imply that people preferred to select the shortest route with bicycle lanes, preferably going through residential roads or at least minor arterial roads, and without cars being allowed to park on-street.

The findings from this research support the expansion of the cycle lane network within the city of Christchurch. However, certain warnings should also be heeded. Although cycle lanes were found to be regarded as a positive factor by cyclists, they are not the only important factor that affects the cyclists' route choice. Travel time is also important. It is something the City Council may have a limited control over, as the Council cannot dictate where individuals live/work. However, the council can design bicycle lanes in such a way that can help minimize travel time, such as by avoiding major intersections. However, the exact actions or measures that can be implemented to reduce travel time for cyclists must be studied carefully and they are not a part of this research project. Also, when new bike lanes are to be constructed, their placement, in relation to car parking, needs to be carefully considered, as it evidently has an impact on the cyclists' route choice. Furthermore, as road hierarchy seems to also influence the route choice, the placement of bicycle lanes should be carefully planned. Ultimately, it is not enough to simply construct bicycle lanes and thereby think the cyclists' needs have been satisfied.

CONCLUSION

This study had addressed the research objective: to systematically investigate commuting cyclists' preferences over factors considered important in their route choice decision. This study, focused on the factors of travel time, road hierarchy, on-street car parking and bicycle lanes, using Christchurch as the case study. It also explored the use of the stated preference (SP) method to collect information about choices that people make in various situations, created from various combinations of levels of factors. This method, despite its increasing popularity overseas, has not been used often in New Zealand.

The results of this study revealed not only the relative importance of the selected factors, but also the mechanism in which these factors influenced the cyclists' route choice (through the utility associated with using a particular route). In this study, four multinomial logit (MNL) models were specified and estimated. Two models (i.e. the model with linear effects only and the model with non-linear effects on the road hierarchy factor) appeared to be superior. Estimates of both models convey a similar message: bicycle lanes appeared to be the most influential factor, followed by travel time, on-street parking, and road hierarchy. Furthermore, their statistical significance levels were also estimated.

The results can be used to predict cyclists' route choice in various situations and to assist with better design of cycling lanes to increase cycle route use. Regarding the latter, the placement of bicycle lanes must carefully be considered. Bicycle lanes should be placed in such a way to avoid major arterial roads and roads with on-street car parking. Furthermore, they should be designed to help reduce cyclists' commuting time, for instance, by avoiding major intersections. These aims may prove challenging to achieve in Christchurch due to the current volume of on-street parking and the nature of inner city roads. However, if cycling promotion is to be a high priority, these issues need to be recognised and addressed.

To maximize the benefit from a large investment in bicycle lanes in New Zealand, further investigation should be done in this field. The Christchurch study should be repeated on a larger scale, including a wider cross-section of participants, and a similar study should be conducted in other NZ cities. Additionally, studies that investigate different designs (and widths) of bicycle lanes or other factors that may influence cyclists' route choice should be supported and encouraged. Results of such studies will deepen our understanding regarding New Zealand cyclists' behaviour and preferences. Accordingly, high impact actions can be formulated to further increase cycle route use.

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