Demographic and Behavioural Factors Affecting Public Support for Pedestrianisation in City Centres: The Case of Edinburgh, UK

Torran Semple
Transport Research Institute
School of Engineering and The Built Environment
Edinburgh Napier University
10 Colinton Rd, Edinburgh, UK EH10 5DT
Email address: torran.semple@nottingham.ac.uk

And

Grigorios Fountas, PhD (Corresponding Author)
Transport Research Institute
School of Engineering and The Built Environment
Edinburgh Napier University
10 Colinton Rd, Edinburgh, UK EH10 5DT
Email address: g.fountas@napier.ac.uk

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ABSTRACT

This paper provides an integrated analytical framework to investigate the demographic and behavioural factors that significantly influence public support for pedestrianisation. Pedestrianisation is often introduced by local authorities with the intention of improving air quality, the walkability of streets, road safety and opportunities for the local economy, however, issues remain regarding how accessible pedestrianised areas are for individuals who have conditions that limit their mobility. Using data from a survey, conducted during 2020 in Edinburgh (UK), public perceptions towards pedestrianisation were investigated through statistical testing and the development of random forest and ordered probit models. The random forest approach can help identify the relative importance of explanatory variables, whereas the ordered probit models can unveil the demographic and behavioural determinants of public support. To account for the potential effect of unobserved heterogeneity within respondents' perceptions, random parameters were also considered in the ordered probit modelling framework. Initial results showed that residents are generally supportive of most issues surrounding pedestrianisation. Random parameters ordered probit modelling identified mode of travel and trip frequency as significant factors affecting key aspects of public support, such that active travellers were significantly more likely to support pedestrianisation, while those who rarely visit Edinburgh city centre were more likely to oppose pedestrianisation. Overall, a variety of independent analyses and modelling approaches suggest common influences on opinion, including behavioural patterns relating to transport modal choice and trip frequency, while disability was also found to have considerable effect on support as a fixed and random parameter. The statistical models are evaluated in terms of goodness-of-fit measures, before policy implications are discussed.

Keywords: Pedestrianisation; Public perceptions; Random forest; Random parameters ordered probit; Unobserved heterogeneity

INTRODUCTION

The transport sector is responsible for 33% of UK carbon emissions, recently overtaking energy supply (27%) as the greatest emitter (HM Government, 2019), while globally, transport emissions are estimated to comprise 14-15% of emissions (IPCC, 2014). Following the UK Government's declaration of a "climate emergency" in 2019, local authorities have reacted to facilitate more sustainable urban mobility. The City of Edinburgh Council (CEC) in Scotland recently unveiled their strategy for a "City Centre Transformation", which intends to pedestrianise and restrict vehicular access (i.e., allowing one-way traffic access or bus-only access) on a selection of inner-city streets (Edinburgh Council, 2019). In 2019 and 2020, the TomTom Traffic Index showed that Edinburgh recorded higher levels of traffic congestion than any other UK city (TomTom, 2021), further intensifying public appetite for radical policy reform. The CEC's plans cite improvements to air quality, sustainable mobility, the local economy and road safety (Edinburgh Council, 2019). Despite many well-known economic and environmental benefits of pedestrianisation (Appleyard, 1972; Brambilla & Longo, 1977; Chung, 2011; Roudsari, 2017; Sastre, et al., 2013; Soni & Soni, 2016; Whitehead, et al., 2006), there is often public resistance to pedestrianisation, as some fear vehicular restrictions will have detrimental impacts on their mobility and access to town centres (Gant, 1997; Levasseur, et al., 2015). Past research has shown that these fears over accessibility are often linked to reduced public parking and rerouting of public transport (Parajuli & Pojani, 2018). This paper explores Edinburgh residents' public perceptions of pedestrianisation and its surrounding effects, with the ultimate aim of identifying the demographic and behavioural characteristics that influence public support for pedestrianisation.

Previous studies focusing on public perceptions of pedestrianisation (Appleyard, 1972; Castillo-Manzano, et al., 2014; Gant, 1997; Melia & Shergold, 2018; Whitehead, et al., 2006) have established key perceived benefits and concerns. The literature suggests that environmental improvements to air quality, which can reduce incidence of respiratory illnesses (Brambilla & Longo, 1977; He, 2018), reductions in noise pollution (Roudsari, 2017) and general improvements to the liveability of urban environments (Appleyard, 1972; Brambilla & Longo, 1977; Whitehead, et al., 2006) are likely benefits of pedestrianisation. The local economy is also likely to benefit from increased visitation to pedestrianised areas and associative rise in footfall (Sastre, et al., 2013; Soni & Soni, 2016; Whitehead, et al., 2006), however, residential and commercial rental costs may increase (Chung, 2011), and public parking spaces may become more scarce (Parajuli & Pojani, 2018). The frequency of road accidents, particularly vehicle collisions with cyclists and pedestrians, is likely to decrease while travel by sustainable transport modes (e.g., public transport, bicycles or on-foot) often increases and leads to reduced traffic congestion (Melia & Shergold, 2018). Residents' overall opinion of pedestrianisation has been found, in the majority of cases, to be broadly supportive post-implementation (Castillo-Manzano, et al., 2014; Gant, 1997; Melia & Shergold, 2018).

The importance of gauging public opinion is well established among researchers and policymakers (Castillo-Manzano, et al., 2014; Edinburgh Council, 2019). The reason for consulting the public, from the perspective of a local authority, is to establish public agenda, determining whether there is appetite for, or opposition against, some form of government intervention. In the context of this research, the recording of public opinion, alongside key respondent demographic and behavioural characteristics, can be utilised to perform more comprehensive analysis of public opinion and the factors which are its greatest influencers, an orthodox method spanning various disciplines (Castillo-Manzano, et al., 2014; Eker, et al., 2020a; Schmitz, et al., 2018). To make reliable inferences regarding the opinions of Edinburgh residents, a survey was conducted on a sample population that is approximately representative of the greater population. An initial assumption that pedestrianisation would disproportionately affect certain demographics, such as people who are reliant on personal vehicles (e.g., a car), and who are more likely to be elderly or disabled individuals (Levasseur, et al., 2015), suggested the survey's dissemination should ensure that these groups in particular are represented fairly (as discussed further in 'Data Collection').

Previous studies that focused on public perceptions of pedestrianisation provide insights into the determinants of public support, typically making use of descriptive statistics analyses or aggregate statistical tests based on survey data. Even though these approaches can outline the primary nuances of perceptions, they have limited potential in unveiling unobserved patterns of perceptions or the relative importance of their influential factors. Over the last few years, a growing number of studies have highlighted the issue of unobserved heterogeneity that may be present in perceptual data drawn from public surveys (Eker, et al., 2020a; Eker, et al., 2020b; Paleti & Balan, 2017). Unobserved heterogeneity refers to the impact of unobserved factors, which cannot be easily identified through the survey questions and may reflect unobserved preferences, taste or experience of the respondents. Not accounting for the effect of unobserved heterogeneity in statistical analysis of survey data may lead to unreliable inferences and, subsequently, to erroneous policy implications (Eker, et al., 2020b; Fountas, et al., 2019; Mannering, et al., 2016).

In this study, we analyse the survey data through a series of statistical tests, random forest models and random parameter ordered probit models, in order to comprehensively identify observed and unobserved statistical relationships between public perceptions of pedestrianisation and their influential factors,. Extensive statistical testing can establish pairwise relationships between public perceptions and their influential factors, while the random forest technique provides the relative importance of explanatory factors. The random parameters ordered probit approach can provide further explanatory insights, as unobserved heterogeneity that may be present in the survey data can be accounted for.

DATA COLLECTION

The survey contained four subsections, which covered environmental issues, economic issues, transport and road safety-related issues, and overall support for pedestrianisation. The survey questionnaire was preceded by a short informational video provided by the CEC, where the terms "pedestrianisation" and "restricted vehicular access" were defined, as well as detailing the city centre streets that would be affected. Table 1 displays the survey questions, categorised by the codes: EN – for environmental issue, EC – for economic issue, TR – for transport and road safety and OV – overall support. Question responses were recorded using an 11-point Likert scale from 0 to 10 (where, 0=strong opposition, 5=undecided/indifference and 10=strong support). The 11-point Likert scale afforded the respondents a greater range of responses so that a more accurate mean level of support may be obtained (Castillo-Manzano, et al., 2014), especially when compared to the conventional 5-point Likert scale. Following the completion of the survey design, using the online platform SurveyMonkey (SurveyMonkey, 2020), a pilot survey (n=20) was completed with respondents of different age groups. The trial respondents completed the survey within the expected duration and reported no problems understanding terminology. The survey was disseminated via several Edinburgh-based distributors, including charities, support groups, workplaces, and latterly, to address possible overrepresentation of several demographics, social media platforms. The dissemination strategy was targeted to accurately represent Edinburgh's demographic strata, with reference to national statistics, and was further informed by the underrepresentation of certain demographics in previous CEC surveys. For example, the CEC deemed those under 25 and over 65 as "hard to reach groups" in their "Open Streets" consultation (Edinburgh Council, 2019). To counteract the expected overrepresentation of those belonging in the age range 25-65, we employed, among other dissemination channels, an additional, yet targeted set of survey distributors including (but not limited to): Edinburgh Napier University, The Royal High School (aimed at those 16-24), The University of The 3rd Age (EU3A) and Edinburgh M.E. Self-help Group (aimed at those over 65 and who are more likely to suffer from mobility-restricting conditions (Levasseur, et al., 2015)).

The survey was active for three weeks (01/13/20 – 02/03/20) and received 314 responses, with 11 responses discarded due to incompleteness. Additional survey questions, beyond those in Table 1, gathered data regarding respondents' demographic and behavioural characteristics, for example, gender, age, postcode, disability, occupation, annual income, highest education level, mode of travel and trip purpose when visiting Edinburgh city centre. Survey data were used and stored with adherence to Edinburgh Napier University's Code of Practice on Research Integrity (Edinburgh Napier University, 2020).

The collected sample consists of 60.6% female respondents (39.4% male), which constitutes an overrepresentation compared to national figures, 51.2% female and 48.8% male (National Records of Scotland, 2021). The age groups of respondents (where the misrepresentation of each, in parentheses, is calculated as the percentage point difference from official statistics for Edinburgh (National Records of Scotland, 2021)) were categorised as follows: 16-24 (+1.79%), 25-34 (-8.93%), 35-44 (-4.01%), 45-

54 (-0.02%), 55-64 (+3.38%) and over 65 (+7.58%)[1]. It is worth noting that the misrepresentations of age groups are relatively minor in comparison to past CEC surveys (Edinburgh Council, 2019). The postcodes of respondents were recorded to ensure respondents resided in Edinburgh (i.e. EH postcodes). Additionally, the postcodes of respondents, categorised as inner-city (EH1-EH17) or Greater Edinburgh (EH18-EH55) postcodes, may be an influential independent variable that could capture spatial effects during the statistical analysis. Overall, 6.6% of respondents reported a disability or mobility limiting condition, which is approximately consistent with a 7% rate of physical disabilities nationwide (Scottish Government, 2018). A large proportion (72.2%) of respondents were currently enrolled in or have completed a form of university level education (PhD, postgraduate or undergraduate) which was a considerable overrepresentation relative to the national average of 26% (Scottish Government, 2018). This may be attributed to greater engagement among employees and students of universities and EU3A (survey distributors). In terms of occupation, 54.2% were employed (41.4% full-time, 12.8% part-time), 29.3% were pensioners, 15.8% were students and the remaining 0.7% were unemployed. For the purpose of drawing comparisons to nationwide data, those who are employed (54.2%) were described as economically active, while students, pensioners and those who are unemployed (45.8%), were assumed to be economically inactive. It should be noted that in reality a proportion of students and pensioners would also have been employed. These figures are approximately consistent with national statistics for Scotland, which show that 59.3% are economically active and 40.7% are economically inactive (Scottish Government, 2018). Preferred mode of travel among respondents was as follows (misrepresentation compared to Edinburgh data (Transport Scotland, 2017) in parentheses): 15.2% on-foot (-13.8%), 12.5% by bicycle (+8.4%), 46.2% by public transport (+16.3%), 24.4% by personal vehicle (car and van) (-11.7%) and 1.7% by other modes of travel (+0.8%).

Table 1 also displays the descriptive statistics for the survey responses. The supportive range can be defined as a mean response greater than 5, however, the extent of standard deviation per survey question should also be noted. Similarly, a median in the supportive range and with a conservative interquartile range (IQR) are likely to indicate the validity of a generally supportive response. The first conclusion that can be drawn from Table 1 is that respondents were generally supportive of most issues surrounding pedestrianisation. Despite this, a question gauging the perceived personal benefits of pedestrianisation (Q.OV1) produced uncertain results – mean=5.16 and median=5. To better understand the influence that respondent characteristics have on public support for pedestrianisation, more sophisticated analyses were required.

[1] These figures were calculated as a proportion of Edinburgh's total population (527,620), minus those aged under 16 (79,150). The total Edinburgh population for those aged over 16 is 448,470.

TABLE 1 Descriptive Statistics for Survey Questions (Likert scale from 0 to 10 (0 = strong opposition, 5 = undecided/indifference and 10 = strong support))

Question	Responses per Question	Median	25th percentile (Q_1)	75th percentile (Q_3)	IQR (Q_3-Q_1)	Mean	Standard Deviation
Q. EN1 – How likely is it that respondent would alter transport habits for environmental purposes?	296	8	6	10	4	7.19	3.05
Q. EN2 – Does respondent believe pedestrianisation is in the interest of public health?	300	8.5	6	10	4	7.81	2.56
Q. EN3 – Does respondent believe it is the responsibility of local government to ensure public's habits are not environmentally damaging?	302	7	5	8	3	6.75	2.5
Q. EC1 – How satisfied is respondent with current city centre amenities?	298	7	6	9	3	7.09	2.23
Q. EC2 – How likely is it that respondent will visit city centre more often following pedestrianisation?	296	7	5	7	2	6.41	2.45
Q. EC3 – Does respondent believe public events – such as The Fringe – are in the interests of profit rather than residents?	297	8	6	10	4	7.34	2.73
Q. TR1 – Does respondent believe the Edinburgh tram should be expanded beyond existing lines?	293	6	4	9	5	5.9	3.41
Q. TR2 – Does respondent believe cyclists and pedestrians should be given priority on city centre streets?	293	8	5	10	5	6.89	3.01
Q. TR3 – Does respondent believe pedestrianisation is the most effective way of reducing pedestrian/cyclist fatalities?	293	6	5	8	3	5.99	2.99
Q. OV1 – Does respondent believe the pedestrianisation of Edinburgh's centre will benefit them personally?	293	5	5	7	2	5.16	2.48

METHODOLOGICAL APPROACH

Many previous studies of public opinion relating to pedestrianisation have presented simple descriptive statistics accompanied by hypothesis tests, gauging variance in population means, most commonly *t*-tests or Analyses of Variance (ANOVAs) (Gant, 1997; Melia & Shergold, 2018; Sastre, et al., 2013). Some adopted more sophisticated approaches; for example, a study investigating public opinion of pedestrianisation in Seville developed ordered logit models to estimate the influence of demographic variables on various survey questions about pedestrianisation (Castillo-Manzano, et al., 2014). The use of discrete choice models, such as the multinomial logit or ordered probit/logit model, are often considered appropriate for transportation survey data, which is frequently discrete (Washington, et al., 2020). Complementary machine learning algorithms, such as random forest regression, can be used as an independent approach to estimate relative variable importance, though the comparison of output from statistical and machine learning approaches is often considered futile (Mannering, et al., 2020).

The ANOVA test relies on the assumption that the data are normally distributed. To test whether this assumption had been violated for Q.OV1 (overall support for pedestrianisation), the Shapiro-Wilke normality test was conducted (Salkind, 2010; Ruxton, et al., 2015). The test, conducted in R, produced a p-value=1.24×10^{-12}, indicative of non-normal distribution. As a result, it was decided that a non-parametric alternative was better suited to the data. To that end, we carry out Kruskal-Wallis tests, which allow the analysis of variance between multiple population levels by ranks, in other words, there is no assumption that the data in question are normally distributed (Salkind, 2010). The null hypothesis assumes that all independent samples are from the same population and therefore do not differ, whereas the alternative hypothesis assumes that at least one sample differs (Salkind, 2010). The Kruskal-Wallis test statistic (H-statistic), which is used to deduce corresponding p-values, is calculated as follows (Salkind, 2010):

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{N_i} - 3(N+1) \, , \tag{1}$$

where, N is total sample size and R_i is the total sum of ranks for all groups. Post-hoc pairwise variance tests, adopting the Benjamini-Hochberg method (Benjamini & Hochberg, 1997) is conducted for significant Kruskal-Wallis tests. The presence of multiple pairwise comparisons increase the likelihood of false discovery rate (FDR), therefore, the critical value is amended as per the Bonferroni correction (Salkind, 2010).

Random forest regression provides a reliable feature importance estimate in the presence of potentially inter-correlated variables (Breiman, 2001). The relative importance of explanatory variables is estimated using R package – 'randomForest' (Liaw & Wiener, 2018). Relative variable importance, measured as the percentage increase in mean squared error (%IncMSE) for a given variable, is calculated as follows (Breiman, 2001; Liaw & Wiener, 2018):

$$\%\, Increase\ MSE\ (Variable\ X) = (\Delta\, Model\ MSE) \times 100 \, , \tag{2}$$

where, variable X is the independent variable in question, Δ model MSE is the difference between total model MSE and the new total model MSE (following permutation of variable X). This means that the more influential a variable is within the model, the greater its associated increase in MSE (Biau & Scornet, 2016; Breiman, 2001).

As stated previously, discrete outcome models were considered to be appropriate for this survey data. Given the discrete, ordinal nature of the dependent variables (survey question shown in Table 1), an adaptation of the ordered probit modelling framework was deemed to be most suitable (Washington, et al., 2020). The ordered probit model can be defined as follows (Eluru & Yasmin, 2015; Fountas, et al., 2020; Yasmin, et al., 2014):

$$z_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon \, , \tag{3}$$

where, $\boldsymbol{\beta}$ is a vector of estimable parameters, $\mathbf{X}$ is a vector of independent variables dictating the discrete ordering for an observation, n, and ε is random disturbance, assumed to be normally distributed across observations with mean = 0 and variance = 1 (Washington, et al., 2020). Using the previous equation, the ordered data, y, for each observation can be defined as follows:

$$y = 1 \; if \; \mathrm{z} \leq \boldsymbol{\mu}_0$$
$$y = 2 \; if \; \boldsymbol{\mu}_0 < \mathrm{z} \leq \boldsymbol{\mu}_1$$
$$y = \text{" ... "}$$
$$y = I \; if \; \mathrm{z} \geq \boldsymbol{\mu}_{I-1} \, , \tag{4}$$

where, $\boldsymbol{\mu}$ are estimable parameters that explain y, which corresponds to integer ordering where I is the highest integer response – 10 in the case of this research. Estimable parameters, $\boldsymbol{\mu}$, are estimated in conjunction with model parameters, $\boldsymbol{\beta}$. The main objective of model estimation then becomes determining the probability of I for each observation. Bearing in mind the assumptions placed upon ε, and that $\boldsymbol{\Phi}$ denotes the cumulative normal distribution, the resulting ordered selection probabilities are as follows (Washington, et al., 2020):

$$P(y = 1) = \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X})$$
$$P(y = 2) = \boldsymbol{\Phi}(\mu_1 - \boldsymbol{\beta}\mathbf{X}) - \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X})$$
$$P(y = 3) = " \dots "$$
$$P(y = I) = 1 - \boldsymbol{\Phi}(\mu_{I-1} - \boldsymbol{\beta}\mathbf{X})\,, \tag{5}$$

To account for the effects of unobserved heterogeneity, the coefficients ($\boldsymbol{\beta}$) are allowed to vary across observations for selected independent variables (Fountas et al., 2021). This approach is known as random parameters ordered probit (RPOP) modelling. To allow for random parameters within the ordered probit framework, the estimable parameters are written as follows (Ahmed, et al., 2020; Sarwar, et al., 2017; Semple, et al., 2021; Zubaidi, et al., 2021):

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \boldsymbol{\omega}_n\,, \tag{6}$$

where, $\boldsymbol{\beta}_n$ is a vector of estimable parameters that may vary across observations, n, $\boldsymbol{\beta}$ is the vector of mean parameter estimates across the dataset and $\boldsymbol{\omega}_n$ is a vector of randomly distributed terms – commonly a normally distributed term with mean = 0 and variance = σ^2 (Washington, et al., 2020). The probabilities of the ordered outcomes are determined as they were for the original, fixed parameters ordered probit model (FPOP). The probability calculations for RPOP models however, are particularly cumbersome, and therefore a simulation-based maximum likelihood is used for model estimation (Anastasopoulos & Mannering, 2009; Fountas, et al., 2018; Guo, et al., 2018). For this process, Halton draws are often considered a more effective alternative to random draws (Bhat, 2003; Halton, 1960).

The ordered probit model provides insights into the effect of a given independent variable at the lowest (y=0) and highest (y=10) dependent variable rank, however, the interior categories remain unexplained. To gauge the influence of independent variables on interior categories, the average marginal effects are calculated. For indicator variables, average marginal effects can be defined as the change in category probabilities as a result of a one unit change (from 0 to 1) in the indicator variable. The results of competing models are evaluated using the Akaike information criterion (AIC) goodness of fit (GOF) metric (Washington, et al., 2020). Subsequently, the statistical fit of the FPOP and RPOP models are assessed using likelihood ratio tests (LRT). The test statistic for the LRT is defined as (Behnood & Mannering, 2016; Fountas & Rye, 2019; Guo, et al., 2020):

$$\chi^2 = -2[\mathrm{LL}(\boldsymbol{\beta}_{\mathrm{F}}) - \mathrm{LL}(\boldsymbol{\beta}_{\mathrm{R}})]\,, \tag{7}$$

where, $\mathrm{LL}(\boldsymbol{\beta}_{\mathrm{F}})$ is the log-likelihood at convergence for the FPOP model and $\mathrm{LL}(\boldsymbol{\beta}_{\mathrm{R}})$ is the log-likelihood at convergence for the RPOP model. The χ^2 statistic follows the chi-square distribution, where degrees of freedom (DOF) are equal to the difference in the number of parameters between the FPOP and RPOP models.

STATISTICAL TESTING

Statistical testing was conducted for the survey question gauging the perceived personal benefits of pedestrianisation only, based on the logic that extensive statistical testing on further questions would increase FDR and compromise the reliability of findings. Table 2 and Table 3 display the results of Kruskal-Wallis tests for the respondent variables gauging mode of travel and trip purpose, respectively. The pairwise matrix succeeding both tests refers to the identification of internal pairwise variation (e.g., between personal vehicle users and bicycle users). The number of pairwise comparisons, and subsequently the amended critical value (α_a) for the mode of travel (MT) and trip purpose (TP) variables can be calculated as follows:

$$Pairwise\ comparisons\ = \frac{(x^2 - x)}{2} = \frac{(4^2 - 4)}{2} = 6 \Rightarrow \alpha_a = {}^{0.05}\!/_{6} = 0.0083$$

where, x is the number of categories within the given independent variable and α_a is the amended critical value. The amended critical value of 0.0083 corresponds to a 95% level of statistical significance.

Tables 2 and 3 show that significant variation exists among the subcategories of the respondent variables gauging mode of travel and trip purpose, when considering the perceived personal benefits of pedestrianisation. As a result, the null hypothesis, that no internal variation exists between the subcategories of the mode of travel and trip purpose variables, can be rejected. For mode of travel (Table 2), post-hoc tests show significant variation between the opinions of bicycle users and personal vehicle users; between those who travel on-foot and vehicle users; and also between those who travel on-foot and those who prefer to use public transport. The pairwise variation between active travellers (on-foot or by bicycle) and vehicle users is intuitive, especially considering Edinburgh's characteristically narrow and congested streets (TomTom, 2021). The differences in opinion between active travellers and vehicle users is well documented in previous studies, particularly perceptual studies regarding road safety (Huemer, et al., 2018; Paschalidis, et al., 2016). For trip purpose (Table 3), differences in opinion were found between those who travel for work and those who rarely visit the centre, and between those who travel for leisure purposes and those who rarely visit the centre. The difference in the opinions of those who rarely visit the centre and those who travel for other purposes, suggests that trip frequency is the defining factor, rather than variation between those with differing trip purposes. Kruskal-Wallis tests were conducted for the remaining independent variables with more than two subcategories (age, income, education), however, the results were statistically insignificant.

TABLE 2 Kruskal-Wallis (KW) Test and Subsequent Pairwise Variance Tests Among Modes of Travel (for Perceived Personal Benefits of Pedestrianisation Question – Q.OV1) [2]

KW 1 (MT)	**DOF**	**R_i^2**	**H-statistic**	***p*-value**
Between groups	3	1.76×10^{9}	26.32	8.00×10^{-6}*

Pairwise matrix (MT) (*p*-values)	On-foot	Public transport	Personal vehicle
Bicycle	0.334	0.125	0.002*
On-foot	–	0.006*	1.002×10^{-5}*
Public transport	0.006*	–	0.009

TABLE 3 Kruskal-Wallis (KW) Test and Subsequent Pairwise Variance Tests among Trip Purposes (for Perceived Personal Benefits of Pedestrianisation Question – Q.OV1)

KW 2 (TP)	**DOF**	**R_i^2**	**H-statistic**	***p*-value**
Between groups	3	1.57×10^{9}	14.80	2.00×10^{-3}*

Pairwise matrix (TP) (*p*-values)	Education	Rarely visits centre	Leisure
Work	0.327	0.003*	0.814
Education	–	0.327	0.327
Rarely visits centre	0.327	–	0.002*

[2] For Tables 2 & 3, significant *p*-values are those less than 0.0083, denoted by an asterisk (*)

RANDOM FOREST MODEL ESTIMATES OF VARIABLE IMPORTANCE

To determine the key survey questions that have the greatest relative importance when explaining the perceived personal benefits of pedestrianisation, a random forest model was developed (considering Q.OV1 as the dependent variable and all other survey questions as possible independent variables). Figure 1 graphically summarises the results of the random forest model and shows that the following questions: Q.EN2 – the perceived effects of pedestrianisation on public health, Q.EC2 – intended city centre visitation following pedestrianisation and Q.TR2 – support for the prioritisation of active travellers (cyclists and pedestrians) on city centre streets, had the most influence on the perceived personal benefits of pedestrianisation. As a result, it was decided that these three questions (Q.EN2, Q.EC2 and Q.TR2) would be analysed further, in addition to the question gauging personal benefits, to obtain a more detailed overview of the factors affecting public perceptions of pedestrianisation. Figures 2, 3, 4 and 5 show the relative importance of demographic and behavioural explanatory variables for opinion regarding Q.OV1, Q.EN2, Q.EC2 and Q.TR2, respectively. The variable importance plot in Figure 2, shows that trip purpose, occupation and mode of travel had greatest effect (in terms of % increase in MSE) on respondents' perceptions regarding the personal benefits of pedestrianisation. The dependent variables for Figures 1-5 use the original Likert scale (0=strong opposition, 5=undecided/indifference, 10=strong support), as described in the 'Data Collection' section.

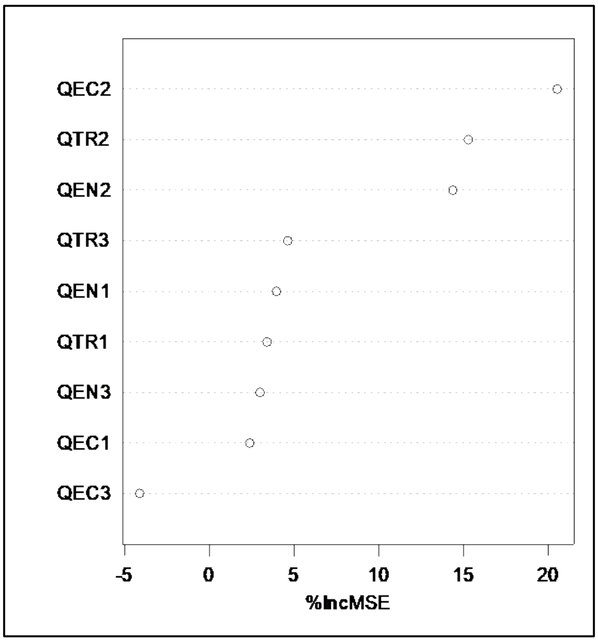
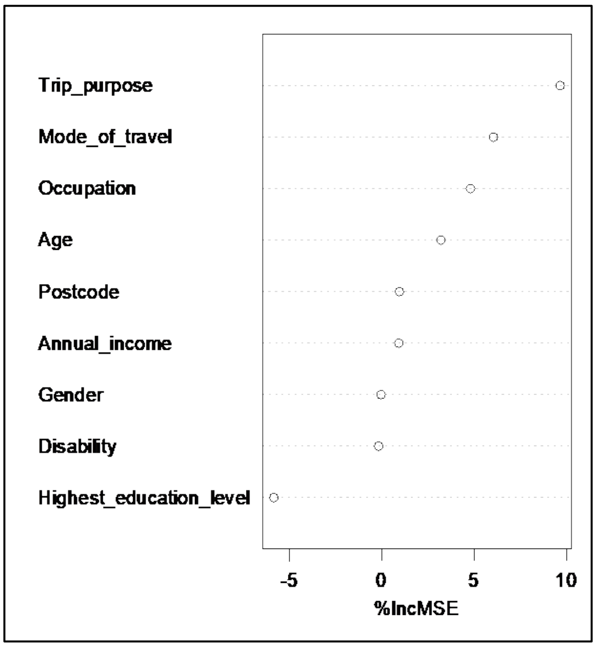


FIGURE 1 Relative importance of survey questions (measured in %IncMSE)[3]

[3] If a variable has negative '%IncMSE' the predictive performance is hindered by the given variable's inclusion; for example, in Figure 1, Q.EC3 would be omitted if prediction was the primary objective.



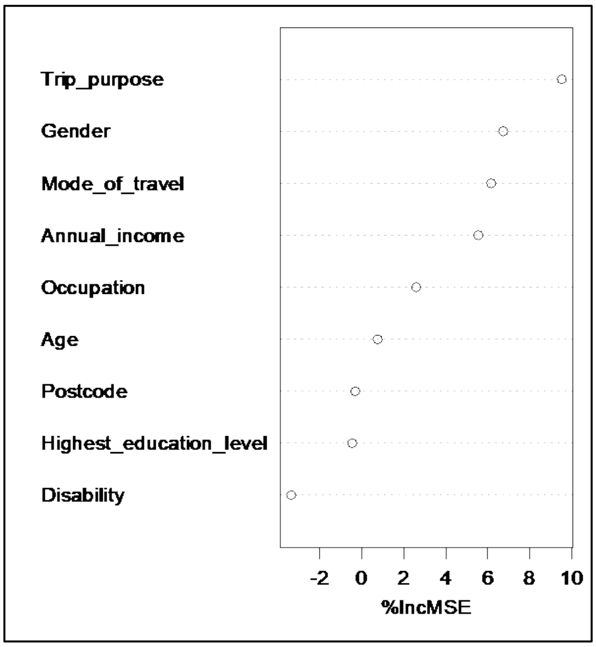
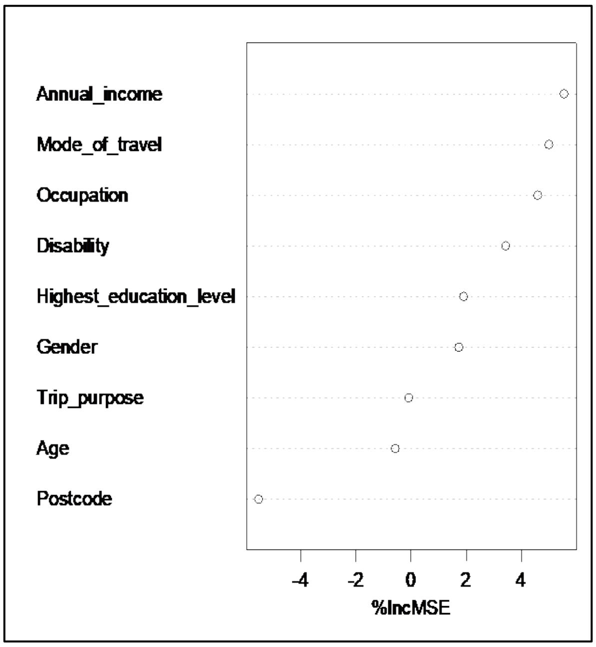


FIGURE 2: Relative Variable Importance Plot for Question: Perceived Personal Benefits of Pedestrianisation (Q.OV1)

FIGURE 3 Relative Variable Importance Plot for Question: Perceived Effects of Pedestrianisation on Public Health (Q.EN2)



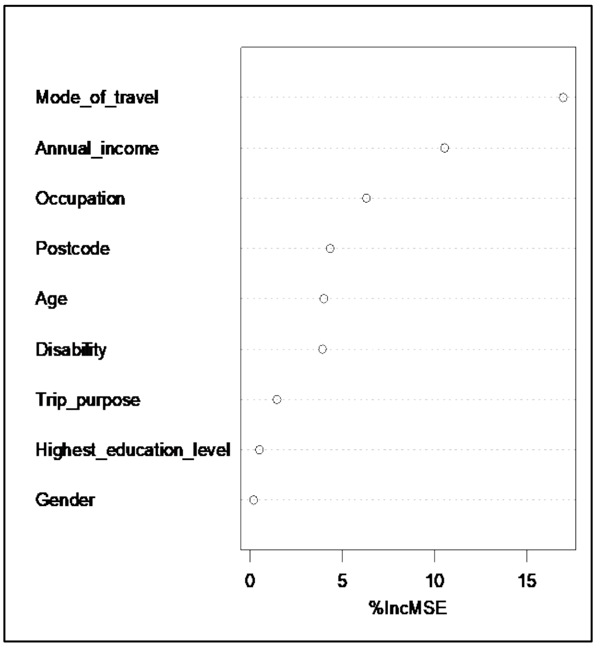


FIGURE 4 Relative Variable Importance Plot for Question: Intended City Centre Visitation Following Pedestrianisation (Q.EC2)

FIGURE 5 Relative Variable Importance Plot for Question: Support for the Prioritisation of Active Travellers on City Centre Streets (Q.TR2)

Mode of travel is consistently among the three most important variables for all questions and has a particularly pronounced effect for the question gauging support for the prioritisation of active travellers on city centre streets (Figure 5). Intuitively, this makes sense, as a variable gauging mode preference is likely to affect opinions of transport-related issues. Disparities in the opinions of active travellers and vehicle users is a common theme found in previous literature (Huemer, et al., 2018; Paschalidis, et al., 2016), as discussed further in subsequent sections. Trip purpose, despite having the greatest importance for the questions gauging perceived personal benefits and the effects of pedestrianisation on public health, has a comparatively insignificant effect for the remaining questions. Socioeconomic factors, specifically, occupation and annual income, have considerable importance for the questions regarding intended visitation following pedestrianisation and the prioritisation of active travellers on city centre streets. Interestingly, annual income is the most important variable for intended visitation post-pedestrianisation, which suggests there may be a relationship between respondent income and willingness to visit the city centre following pedestrianisation. This may be related to the increase in footfall and public spend often associated with pedestrianised areas (Sastre, et al., 2013; Whitehead, et al., 2006), which is possibly more appealing to higher income groups.

It should be noted that the explanatory power of the random forests is particularly low (in the region of 5-8% explained variance across estimations), though variable importance measures are still considered informative in this context. The predictive performance of random forests is particularly sensitive to minor changes in the training data and a greater number of dependent variable outcomes (Klausch & Kreuter, 2019). Given the highly perceptual nature of the survey questions, predictive performance is expectedly low, and may only be enhanced by greater sample size and/or panel data (Klausch & Kreuter, 2019). Since random forest regression is an iterative process, the explained variance also tends to vary by several percentage points every time the models are re-estimated.

ORDERED PROBIT MODEL ESTIMATION

Table 4 shows the descriptive statistics for independent variables that were found to have statistically significant influence within any of the ordered probit models. Throughout probit modelling, the trip purpose variable is effectively a metric of trip frequency, i.e., 1 if rarely visits city centre, 0 otherwise (people who visit frequently for work, education or leisure purposes). As a result, the trip purpose variable is referred to as the "city centre travel variable" from here on.

TABLE 4 Descriptive Statistics of Key Independent Variables

Variable description	Percentage
Mode of travel indicator (1 if active travel (on-foot or by bicycle), 0 otherwise)	28.19%
City centre travel indicator (1 if rarely visits city centre, 0 otherwise)	9.09%
Disability indicator (1 if yes, 0 otherwise)	6.60%
Postcode indicator (1 if inner Edinburgh, 0 if greater Edinburgh)	91.41%

The results for the fixed parameters ordered probit (FPOP) and random parameters ordered probit (RPOP) model estimations (estimated using package: 'Rchoice' (Sarrias, 2020)), are displayed in Table 5 and Table 6, while Table 7 shows the average marginal effects for the parameter estimates of the RPOP models. It should be noted that the marginal effects for the FPOP models are not provided as the framework's explanatory power was shown to be significantly inferior to the RPOP. Statistically significant coefficients are those with *t*-stats greater than 1.65, corresponding to a 90% level of confidence (l.o.c.). For the parameter density function of the random parameters, the normal distribution provided the best statistical fit compared to several trialled distributions (log-normal, truncated normal and triangular). The following independent variables were significant, as fixed or random parameters, in all models: mode of travel (1 if active travel, 0 otherwise), city centre travel (1 if rarely visits city centre, 0 otherwise) and disability (1 if yes, 0 otherwise). If we consider the variable representing mode of travel, positive coefficients across all models indicate that active travellers were significantly more likely to select the highest ordered response (y=10), i.e., the highest level of support, and less likely to select the lowest response (y=0); whereas the city centre travel variable had a negative coefficient in all models, indicating that those who rarely visit the city centre were more likely to select the lowest level of support for all questions (y=0) and less likely to select the most supportive response (y=10).

TABLE 5 FPOP & RPOP Model Estimations for Q.OV1 – Perceived Personal Benefits and Q.EN2 – Perceived Effects on Public Health [4]

Variable	Q.OV1 – Perceived Personal Benefits of Pedestrianisation						Q.EN2 – Perceived Effects of Pedestrianisation on Public Health					
	FPOP			RPOP			FPOP			RPOP		
	Coef.	Std. error	*t*-stat	Coef.	Std. error	*t*-stat	Coef.	Std. error	*t*-stat	Coef.	Std. error	*t*-stat
Constant	1.37	0.24	5.61	2.35	0.51	4.60	2.19	0.20	10.90	2.27	0.22	12.27
Mode of travel (1 if active travel, 0 otherwise)	0.51	0.14	3.62	0.80	0.25	3.17	0.67	0.15	4.48	0.68	0.15	4.53
City centre travel (1 if rarely visits city centre, 0 otherwise)	-0.75	0.22	-3.39	-1.14	0.39	-2.90	-0.58	0.22	-2.65	-0.61	0.22	-2.74
Disability (1 if yes, 0 otherwise)	-0.43	0.26	-1.64	-0.91	0.62	-1.46	-0.37	0.26	-1.44	-0.28	0.38	-0.75
Standard deviation of parameter density function	–	–	–	*1.79*	*0.78*	*2.30*	–	–	–	*1.04*	*0.49*	*2.09*
Postcode (1 if inner Edinburgh, 0 if greater Edinburgh)	0.14	0.23	0.60	0.09	0.27	0.32	–	–	–	–	–	–
Standard deviation of parameter density function	–	–	–	*1.24*	*0.37*	*3.36*	–	–	–	–	–	–
Threshold 1	0.36		4.20	0.61	0.18	3.37	0.33	0.14	2.32	0.35	0.15	2.32
Threshold 2	0.48		5.10	0.81	0.21	3.80	0.58	0.17	3.47	0.61	0.18	3.45
Threshold 3	0.59		5.88	0.99	0.24	4.10	0.78	0.18	4.41	0.83	0.19	4.37
Threshold 4	0.71		6.76	1.19	0.27	4.39	0.90	0.18	4.96	0.96	0.19	4.90
Threshold 5	1.79		13.91	2.88	0.52	5.53	1.33	0.19	6.96	1.40	0.21	6.81
Threshold 6	2.24		16.41	3.59	0.63	5.67	1.62	0.19	8.30	1.70	0.21	8.08
Threshold 7	2.67		18.23	4.27	0.75	5.72	1.93	0.20	9.77	2.02	0.21	9.45
Threshold 8	3.16		18.97	5.08	0.89	5.68	2.31	0.20	11.54	2.41	0.22	11.10
Threshold 9	3.37		18.67	5.43	0.96	5.64	2.60	0.20	12.82	2.70	0.22	12.27
Sample size (N)	281			281			293			293		
LL constant only, LL(c)	-555.1			-555.1			-556.8			-556.8		
LL at convergence, LL(β)	-538.0			-532.7			-539.4			-538.1		
AIC constant only	1130.2			1130.2			1133.6			1133.6		
AIC at convergence	1104.0			1097.3			1104.8			1104.2		

[4] Coef. = Variable coefficient, AIC = Akaike Information Criterion, LL = log-likelihood, *t*-stats > 1.65 = statistically significant >90% level of confidence (l.o.c.), *t*-stats > 1.96 = >95% l.o.c.

TABLE 6 FPOP & RPOP Model Estimations for Q.OV1 – Perceived Personal Benefits and Q.EN2 – Perceived Effects on Public Health [5]

Variable	Q.EC2 – Intended City Centre Visitation Following Pedestrianisation						Q.TR2 – Prioritisation of Active Travellers on City Centre Streets					
	FPOP			RPOP			FPOP			RPOP		
	Coef.	**Std. error**	***t*-stat**	**Coef.**	**Std. error**	***t*-stat**	**Coef.**	**Std. error**	***t*-stat**	**Coef.**	**Std. error**	***t*-stat**
Constant	1.84	0.15	11.83	2.13	0.20	10.64	1.47	0.13	11.27	1.57	0.14	11.01
Mode of travel (1 if active travel, 0 otherwise)	0.44	0.14	3.23	0.47	0.14	3.36	1.01	0.15	6.80	1.04	0.15	6.95
City centre travel (1 if rarely visits city centre, 0 otherwise)	-0.52	0.22	-2.37	-0.62	0.30	-2.06	-0.17	0.22	-0.79	-0.15	0.27	-0.55
Standard deviation of parameter density function	–	–	–	*0.91*	*0.37*	*2.43*	–	–	–	*0.74*	*0.44*	*1.66*
Disability (1 if yes, 0 otherwise)	-0.64	0.26	-2.43	-0.86	0.58	-1.49	-0.36	0.26	-1.38	-0.32	0.44	-0.73
Standard deviation of parameter density function	–	–	–	*1.98*	*0.67*	*3.00*	–	–	–	*1.37*	*0.56*	*2.43*
Threshold 1	0.23	0.09	2.53	0.32	0.13	2.50	0.21	0.07	2.92	0.23	0.08	2.91
Threshold 2	0.41	0.11	3.63	0.55	0.16	3.55	0.32	0.09	3.78	0.36	0.09	3.75
Threshold 3	0.50	0.12	4.20	0.67	0.17	4.07	0.48	0.10	4.88	0.53	0.11	4.83
Threshold 4	0.52	0.13	4.34	0.70	0.18	4.19	0.70	0.11	6.41	0.77	0.12	6.29
Threshold 5	1.62	0.15	10.79	1.91	0.19	9.59	1.13	0.12	9.28	1.23	0.14	8.98
Threshold 6	1.83	0.15	11.99	2.13	0.20	10.56	1.44	0.13	11.29	1.55	0.14	10.80
Threshold 7	2.28	0.16	14.50	2.61	0.21	12.58	1.69	0.13	12.87	1.82	0.15	12.21
Threshold 8	2.81	0.16	17.05	3.16	0.22	14.67	2.07	0.14	15.11	2.22	0.16	14.17
Threshold 9	3.13	0.17	18.25	3.51	0.22	15.70	2.36	0.14	16.68	2.53	0.16	15.50
Sample size (N)	293			293			293			293		
LL constant only, LL(c)	-577.1			-577.1			-625.3			-625.3		
LL at convergence, LL(β)	-563.6			-555.2			-597.9			-594.6		
AIC constant only	1174.2			1174.2			1270.6			1270.6		
AIC at convergence	1153.2			1140.4			1221.8			1217.2		

[5] Coef. = Variable coefficient, AIC = Akaike Information Criterion, LL = log-likelihood, *t*-stats > 1.65 = statistically significant >90% level of confidence (l.o.c.), *t*-stats > 1.96 = >95% l.o.c.

TABLE 7 Average Marginal Effects for RPOP Models in Tables 5 & 6 where, [Y=0] = Strong Opposition, [Y=5] = Undecided, [Y=10] = Strong Support

Variable Description	**Average Marginal Effects for Q.OV1 – Perceived Personal Benefits of Pedestrianisation**										
	[y=0]	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**	**[y = 5]**	**[y = 6]**	**[y = 7]**	**[y = 8]**	**[y = 9]**	**[y = 10]**
Mode of travel (1 if active travel, 0 otherwise)	-0.2761	-0.0103	0.0160	0.0209	0.0295	0.2026	0.0147	0.0025	0.0003	9.2×10^{-6}	2.3×10^{-6}
City centre travel (1 if rarely visits city centre, 0 otherwise)	0.3809	-0.0956	-0.0409	-0.0367	-0.0401	-0.1596	-0.0068	-0.0010	-0.0001	-3.3×10^{-6}	-8.1×10^{-7}
Disability (1 if yes, 0 otherwise)	0.3076	-0.0676	-0.0320	-0.0295	-0.0330	-0.1382	-0.0063	-0.0010	-9.9×10^{-5}	-3.2×10^{-6}	-7.7×10^{-7}
Postcode (1 if inner Edinburgh, 0 if greater Edinburgh)	-0.0291	0.0019	0.0022	0.0024	0.0031	0.0179	0.0013	0.0002	2.8×10^{-5}	1.0×10^{-6}	2.6×10^{-7}
Variable Description	**Average Marginal Effects for Q.EN2 – Perceived Effects of Pedestrianisation on Public Health**										
	[y=0]	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**	**[y = 5]**	**[y = 6]**	**[y = 7]**	**[y = 8]**	**[y = 9]**	**[y = 10]**
Mode of travel (1 if active travel, 0 otherwise)	-0.2522	-0.0085	0.0129	0.0214	0.0158	0.0667	0.0428	0.0383	0.0322	0.0143	0.0164
City centre travel (1 if rarely visits city centre, 0 otherwise)	0.2275	-0.0205	-0.0276	-0.0268	-0.0161	-0.0546	-0.0285	-0.0225	-0.0169	-0.0069	-0.0071
Disability (1 if yes, 0 otherwise)	0.1046	-0.0055	-0.0105	-0.0113	-0.0072	-0.0259	-0.0145	-0.01200	-0.0094	-0.0040	-0.0044
Variable Description	**Average Marginal Effects for Q.EC2 – Intended City Centre Visitation Following Pedestrianisation**										
	[y=0]	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**	**[y = 5]**	**[y = 6]**	**[y = 7]**	**[y = 8]**	**[y = 9]**	**[y = 10]**
Mode of travel (1 if active travel, 0 otherwise)	-0.1776	0.0005	0.0105	0.0082	0.0020	0.1142	0.0137	0.0181	0.0079	0.0016	0.0008
City centre travel (1 if rarely visits city centre, 0 otherwise)	0.2270	-0.0231	-0.0255	-0.0147	-0.0034	-0.1294	-0.0122	-0.0133	-0.0051	-0.0009	-0.0004
Disability (1 if yes, 0 otherwise)	0.3042	-0.0407	-0.0385	-0.0210	-0.0047	-0.1645	-0.0129	-0.0149	-0.0056	-0.0010	-0.0005
Variable Description	**Average Marginal Effects for Q.TR2 – Prioritisation of Active Travellers on City Centre Streets**										
	[y=0]	**[y = 1]**	**[y = 2]**	**[y = 3]**	**[y = 4]**	**[y = 5]**	**[y = 6]**	**[y = 7]**	**[y = 8]**	**[y = 9]**	**[y = 10]**
Mode of travel (1 if active travel, 0 otherwise)	-0.3559	-0.0294	-0.0084	-0.0031	0.0135	0.0734	0.0722	0.0595	0.0756	0.0422	0.0604
City centre travel (1 if rarely visits city centre, 0 otherwise)	0.0533	0.0003	-0.0007	-0.0020	-0.0045	-0.0118	-0.0089	-0.0067	-0.0080	-0.0044	-0.0066
Disability (1 if yes, 0 otherwise)	0.1132	-0.0009	-0.0024	-0.0052	-0.0107	-0.0258	-0.0185	-0.0135	-0.0158	-0.0084	-0.0120

The disability variable, which had statistically insignificant coefficients in three of four FPOP models, produced statistically significant random parameters across all RPOP models (i.e. statistically significant standard deviation at 90% l.o.c.). In line with previous research (Fountas & Anastasopoulos, 2017), to ensure the variables assigned as random parameters were classified correctly, LRTs were conducted on the initial FPOP models versus RPOP models that include each single random parameter of the final model individually. Take Q.OV1 for example, LRTs were conducted on the initial FPOP model versus both, a model with disability as a random parameter and a model with postcode as a random parameter. Both LRTs produced statistically significant results: 97.2% l.o.c. for disability and 98.3% l.o.c. for postcode, indicating significant improvement in model performance and justifying the inclusion of random parameters in the modelling framework. For the remaining models, the results of LRTs were as follows: Q.EN2 – 90.0% l.o.c. for disability, Q.EC2 – 93.2% l.o.c. for city centre travel and 99.9% l.o.c. for disability, Q.TR2 – 82.5% l.o.c. for city centre travel and 98.1% l.o.c. for disability.

As discussed previously, the average marginal effects explain the change in probabilities for all levels of the dependent variable, following a one unit change in the independent variable (i.e. zero to one). For example, the mode of travel variable in the perceived personal benefits of pedestrianisation (Q.OV1) model, shows that active travellers were more likely to select an answer in the supportive range (y=6 to y=10) and less likely to select the categories of strongest opposition (y=0 to y=1), in comparison to the remaining preferred modes of travel (personal vehicle and public transport) (see Tables 5 & 7). For the mode of travel variable, this trend was consistent across all models. In other words, active travellers were more likely to select answers in the supportive range and considerably less likely to select a category that indicates strong opposition. As expected, this effect was particularly pronounced for the transport related issue (Q.TR2 – prioritisation of active travellers on city centre streets), where the specific variable results in marginal effects of greater magnitude, in comparison to the models for other issues. Conversely, the average marginal effects for the city centre travel variable show that those who rarely visit the city centre were more inclined to select the most extreme level of opposition (y=0) and less likely to select any other response (y=1 to y=10). A similar trend can be observed across all questions for the disability variable. For example, considering intended visitation following pedestrianisation (Q.EC2), it was found that respondents with a disability have a higher probability (0.3042) of selecting the lowest level of support, compared to those who do not have a disability. Those with no disability were more likely to select any of the remaining responses (y=1 to y=10).

For the random parameters, model coefficients and marginal effects cannot reveal all the nuances of unobserved heterogeneity they capture. For this reason, we also provide the distributional effect of variables that produced statistically significant random parameters, as shown in Table 8. These results demonstrate highly heterogeneous effects on support for pedestrianisation, which are induced by the variables that result in random parameters. For example, Table 8 shows that that for 69.35% of those with a disability, the probability of a response below the mean (<0) increased. For the remaining 30.65% the parameter is positive (>0), hence the probability of a supportive response increases.

TABLE 8 Distributional Effect of Random Parameters for all Key Questions (Question code in parentheses)

Variable as random parameter	Below zero	Above zero
Disability (1 if yes, 0 otherwise) (Q.OV1)	69.35%	30.65%
Postcode (1 if inner Edinburgh, 0 if greater Edinburgh) (Q.OV1)	47.27%	52.73%
Disability (1 if yes, 0 otherwise) (Q.EN2)	60.63%	39.37%
Disability (1 if yes, 0 otherwise) (Q.EC2)	66.81%	33.19%
City centre travel (1 if rarely visits city centre, 0 otherwise) (Q.EC2)	75.16%	24.84%
Disability (1 if yes, 0 otherwise) (Q.TR2)	59.20%	40.80%
City centre travel (1 if rarely visits city centre, 0 otherwise) (Q.TR2)	58.11%	41.89%

Heterogeneous effects were observed within the disability variable across all RPOP models. The heterogeneity in perceptions among this demographic are attributable to unobserved characteristics not captured by the survey questions. A possible explanation is that there may be disabled individuals who are particularly reliant on cars or public transport, possibly due to the impact of their personal restrictions or conditions on travel behaviour. Intuitively, these individuals are likely to be less supportive of pedestrianisation if they believe reduced city centre parking and disrupted public transport routes are an inevitable side-effect (Parajuli & Pojani, 2018). The remaining respondents with a disability, who increased the likelihood of a supportive response, may not be as reliant on these modes of travel, and as a result, are less concerned about the effects on parking and public transport.

A similarly interesting finding is the heterogeneous effect observed in the postcode variable for the question gauging the perceived personal benefits of pedestrianisation. The prospect of pedestrianisation was found to result in mixed perceptions for the residents of the inner area, who are most affected by the plans for pedestrianisation. Even though some of them may believe that pedestrianisation will improve their mobility patterns and quality of life, there may be a group of residents that could perceive pedestrianisation as a potential source of nuisance stemming from the overdevelopment observed in pedestrianised areas (Ebejer, 2020). It may be the case that this applies to Edinburgh, given its status as a major tourist destination in the UK and worldwide.

MODEL EVALUATION

All model estimation results display the AICs for models with no independent variables (constant only), with fixed parameters (FPOP) and including random parameters (RPOP). A lower AIC indicates greater model fit (Fountas & Anastasopoulos, 2018; Washington, et al., 2020). The AIC of both FPOP and RPOP models are expected to be less than the initial model with a constant only. For all dependent variables that were modelled, a decrease in AIC can be observed when comparing FPOP or RPOP models with the initial (constant only) model. A decrease in AIC can also be observed for the RPOP models versus their respective FPOP models. This is further evidence to suggest that the inclusion of random parameters improves the statistical performance of the modelling framework. To reaffirm the statistical superiority of the RPOP models, LRTs were conducted for FPOP versus RPOP frameworks. The results of the LRTs showed that the RPOP had significantly improved explanatory compared to the FPOP framework, at the following confidence levels: Q.OV1 = >99.4% l.o.c., Q.EN2 = >90.0% l.o.c., Q.EC2 = >99.9% l.o.c. and Q.TR2 = >96.4% l.o.c. In most cases, the variables resulting in statistically significant random parameters in the RPOP models generated statistically insignificant parameters in the FPOP models. This is another indication of the capacity of the RPOP models to unveil underlying effects on the various dependent variables. The consistent superiority of the RPOP framework shows that the models were enhanced with the inclusion of random parameters, which, in principle, account for unobserved heterogeneity (Mannering et al., 2016).

DISCUSSION OF RESULTS

Statistical testing provided valuable insights into the existence of substantial variation in respondents' opinions regarding the perceived personal benefits of pedestrianisation. For the mode of travel variable, the most prominent pairwise variance in opinion was between those who travel on-foot or by bicycle versus those who travel by personal vehicle. For the trip purpose variable, pairwise variance was observed between those who visit the city centre for work or leisure purposes versus those who rarely visit the centre. As mentioned previously, this suggests that a respondent's trip frequency is the primary cause for variation within the trip purpose variable, hence, the creation of the city centre travel variable for ordered probit modelling.

The first random forest estimate offered insights into the key survey questions, other than the perceived personal benefits (Q.OV1), which have the greatest influence over opinion of pedestrianisation. The key questions gauged perceptions on the following issues: the effects of pedestrianisation on public health (Q.EN2), an individual's intended city centre visitation following pedestrianisation (Q.EC2) and whether active travel modes should be prioritised on city centre streets (Q.TR2). Subsequent random forest regression and ordered probit models were then estimated for these survey questions. The mode of travel variable was found to be among the top three most important independent variables for all questions, while the trip purpose, annual income and occupation variables also had considerable influence, however, their effect was less consistent across all questions.

The results of the ordered probit models (summarised in Table 9) demonstrated that the active travel, city centre travel and disability indicators were statistically significant factors, resulting in either fixed or random parameters, across all questions, while respondent postcode was a significant factor on one occasion. Overall, active travellers were found to be strongly supportive of pedestrianisation and all key surrounding issues compared to those who travel by personal vehicle or public transport. As discussed in the 'Statistical Testing' section, the conflicting opinions of active travellers and vehicle users is a common theme observed in similar perceptual studies (Huemer, et al., 2018; Paschalidis, et al., 2016), and may be related to fears of scarce public parking among those reliant on personal vehicles (Parajuli & Pojani, 2018). Within the city centre travel variable, those who rarely visit the city centre were significantly more likely to be in strong opposition, and less likely to be supportive, when compared to those who travel to the centre frequently for work, education or leisure. This may be because those who rarely visit the city centre are likely to have negative preconceptions of Edinburgh city centre and are therefore less likely to reap the benefits of the city's pedestrianisation.

The disability variable showed that those with a disability were significantly less likely to visit the city centre following pedestrianisation, compared to those who do not have a disability. This sentiment is likely related to concerns over city centre accessibility following pedestrianisation, in particular, proximity parking and bus stop locations, as suggested by previous research (Gant, 1997; Levasseur, et al., 2015; Parajuli & Pojani, 2018). The inclusion of random parameters significantly improved model performance for the RPOP framework versus the original FPOP, suggesting that there is considerable heterogeneous effect on support for pedestrianisation, particularly within disability, city centre travel and postcode variables.

TABLE 9 – Summary of Variable Effects on Key Survey Questions[6]

	Q.OV1		Q.EN2		Q.EC2		Q.TR2	
Variable	**FPOP**	**RPOP**	**FPOP**	**RPOP**	**FPOP**	**RPOP**	**FPOP**	**RPOP**
Mode of travel (1 if active travel, 0 otherwise)	↑	↑	↑	↑	↑	↑	↑	↑
City centre travel (1 if rarely visits city centre, 0 otherwise)	↓	↓	↓	↓	↓	[↓]	–	[↓]*
Disability (1 if yes, 0 otherwise)	–	[↓]*	–	[↓]*	↓	[↓]*	–	[↓]*
Postcode (1 if inner Edinburgh, 0 if greater Edinburgh)	–	[↓]*	N/A	N/A	N/A	N/A	N/A	N/A

Q.OV1: perceived personal benefits of pedestrianisation; Q.EN2: perceived effects of pedestrianisation on public health; Q.EC2: intended visitation of the city centre following pedestrianisation; Q.TR2: whether active travel modes should be prioritised on city centre streets

POLICY IMPLICATIONS AND CONCLUSIONS

The findings in this paper should be used to aid the general direction of future policies regarding pedestrianisation. However, sample in this study is narrow and specific to Edinburgh's transportation infrastructure and residents. As a result, we recommend that pedestrianisation is investigated on a local, city-by-city or town-by-town, basis prior to implementation, thus allowing pedestrianisation schemes to be tailored to the needs of local people, or within the limits of existing infrastructure. It is our suggestion that the disillusionment of disabled individuals is addressed by ensuring widespread parking provision is available, within proximity of the city centre, and public transport routes and stops are relocated with this demographic in mind. The introduction of these provisions in Kent, UK, was successful in transforming the negative perceptions of pedestrianisation among disabled and elderly individuals (Gant, 1997). The disparity in opinion observed between active travellers and vehicle users is a consistent theme throughout. The literature suggests that conflict between active travellers and vehicle users is common, and is exacerbated by narrow streets that deprive bicycle users, pedestrians and vehicle users the space they feel is required (Huemer, et al., 2018; Paschalidis, et al., 2016). As a result, aggressive driving behaviours increase, leading to more vehicle-cyclist and vehicle-pedestrian collisions (Huemer, et al., 2018). Pedestrianisation is a potential resolution to this issue, however, conflicts between those with different modal preferences will persist on other urban streets. We suggest that this issue be resolved through the physical segregation of cycle lanes and roads, which depends on the amount of land available to expand or adapt existing transport infrastructure. This type of intervention has successfully reduced cyclist collisions in various instances across Europe and North America, whilst encouraging active travel (Ling, et al., 2020; Marshall & Ferenchak, 2019; Reid & Adams, 2010).

We conclude that a variety of independent analyses and modelling approaches suggest common or overlapping influences on respondents' opinions of pedestrianisation and surrounding key issues. These influences appear to be dominated by behavioural variables relating to transport preferences or trip frequency, as may be expected, while considerable unobserved heterogeneity was present within the following variables: disability (across all questions), city centre travel (on two occasions) and postcode (on one occasion).

[6] Interpretation of Table 9: ↑ / ↓ = significantly positive/negative coefficient (i.e. *t*-stat>1.65, corresponding to 90% l.o.c.) as a fixed parameter, [↑] / [↓] = significantly positive/negative coefficient and significant standard deviation as a random parameter, [↑]* / [↓]* = significant as a random parameter, but with an insignificant mean coefficient, dashes (–) signal a variable's inclusion within a model but with an insignificant coefficient and N/A shows a variable was not included in a given model.

Several limitations of this study should be noted. These are mainly related to sample size and misrepresentation of some demographics (as discussed in 'Data collection), which may induce a level of bias in the survey results. However, we were able to control, at least partially, for potential bias in the factors that shape public perceptions of pedestrianisation at the data analysis stage. This was achieved through the use of an integrated modelling approach, which can incorporate underlying patterns within the determinants of public opinion. Specifically, the random parameter modelling framework, as informed by the random forest estimates, unveiled the presence of heterogeneous patterns in the effect of behavioural and demographic factors, thus accounting for the impact of unobserved characteristics which cannot be readily captured through the analysis of limited samples (Mannering et al., 2016). Future studies may wish to address these issues through collecting larger samples and targeting dissemination in a way that reaches groups who are not adequately represented in travel surveys, such as individuals from lower income groups and those who have not received any form of tertiary education.

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