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Investigation of Interaction between Age and Gender Effects of Car Users by using Log-Linear Model: A Bayesian Inference Approach

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Abstract The growth in car ownership, demand for personal mobility and traffic congestion all generate negative impacts on the environment. In addition to adverse impacts, car use contributes to urban sprawl, unhealthy micro environments and increased accidents. In western countries, chronic traffic congestion due to increasing travel demand resulting from economic growth is placing governments under pressure to promote and incentivise mode shift to non-motorised modes. Therefore, this paper aims to investigate the relationships of car users' perceptions and attitudes with age-gender factors to investigate respondents' willingness to reduce car use for the sake of the environment. A log linear model for categorical data was developed using Bayesian inference approach. Models were constructed separately with and without interaction between age and gender effect. Attitudinal data from British Social Attitudes (BSA) surveys from 2011 to 2014 were used in this study. The application of the Bayesian inference approach to the BSA data demonstrated useful properties shared by population groups. The results indicate that significant differences exist among different age and gender groups. The knowledge is useful to policy makers and transport managers in designing targeted solutions to specific population groups. The outcome of this research will be vital from a policy-making perspective, as appropriate clusters of the population can be targeted when implementing sustainability policies.

Keywords Log-Linear Models, Bayesian Inference, Age-Gender Effects

1. Introduction

The demand for transport, an important component of any urban system continues to grow. Many countries struggle to cope with the challenges posed by traffic congestion and the consequential environment impacts including air quality, noise, and greenhouse gases emissions (GHG). In addition to these adverse impacts, car use contributes to urban sprawl, unhealthy micro environments and increased accidents. In western countries, chronic traffic congestion due to increasing travel demand resulting from economic growth [1] is placing governments under pressure to promote and incentivise mode shift to non-motorised modes. Prillwitz and Barr [2] present evidence that investment in public transport can help mitigate congestion in urban areas. Undoubtedly the growth in car ownership, demand for personal mobility and traffic congestion all generate negative impacts on the environment [3].

In recent years, there has been an increasing amount of literature on the use of Bayesian approaches in travel behaviour research because of the benefits that they offer [6, 7, 8] also for estimation in piecewise constant model [14].

Bayesian statistics help people to make decisions under uncertainty, allow for the remaining uncertainty in the model parameter, and to quantify the strength of our beliefs when actual data have been taken into account. Furthermore, gender differences were found by Waygood and Avineri [9] to be an influence in general environmental concern. They suggested that women were more willing to pay to reduce their personal impacts. The knowledge proposed that women are either more willing to change their behaviour or that their response to information on climate change is stronger.

Travellers are aware of environmental problems, but their interpretations do not necessarily match their travel behaviour [3]. This is consistent with studies which recommend that even though facts about the negative environmental effects of car use raises some consciousness, it is usually insufficient to change behaviour [4]. According to Anable et al. [5], there are certain car-owner groups of travellers whose environmental concerns, as well as sense of responsibility, are greater than others. This suggests that there is potential for mode choice behaviour change.

Moreover, age will also be taken into account to complement the investigation in this study. Therefore, this paper aims to investigate the relationships of car users' perceptions and attitudes with age-gender factors to investigate respondents' willingness to reduce car use for the sake of the environment. First, the methodology is outlined for separate model for age-gender groups and model with interaction between age-gender are explained, and the results are presented. The paper is concluded with discussion.

2. Methodology

Data from the British Social Attitudes (BSA) survey was used in this study. The datasets that were collected during 2011 to 2014 were chosen for the analysis. In 2010, the transport section in the BSA questionnaire was changed so as to collect data regarding people's attitudes towards, and opinions on, climate change and the environment. Therefore, the BSA data collected after 2010 were considered in this study and all data records appertaining to car users, whether as drivers or passengers were selected from the BSA using a filter. The scales have been tested for reliability by using Cronbach's alpha measurement. The Cronbach's alpha for the scales is 0.82. At the initial stage of this analysis, incomplete samples were removed during the data cleaning process, bringing the final dataset to a total of 1509 respondents of adults aged 18+ who were car users whether as drivers or passengers or both.

2.1. Separate Model for Age and Gender Groups

This analysis develops model by ignoring the interaction between age and gender. The respondents were divided into twelve age-gender groups, given six age groups each for males and females. The groups were labelled 1 to 12 and responses to the question were categorised into one of the five labelled 1 to 5 (1 = Agree strongly; 2 = Agree; 3 = Neither agree nor disagree; 4 = Disagree; and 5 = Disagree strongly). It was assumed that the respondents in each group were a random sample of people in that group. For the population of people in group i, the proportion who would give response k is given in equation 1.

$$\Pr(\text{response}, k / \text{group}, i) = \pi_{i,k} \tag{1}$$

So, we write:

$$\pi_{i,k} = \frac{\phi_{i,k}}{\sum_{k=1}^{5} \phi_{i,k}} \tag{2}$$

and:

$$\eta_{i,k} = \ln \phi_{i,k} \tag{3}$$

where *ln* stands for natural logarithm, so $\phi_{i,k} = \exp(\eta_{i,k})$, except for the case that $\eta_{i,3} = 0$ which means that the response 3, "neither agree nor disagree", was chosen as the baseline response. It follows that:

$$\phi_{i,k} = \frac{\Pr(\text{response } k \mid \text{group } i)}{\Pr(\text{response } 3 \mid \text{group } i)} \tag{4}$$

are the *odds* in favour of response k compared to response 3. Then $\eta_{i,k}$ is the corresponding *log odds*. So, if $\eta_{i,1} = \ln 2 \approx 0.69$, then the response "Agree strongly" would be twice as likely as the response "Neither agree nor disagree" for members of group i. Similarly, if $\eta_{i,5} = -\ln 2 \approx -0.69$, then the response "Disagree strongly" would be half as likely as the response "Neither agree nor disagree" for members of group i. Furthermore,

$$\eta_{i,k} - \eta_{i,j} = \ln\left\{\frac{\pi_{i,k}/\pi_{i,3}}{\pi_{i,j}/\pi_{i,3}}\right\} = \ln\left\{\frac{\pi_{i,k}}{\pi_{i,j}}\right\} \tag{5}$$

So, if $\eta_{i,k} - \eta_{i,j} = \ln 2$, then response k is twice as likely as response j for members of group i. Normal prior distributions were given to the parameters $\eta_{1,1}, \ldots, \eta_{12,5}$, except for $\eta_{i,3}$, for $i = 1, \ldots, 12$, which are fixed as equal to zero. A hierarchical prior specification induces prior correlations between the parameters. For $i = 1, \ldots, 12$ and for $k = 1, 2, 4, 5$, given the values of $\beta_1, \beta_2, \beta_4, \beta_5$, the conditional prior distribution of $\eta_{i,k}$ given β_k is:

$$\eta_{i,k} \mid \beta_k \sim N(\beta_k, 1.25) \tag{6}$$

where $\eta_{i,k}$ is conditionally independent of $\eta_{i',k'}$ given $\beta_k, \beta_{k'}$ unless $i = i'$ and $k = k'$. Then, for $k = 1, 2, 4, 5$:

$$\beta_k \sim N(0, 5) \tag{7}$$

With β_k independent of $\beta_{k'}$ unless $k = k'$. Thus, the marginal prior distribution of $\eta_{i,k}$ for $k = 1, 2, 4, 5$ is:

$$\eta_{i,k} \sim N\left(0, 6.25\right) \quad (8)$$

and $\eta_{i,k}$ and $\eta_{i',k}$ have a prior correlation of:

$$\mathrm{Corr}\left(\eta_{i,k}, \eta_{i',k}\right) = \frac{5}{6.25} = 0.8 \quad (9)$$

For this purpose, JAGS [10], which is a program used for the analysis of Bayesian graphical models using Gibbs sampling, via the rjags package in R [12], has been used to compute the posterior distribution by Markov Chain Monte Carlo (MCMC) sampling [11, 13].

2.2. Model with Interaction between Age and Gender Effects

In this section, the effect of age and gender on responses to question "For the sake of the environment, everyone should reduce how much they use their cars" was investigated. The respondents are categorised as either "males" or "females" associated with six age-groups. Interest lies in the effects of the respondents' age and gender on the outcome for the responses. The effects of age and gender are introduced using six orthogonal contrasts, labelled as gender, a_1, a_2, a_3, a_4, and a_5, as shown in Table 1.

In this analysis, $k = 3$ (neither agree nor disagree) was used as a baseline. The other four categories where $k = 1,2,4,5$, $\eta_{i,k}$ can be modelled in terms of an age effect $\beta_{a,k}$, a gender effect $\beta_{g,k}$ and an interaction effect between age and gender $\beta_{ag,k}$ as shown in Appendix.

The covariate a_1 takes the values (1, 1, 1, -1, -1, and -1) in the first six male groups, similarly for female groups. This list of contrasts can be extended to all 12 groups by taking $\beta_{0,3} = \beta_{a,3} = \beta_{g,3} = \beta_{ag,3} = 0$, which in turn gives $\eta_{1,3} = \eta_{2,3} = \ldots = \eta_{12,3} = 0$. In this way, the parameters are made relative to the baseline response category $k = 3$ (neither agree nor disagree).

Apart from the baseline values $\beta_{0,k}$, the coefficients of β_g in η_g are orthogonal contrasts. Briefly, using such contrasts gives some useful structure upon which to develop the prior distribution for the η_g. The contrasts have a useful property if a particular type of prior is taken for the non-baseline β_g: the same prior is used for each $\beta_{0,k}\left(k \neq 3\right)$ as well as the same prior for each $\beta_{a,k}\left(k \neq 3\right)$, but possibly different from that for the $\beta_{0,k}$. Similarly, for $\beta_{g,k}\left(k \neq 3\right)$ and for $\beta_{ag,k}\left(k \neq 3\right)$, and these blocks are independent of one another.

More time could be spent on looking at how to construct the various elements of the prior distribution in detail. However, for clarity, a fairly simple example is used here. There was no evidence that inferences were sensitive to changes in details of the prior. The prior distribution is taken to have independent components, for $k = 1,2,4,5$.

Next, plots of the posterior probability functions were produced by extracting the sampled values first and then using the standard R plot functions to produce the plots. Group 3, male, 35-44 years old, "agree strongly" was chosen and a plot for $\eta_{3,1}$ was produced and presented in the next section.

Table 1. Cross tabulations of responses to question according to age and gender, and proposed orthogonal contrasts.

Gender	Age	Responses to Question					Total	Gender	a_1	a_2	a_3	a_4	a_5
		1	2	3	4	5							
Male	18-24	3	7	5	2	2	19	1	1	1	-1	0	0
	25-34	2	42	24	15	6	89	1	1	-1	-1	0	0
	35-44	12	55	39	20	4	130	1	1	0	2	0	0
	45-54	8	80	31	33	7	159	1	-1	0	0	1	-1
	55-64	7	74	37	25	10	153	1	-1	0	0	-1	-1
	65+	11	107	48	33	8	207	1	-1	0	0	0	2
Female	18-24	1	12	10	6	1	30	-1	1	1	-1	0	0
	25-34	11	68	31	13	3	126	-1	1	-1	-1	0	0
	35-44	12	99	56	12	6	185	-1	1	0	2	0	0
	45-54	8	86	45	17	2	158	-1	-1	0	0	1	-1
	55-64	8	66	34	17	4	129	-1	-1	0	0	-1	-1
	65+	8	70	22	22	2	124	-1	-1	0	0	0	2

Note: Responses to question; 1= agree strongly, 2= agree, 3= neither agree nor disagree, 4= disagree, 5= disagree strongly

Table 2. Gender and age groups

Gender	Age	Responses					Total
		1	2	3	4	5	
Male	18-24	3	7	5	2	2	19
	25-34	2	42	24	15	6	89
	35-44	12	55	39	20	4	130
	45-54	8	80	31	33	7	159
	55-64	7	74	37	25	10	153
	65+	11	107	48	33	8	207
Female	18-24	1	12	10	6	1	30
	25-34	11	68	31	13	3	126
	35-44	12	99	56	12	6	185
	45-54	8	86	45	17	2	158
	55-64	8	66	34	17	4	129
	65+	8	70	22	22	2	124

Note: 1=agree strongly, 2=agree, 3=neither agree nor disagree, 4=disagree, 5=disagree strongly

Table 3. Posterior summaries: means and standard deviations

Parameter	Mean	SD	Parameter	Mean	SD
Group 1 (Male, 18-24)			**Group 2 (Male, 24-34)**		
$\eta_{1,1}$	-1.28	0.32	$\eta_{2,1}$	-1.68	0.29
$\eta_{1,2}$	0.51	0.28	$\eta_{2,2}$	0.60	0.19
$\eta_{1,4}$	-0.66	0.31	$\eta_{2,4}$	-0.51	0.23
$\eta_{1,5}$	-1.84	0.34	$\eta_{2,5}$	-1.76	0.30
Group 3 (Male, 35-44)			**Group 4 (Male, 45-54)**		
$\eta_{3,1}$	-1.28	0.24	$\eta_{4,1}$	-1.48	0.26
$\eta_{3,2}$	0.44	0.17	$\eta_{4,2}$	0.78	0.16
$\eta_{3,4}$	-0.61	0.21	$\eta_{4,4}$	-0.22	0.19
$\eta_{3,5}$	-2.04	0.29	$\eta_{4,5}$	-1.85	0.28
Group 5 (Male, 55-64)			**Group 6 (Male, 65+)**		
$\eta_{5,1}$	-1.56	0.26	$\eta_{6,1}$	-1.48	0.24
$\eta_{5,2}$	0.65	0.16	$\eta_{6,2}$	0.75	0.14
$\eta_{5,4}$	-0.49	0.20	$\eta_{6,4}$	-0.46	0.18
$\eta_{5,5}$	-1.68	0.27	$\eta_{6,5}$	-1.91	0.27
Group 7 (Female, 18-24)			**Group 8 (Female, 25-34)**		
$\eta_{7,1}$	-1.51	0.32	$\eta_{8,1}$	-1.24	0.25
$\eta_{7,2}$	0.51	0.25	$\eta_{8,2}$	0.77	0.17
$\eta_{7,4}$	-0.50	0.29	$\eta_{8,4}$	-0.76	0.23
$\eta_{7,5}$	-1.97	0.34	$\eta_{8,5}$	-2.06	0.30
Group 9 (Female, 35-44)			**Group 10 (Female, 45-54)**		
$\eta_{9,1}$	-1.44	0.24	$\eta_{10,1}$	-1.53	0.25
$\eta_{9,2}$	0.68	0.14	$\eta_{10,2}$	0.75	0.16
$\eta_{9,4}$	-1.09	0.22	$\eta_{10,4}$	-0.77	0.21
$\eta_{9,5}$	-2.03	0.27	$\eta_{10,5}$	-2.21	0.29
Group 11 (Female, 55-64)			**Group 12 (Female, 65+)**		
$\eta_{11,1}$	-1.44	0.26	$\eta_{12,1}$	-1.34	0.27
$\eta_{11,2}$	0.69	0.17	$\eta_{12,2}$	0.93	0.18
$\eta_{11,4}$	-0.64	0.22	$\eta_{12,4}$	-0.32	0.21
$\eta_{11,5}$	-2.01	0.29	$\eta_{12,5}$	-2.10	0.31

3. Results and Discussion

3.1. Separate Model for Age and Gender Groups

Table 2 presents the sample distribution according to age and gender variables that are used in this model. Two parallel MCMC chains were used to fit the log-linear model. Convergence was checked with trace plots and found to be satisfactory. A burn-in for the MCMC sampler of 1000 iterations of both chains was used and samples of the values of η were collected from 2000 further iterations in two chains. Summaries of the posterior distributions of the various η parameters were obtained, based on 4000 samples, from the posterior distribution. The results are presented in Table 3, where $\eta_{i,3}$, which is fixed at zero for all *i*, has been removed.

Table 3 presents the posterior means and standard deviations of 12 groups for question – "for the sake of the environment, everyone should reduce how much they use their cars". Next, plots of the posterior probability functions were produced by extracting the sampled values first and then using the standard R plot functions to produce the plots. For illustration, group 3, male, 35-44 years old, "agree strongly" was chosen and a plot for $\eta_{3,1}$ was produced. The resulting graph is shown in Figure 1.

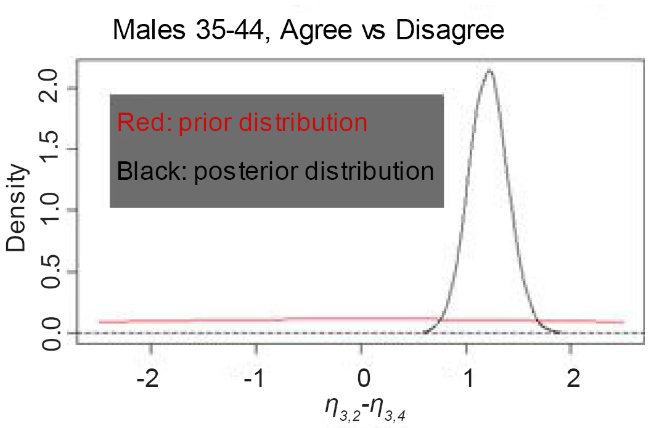

Figure 1. Probability density functions for $\eta_{3,2} - \eta_{3,4}$, the log odds for "agree" compared to "disagree" for males aged 35-44.

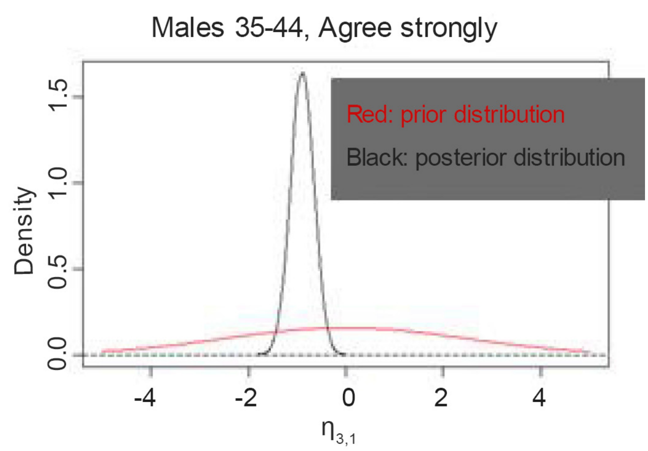

Figure 2. Probability density functions for $\eta_{3,1}$, the log odds for "agree strongly" for males aged 35-44.

The prior distribution $\eta_{3,2} - \eta_{3,4}$ is normally distributed assumed to have a mean 0 and variance $12.5 \sim N(0,12.5)$ since they are independent in the prior. The standard deviation is thus $\sqrt{12.5} = 3.54$. The resulting graph is shown in Figure 2. It can be clearly seen that a person in this group (male, 35-44 years old) was more likely to respond "agree" than "disagree" when they were asked to reduce the amount of car use for the sake of the environment.

3.2. Model with Interaction between Age and Gender Effects

The posterior means and standard deviations are presented in Table 4 where $\eta_{i,3}$, which is fixed at zero for all *i*, has been removed, and the resulting graphs are shown in Figure 3 and Figure 4. Figure 3 has two distributions, the flat red curve being the prior distribution and the sharper normal curve being the posterior. With reference to Table 4, it is apparent that the value of $\eta_{3,1}$ of the posterior distribution is negative -1.23 and SD = 0.33. This finding suggests that members of this group were less likely to respond "agree strongly" than to respond "neither agree nor disagree", when they were asked to reduce how much they used their cars for the sake of the environment.

Subsequently, the same group was chosen to compare their level of perceptions for the same question instead of relative to "neither agree nor disagree", but instead $\eta_{3,2}$ ("agree") is compared to $\eta_{3,4}$ ("disagree"). The resulting graph is shown in Figure 3. It can be clearly seen that a person in this group (male, 35-44 years old) was more likely to respond "agree" than "disagree", when they were asked to reduce the amount of car use for the sake of the environment.

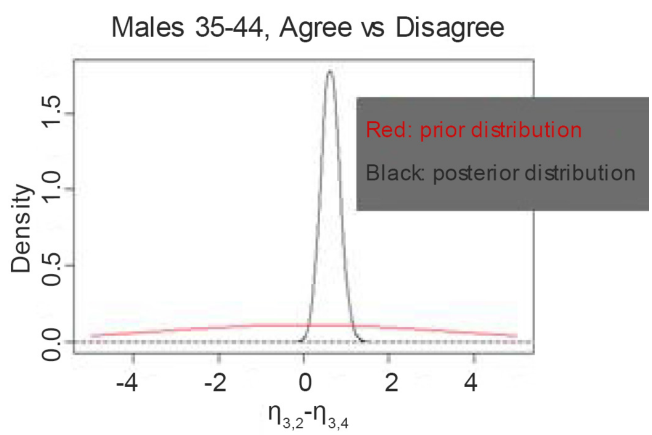

Figure 3. Probability density functions for $\eta_{3,2} - \eta_{3,4}$, the log odds for "agree" compared to "disagree" for males aged 35-44.

It is worth noting that most of the posterior means were negatives in Table 3 except for $\eta_{i,2}$. This seems to suggest that "agree" tends to be a popular choice for question, whereas $\eta_{i,2}$ is sometimes positive, but did not always emerge when the interaction of age and gender effect was considered in the models, as shown in Table 4. The results for model with age-gender effect shows that it is more accurate and significant because the correlation occur between them is not ignored. Bayesian inference was taken into consideration because it allows the uncertainty in the parameters to be incorporated in the model.

Table 4. Posterior means and standard deviations

Parameter	Mean	SD	Parameter	Mean	SD
Group 1 (Male, 18-24)			**Group 2** (Male, 25-34)		
$\eta_{1,1}$	-0.76	0.55	$\eta_{2,1}$	-1.95	0.49
$\eta_{1,2}$	-0.36	0.51	$\eta_{2,2}$	0.57	0.25
$\eta_{1,4}$	-0.66	0.59	$\eta_{2,4}$	-0.51	0.32
$\eta_{1,5}$	-1.31	0.68	$\eta_{2,5}$	-1.48	0.43
Group 3 (Male, 35-44)			**Group 4** (Male, 45-54)		
$\eta_{3,1}$	-1.23	0.33	$\eta_{4,1}$	-1.40	0.36
$\eta_{3,2}$	0.35	0.21	$\eta_{4,2}$	0.93	0.20
$\eta_{3,4}$	-0.69	0.27	$\eta_{4,4}$	0.01	0.24
$\eta_{3,5}$	-2.24	0.47	$\eta_{4,5}$	-1.54	0.38
Group 5 (Male, 55-64)			**Group 6** (Male, 65+)		
$\eta_{5,1}$	-1.64	0.37	$\eta_{6,1}$	-1.49	0.33
$\eta_{5,2}$	0.70	0.20	$\eta_{6,2}$	0.81	0.17
$\eta_{5,4}$	-0.38	0.25	$\eta_{6,4}$	-0.37	0.23
$\eta_{5,5}$	-1.39	0.34	$\eta_{6,5}$	-1.83	0.38
Group 7 (Female, 18-24)			**Group 8** (Female, 25-34)		
$\eta_{7,1}$	-1.68	0.62	$\eta_{8,1}$	-1.18	0.35
$\eta_{7,2}$	0.27	0.40	$\eta_{8,2}$	0.78	0.21
$\eta_{7,4}$	-0.65	0.48	$\eta_{8,4}$	-0.84	0.311
$\eta_{7,5}$	-2.30	0.68	$\eta_{8,5}$	-2.26	0.49
Group 9 (Female, 35-44)			**Group 10** (Female, 45-54)		
$\eta_{9,1}$	-1.56	0.31	$\eta_{10,1}$	-1.74	0.36
$\eta_{9,2}$	0.57	0.17	$\eta_{10,2}$	0.66	0.18
$\eta_{9,4}$	-1.51	0.31	$\eta_{10,4}$	-0.95	0.27
$\eta_{9,5}$	-2.32	0.42	$\eta_{10,5}$	-2.81	0.50
Group 11 (Female, 55-64)			**Group 12** (Female, 65+)		
$\eta_{11,1}$	-1.50	0.37	$\eta_{12,1}$	-1.07	0.40
$\eta_{11,2}$	0.66	0.21	$\eta_{12,2}$	1.15	0.24
$\eta_{11,4}$	-0.72	0.29	$\eta_{12,4}$	-0.03	0.29
$\eta_{11,5}$	-2.24	0.47	$\eta_{12,5}$	-2.29	0.60

Note: SD = standard deviation

4. Conclusion

This paper subsequently presented an analysis of the categorical variables using log-linear and, aiming to investigates respondents' willingness to reduce their car usage for the sake of the environment. Overall, this paper demonstrates how the novel approach presented here assists considerably in understanding the perceptions of individuals regarding environmental issues and their potential to take action to reduce the impact of climate change. The results of the study have demonstrated that fitting a log-linear model using Bayesian inference is both a practical and effective way to analyse ordinal survey data. There is evidence that susceptibility to change appears to be linked to age and gender. Those in younger and older categories are the least likely to be susceptible to change, whilst those in their middle-age are the most susceptible. Females are undifferentiated from males in terms of their susceptibility to change. In addition, there was a greater tendency to agree to use cars with lower CO_2 emissions for the sake of the environment among respondents with one car per household compared to respondents with four or more.

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Appendix

Group 1:

$$\eta_{1k} = \beta_{0,k} + \beta_{a_1,k} + \beta_{a_2,k} - \beta_{a_3,k} + \beta_{g,k} + \beta_{a_1g,k} + \beta_{a_2g,k} - \beta_{a_3g,k}$$

Group 2:

$$\eta_{2k} = \beta_{0,k} + \beta_{a_1,k} - \beta_{a_2,k} - \beta_{a_3,k} + \beta_{g,k} + \beta_{a_1g,k} - \beta_{a_2g,k} - \beta_{a_3g,k}$$

Group 3: $\eta_{3k} = \beta_{0,k} + \beta_{a_1,k} + 2\beta_{a_3,k} + \beta_{g,k} + \beta_{a_1g,k} + 2\beta_{a_3g,k}$

Group 4:

$$\eta_{4k} = \beta_{0,k} - \beta_{a_1,k} + \beta_{a_4,k} - \beta_{a_5,k} + \beta_{g,k} - \beta_{a_1g,k} + \beta_{a_4g,k} - \beta_{a_5g,k}$$

Group 5:

$$\eta_{5k} = \beta_{0,k} - \beta_{a_1,k} - \beta_{a_4,k} - \beta_{a_5,k} + \beta_{g,k} - \beta_{a_1g,k} - \beta_{a_4g,k} - \beta_{a_5g,k}$$

Group 6:

$$\eta_{6k} = \beta_{0,k} - \beta_{a_1,k} - \beta_{a_4,k} - \beta_{a_5,k} + \beta_{g,k} - \beta_{a_1g,k} - \beta_{a_4g,k} - \beta_{a_5g,k}$$

Group 7:

$$\eta_{7k} = \beta_{0,k} + \beta_{a_1,k} + \beta_{a_2,k} - \beta_{a_3,k} - \beta_{g,k} + \beta_{a_1g,k} + \beta_{a_2g,k} - \beta_{a_3g,k}$$

Group 8:

$$\eta_{7k} = \beta_{0,k} + \beta_{a_1,k} - \beta_{a_2,k} - \beta_{a_3,k} - \beta_{g,k} + \beta_{a_1g,k} - \beta_{a_2g,k} - \beta_{a_3g,k}$$

Group 9: $\eta_{9k} = \beta_{0,k} + \beta_{a_1,k} + 2\beta_{a_3,k} - \beta_{g,k} + \beta_{a_1g,k} + 2\beta_{a_3g,k}$

Group 10:

$$\eta_{10k} = \beta_{0,k} - \beta_{a_1,k} + \beta_{a_4,k} - \beta_{a_5,k} - \beta_{g,k} - \beta_{a_1g,k} + \beta_{a_4g,k} - \beta_{a_5g,k}$$

Group 11:

$$\eta_{11k} = \beta_{0,k} - \beta_{a_1,k} - \beta_{a_4,k} - \beta_{a_5,k} - \beta_{g,k} - \beta_{a_1g,k} - \beta_{a_4g,k} - \beta_{a_5g,k}$$

Group 12:

$$\eta_{12k} = \beta_{0,k} - \beta_{a_1,k} + 2\beta_{a_5,k} - \beta_{g,k} - \beta_{a_1g,k} + 2\beta_{a_5g,k}$$

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