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Modelling participation in road accidents of drivers with disabilities who use hand controls

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ABSTRACT

Almost 200 million persons with disabilities face specific difficulties in everyday life. Private vehicles provide persons with disabilities with a high level of flexibility, a high level of time efficiency, and a better quality of life. It is sometimes necessary to make vehicle modifications to enable persons with disabilities to drive. One of the most frequent modifications is hand controls. Although drivers with disabilities who use hand controls face the same risk of road accidents as non-disabled drivers, predictors of road accidents for drivers with disabilities who use hand controls have not been the subject of earlier research. The predictors show which factors influence the occurrence of road accidents of drivers with disabilities who use hand controls. This paper aims to develop a model that describes the participation in road accidents of drivers with disabilities who use hand controls and recognises contributing predictors. A multidisciplinary team of experts identified twenty-three predictors that impact road accidents of drivers with disabilities who use hand controls. Bayesian logistic regression models have identified speeding, alcohol consumption, mobile phone usage, and especially fatigue as risky behaviours. This paper proposes several important measures that would improve the safety of drivers with disabilities using hand controls.

KEYWORDS
persons with disabilities; road safety; road accidents; Bayesian approach; expert priors

1. Introduction

According to World Health Organization (2021), over a billion people have some form of disability (around 15% of the population), and almost 190 million people (4%) face specific difficulties when performing everyday activities. In Europe, the percentage of persons with disabilities (PwD), as well as the number of PwD experiencing specific difficulties in everyday activities, is higher, reaching 25% (87 million) and 7% (25 million), respectively (European Commission, 2021b). There are many problems that PwD

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face in their daily lives. One of the most significant problems is noticed in transportation (European Commission, 2010; United Nations, 2019).

The lack of transportation accessibility for PwD negatively impacts their mobility. Namely, PwD make fewer trips per day than non-disabled persons (Brumbaugh, 2018; Henly & Brucker, 2019). One way to improve transportation accessibility and mobility is to enable PwD to drive private vehicles. Private vehicles provide PwD with a high level of flexibility (Jansuwan, Christensen, & Chen, 2013), a high level of time efficiency (Bascom & Christensen, 2017), and a better quality of life (Pyer & Tucker, 2017). This kind of transportation offers significant advantages in areas with poor access to public transportation and rural areas (Jansuwan et al., 2013) and during public health crises (Cochran, 2020). On the other hand, increased mobility and exposure to traffic also bring higher risks of road accident participation (Chu, Wu, Atombo, Zhang, & Özkan, 2019; Lourens, Vissers, & Jessurun, 1999).

In order for PwD to drive a vehicle independently, vehicle modifications are sometimes necessary. A widespread modification of the vehicle is hand controls (HC) installation (Dahuri, Hussain, Yusof, & Jalil, 2017; Di Stefano, Stuckey, Macdonald, & Lavender, 2015; Henriksson & Peters, 2004). According to Bouman and Pellerito (2006) and Pilkey, Thacker, and Shaw (2001), HC can be defined as a mechanical device attached under the vehicle's dashboard with a single handle that connects to the accelerator and brake pedals. This device is used by persons who are unable to operate the pedals with their feet due to physical limitations. In this way, mobility and quality of life are improved (Di Stefano et al., 2015; Norweg, Jette, Houlihan, Ni, & Boninger, 2011), and certain economic benefits are created (Hutchinson et al., 2020). However, HC can increase the workload during driving (Benoit, Gelinas, Mazer, Porter, & Duquette, 2009). Also, the presence of HC in the vehicle has been shown to increase the risk of injury to the driver's knee (Pilkey et al., 2001; Schneider et al., 2016) and challenges the effectiveness of airbags (Hu, Orton, Manary, Boyle, & Schneider, 2020).

Regarding road safety, a significant difference has not been observed in the risk of participation in road accidents for drivers with disabilities (DwD) who use HC compared to the general population (Henriksson & Peters, 2004; Sagberg, Amundsen, & Glad, 2003). Namely, Henriksson and Peters (2004) found that the risk of participation in road accidents for DwD was 0.85 per million kilometres driven. On the other hand, the risk for non-disabled drivers was 0.98 per million kilometres driven. However, a statistically significant difference between these risks has not been observed. The differences between the risk of fatality/injury in road accidents are less pronounced (DwD – 0.21 per million kilometres; non-disabled drivers – 0.20 per million kilometres). This finding was supported by Santos, Brech, Alonso, and Greve (2021) who had found that DwD who use HC do not have a higher brake response time than non-disabled drivers. Although they have equal risk as non-disabled drivers, predictors of participation of DwD who use HC in road accidents have not been the subject of research so far. The predictors refer to factors that can predict the occurrence of road accidents involving DwD who use HC.

This paper aims to develop a model that describes the participation in road accidents of DwD who use HC and recognises contributing predictors. Previous research has analysed the risk of DwD participating in a road accident (Henriksson & Peters, 2004; Sagberg et al., 2003), but not the predictors that affect it. Predictors of participation of DwD who use HC in road accidents are helpful in identifying problems and defining adequate measures. Combining expert knowledge and the Bayesian approach has shown promising results in previous research in road safety (Schlüter, Deely, & Nicholson, 1997; Washington & Oh, 2006; Yu & Abdel-Aty, 2013). In this paper, we used a unique procedure for identifying the contributing predictors using expert knowledge, the multicriteria decision-making method (PROMETHEE II method), and the Bayesian approach. The research of DwD who use HC was realised in Serbia. Serbia represents a country with a lower inclusion rate for PwD (ANED, 2018; European Commission, 2021a; Grujičić, Ivanović, Jović, & Đorić, 2014), but their position is expected to improve in the future, and thus, the number of DwD who use HC will increase. Considering the specificities of DwD who use HC (small sample size and a small number of the previous studies), we created Bayesian logistic regression models with a few prior distributions. Based on the identified contributing predictors, a proposal of measures to improve the road safety of DwD who use HC is recommended. Additionally, the proposed measures would encourage potential DwD who use HC to take active participation in traffic as drivers. Consequently, the measures would improve the quality of life of PwD (better social life, greater economic activity, better access to health services, more accessible education, etc.). All these findings and measures contribute to achieving the global goal of improving the accessibility of transport for PwD recognised by the United Nations (2019) – target 11.2.

2. Methodology

In this paper, the research was performed in three parts. In the first phase, the research on the significant predictors of road accidents involving DwD who use HC was conducted with the help of experts from several fields (Chapter 2.1.). Then, based on the defined significant predictors, the

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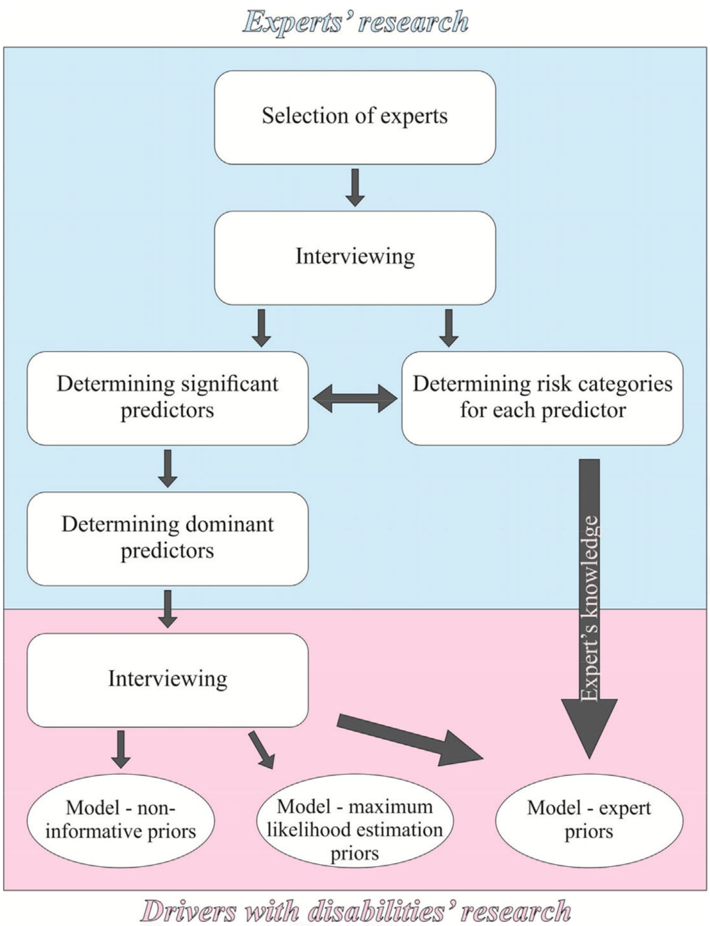

Figure 1. Algorithm realisation of research.

research of participation in road accidents of DwD who use HC was realised (Chapter 2.2.). Further, Bayesian logistic regression models were created based on the collected data with the dependent variable participation in road accidents DwD who use HC (Chapter 2.3.). Non-informative, maximum likelihood estimation and expert priors were adopted as prior distributions in the models. The algorithm for conducting the research is shown in Figure 1.

2.1. Experts' research

2.1.1. Selection of experts

Considering that the road safety of DwD who use HC is a multidisciplinary problem (Petrović, Pešić, & Mijailović, 2020), the expert team's fields of study should also be multidisciplinary. Therefore, in this study, three groups of experts were selected:

- ***Experienced DwD who use HC.*** Experts from this group needed to have many years of experience driving with HC and to be active participants in traffic, especially in the last 12 months. Also, it was advisable that experts actively participate in improving the inclusion and quality of life of PwD (through governmental and non-governmental organisations, local communities, sports associations, etc.).
- ***Medical experts.*** Experts needed to be specialised in assessing the ability of PwD to participate safely in traffic as drivers.
- ***Transportation engineers.*** This group of experts needed to consist of engineers who primarily deal with road safety and have performed activities related to PwD in their work so far.

Within each group of experts, several potential experts were defined, based on which the final selection of the expert team was made. According to the recommendations of Knol, Slottje, Van Der Sluijs, and Lebret (2010), a sufficient number of experts from each group was six.

2.1.2. Research procedure

After the initial introduction to the research goal, the authors interviewed each expert. The interviews lasted, on average, about 30-40 minutes. The interviewing of experts took place in two stages:

- ***Determining significant predictors***. In the first stage, the expert listed the predictors that he/she believed to affect the probability of a road accident with DwD who use HC. Then, for each predictor, the expert estimated the importance on a five-point scale.
- ***Determining significant categories for each predictor***. For each predictor, the expert defined which category of that predictor is riskier. Experts gave this information as a ratio of the odds of the riskier category for participating in the road accident compared to other categories (odds ratio). For ease of understanding, all predictors were considered as categorical variables with two or more categories.

2.1.3. Procedure for dominant predictors selection

A large number of experts defined a large number of significant predictors. A procedure for reducing the number of significant predictors was defined to create more practical models. In this paper, the PROMETHEE II method of multicriteria decision-making was used to filter the predictors. PROMETHEE (The Preference Ranking Organisation METHod for Enrichment of Evaluations) analyses the interrelationship of alternatives by expressing their dominance over others and the dominance of others over them (Brans & De Smet, 2016). The PROMETHEE II method gives a unique value representing the difference between the dominance of the alternative over other alternatives and the dominance of other alternatives over them (Brans & De Smet, 2016). This value ranges from 1, which shows that the predictor is dominant over all others, to −1, which shows that all others are dominant over the predictor. The value 0.5 was adopted as the limit value, and the adopted preference function was linear. All predictors with dominance over this value were adopted in further analysis and were considered as dominant predictors.

The PROMETHEE II method is multicriteria, so it was necessary to define criteria for its application. In this study, the following two criteria were defined:

- „% of experts who recognised the criterion as significant "– Criterion 1.
- The average of the difference between the predictor importance and the average of the expert's estimators of all predictors' importance – Criterion 2. Criterion 2 was calculated according to Equation (1):

$$z_i = \frac{\sum_j^m (z_{ij} - \bar{y}_j)}{m} \tag{1}$$

z_i represents the value of Criterion 2 for i_{th} predictor; m is the number of experts who recognised i_{th} predictor as significant. The z_{ij} value represents the importance of i_{th} predictor estimated by the j_{th} expert. The value $\bar{y}_j$ represents the average of the importance of all predictors by the j_{th} expert.

2.2. Drivers with disabilities' research

2.2.1. Research procedure

Based on the significant predictors defined by the experts, a questionnaire was created for DwD who use HC. The questionnaire contained basic questions about the participants (sociodemographic and medical status), questions that the experts recognised as significant, and questions about their involvement in previous road accidents.

Thanks to the Union of Persons with Paraplegia and Quadriplegia of Serbia (UPPQS), DwD who use HC were contacted. Data collection was performed by interviewing DwD who use HC (in person or by telephone), in accordance with health protocols due to the COVID-19 pandemic. The interviews lasted between 20 and 25 minutes. After the initial introduction (5-10 minutes), the respondents were asked whether they wanted to take part in the research and whether they were willing to give their consent to the authors for using the collected data for research purposes. Following the respondent's consent, the authors proceeded with the interview.

2.3. Analysis

2.3.1. Bayesian logistic regression

Logistic regression models were created to examine the impact of dominant predictors on the dependent variable. The logistic regression model can be written as follows (Equation 2):

$$\frac{p}{1-p} = e^{b_0 + x_1 b_1 + \ldots + x_i b_i + \ldots + x_k b_k} \tag{2}$$

The ratio *p/(1-p)* represents the ratio of the probability that a road accident will occur and the probability that a road accident will not occur. This ratio is called *odds*. The values b_i represent the regression coefficients of the logistic regression model, and x_i is the values of the i_{th} predictors. The parameter k represents the number of predictor variables.

The Bayesian statistical inference is different from the frequentist approach. The Bayesian approach has many advantages in certain circumstances (Wagenmakers et al., 2018). The specificity of the analysed problem, a small sample size, a small number of previous studies, and the possibility of incorporating expert knowledge are the reasons why the Bayesian approach was chosen.

The Bayesian approach gives us a possibility to update the posterior probability of the parameters and to construct credibility intervals with a natural interpretation in terms of probabilities. Moreover, the Bayesian approach can effectively avoid overfitting that occurs when the sample size is small. According to Gelman, Carlin, Stern, and Rubin (2004), the posterior distribution of parameters θ can be derived as follows (Equation 3):

$$\pi(\theta\varphi) = \frac{\pi(\theta,\varphi)}{\pi(\varphi)} = \frac{\pi(\theta)\pi(\varphi\theta)}{\pi(\varphi)} \quad \propto \pi(\theta)\pi(\varphi\theta) \tag{3}$$

where $\pi(\theta|\varphi)$ is the posterior distribution of parameters θ conditional on observed dataset φ $\pi(\varphi,\theta)$ is the joint probability distribution of observed dataset y and parameters θ; $\pi(\theta)$ is the prior distribution of parameters θ; $\pi(\varphi|\theta)$ is the likelihood conditional function based on parameters θ.

Monte Carlo Markov Chains (MCMC) performs the posterior distribution estimation for each parameter with diverse initial values run for 40,000 iterations. The first 10,000 iterations in each chain are used for monitoring convergence and then discarded as burn-in runs. The assessment of the quality of MCMC is used acceptance rate and visual inspection of autocorrelation, trace, histogram, and density diagrams. Bayesian generalisation of Akaike Information Criterion - The Deviance Information Criterion (DIC) was used to measure the model complexity and fit. Considering the sample size and Royall's (1986) recommendation, the 90% Bayesian credible interval (BCI) was used to assess the parameter's influence. BCI provides probability interpretations with normality assumptions on unknowns and credible interval estimations (Gelman et al., 2004).

2.3.2. Prior distributions

In this study, we compared models with three different prior distributions. The first prior distributions were non-informative, i.e., they did not provide prior information about the impact of the predictor on the dependent variable. In the second approach, although not completely in accordance with Bayesian, nor empirical Bayesian methodology, due to its simplicity, rather following (Yu & Abdel-Aty, 2013), the prior distribution for each parameter was the normal distribution with parameters obtained using the maximum likelihood estimation (MLE). In this method, each coefficient's prior distribution was normal with parameters equal to MLE in the logistic regression model with only one independent variable and observed dependent variable.

The last approach involved creating prior distributions based on expert estimates obtained during expert research. The selection of the values of the prior distributions was performed based on the information provided by the experts on which category of predictors was riskier. Since the experts expressed their opinion as an odds ratio (measuring change when all other predictors are assumed constant), based on these values, it was possible to estimate the mean value of priors for the logistic regression coefficients ($\hat{b}_{ij}$). These values were obtained as follows (Equation 4 and Equation 5):

$$\frac{odds\ (x_i = 1)}{odds\ (x_i = 0)} = \frac{e^{\hat{b}_{0j}+x_1\hat{b}_{1j}+\ldots+1\hat{b}_{ij}+\ldots+x_n\hat{b}_{nj}}}{e^{\hat{b}_{0j}+x_1\hat{b}_{1j}+\ldots+0\hat{b}_{ij}+\ldots+x_n\hat{b}_{nj}}} = e^{\hat{b}_{ij}} \tag{4}$$

$$\ln\left(\frac{odds\ (x_i = 1)}{odds\ (x_i = 0)}\right) = ln\left(e^{\hat{b}_{ij}}\right) = \hat{b}_{ij} \tag{5}$$

The assessment of the logistic regression coefficients was performed for each predictor and each expert. The normal distributions with the average values of $\hat{b}_{ij}$ for all experts, and the corresponding variance was adopted as the prior distributions (Equation 6):

$$b_i \sim N\left(\overline{\hat{b}_{ij}}, \frac{\sum\left(\hat{b}_{ij} - \overline{\hat{b}_{ij}}\right)^2}{m-1}\right) \tag{6}$$

3. Results

3.1. Research with experts

Following the recommendations of Knol et al. (2010), six experts were selected from each recognised expert field. The list of experts, with

Table 1. Experts list.

	Expert area	Position	Gender	Age	Experience (years)
1	Experienced driver	Private company	Male	62	40
2	Experienced driver	NGO	Female	54	20
3	Experienced driver	Parasportist	Male	51	32
4	Experienced driver	Local authority	Male	48	15
5	Experienced driver	NGO	Male	46	20
6	Experienced driver	NGO	Female	30	12
7	Medicine	Hospital specialist	Male	38	11
8	Medicine	Hospital specialist	Female	39	13
9	Medicine	Hospital specialist	Male	43	10
10	Medicine	Hospital specialist	Male	40	8
11	Medicine	Hospital specialist	Male	38	7
12	Medicine	Hospital specialist	Male	40	13
13	Transportation engineer	University	Male	40	12
14	Transportation engineer	National agency	Female	38	17
15	Transportation engineer	National agency	Male	38	10
16	Transportation engineer	University	Male	33	9
17	Transportation engineer	NGO	Male	33	10
18	Transportation engineer	University	Female	32	7

information about the position, gender, age, and experience, is shown in Table 1. The group of experienced drivers consists of DwD had been using HC for about twenty-three years on average. Medical experts' average length of experience working with DwD was over ten years. Additionally, experts in transportation engineering had slightly more experience, an average of about eleven years.

The experts identified twenty-three predictors as significant for the participation of DwD who use HC in road accidents. Identified significant predictors can be divided into the following groups:

- ***Sociodemographic*** (2): Age, Reason for disability.
- ***Medical*** (6): Functional limitation – Spine/Back, Trunk, Neck, Right upper arm, Right hand and forearm, and eyesight.
- ***Driving habits*** (8): Experience with hand controls, Average annual mileage, Driving lecture on hand control's vehicle, Driving – unfamiliar destinations, Driving – long distances, Driving – bad weather, Driving – peak hours, Driving – night conditions.
- ***Risky behaviours in traffic*** (6): Seat belt usage, Speeding, Traffic lights – yellow light, Alcohol consumption, Mobile phone usage, Fatigue.
- ***Vehicle characteristics*** (1): Vehicle age.

3.1.1. Selection of dominant predictors

The significant predictors were filtered to reduce the number of predictors that will have been used in the models. Reducing the number of predictors was essential to obtain more practical and more straightforward models. The PROMETHEE II method of multicriteria decision-making reduces the number of predictors. Based on Criterion 1, eleven predictors were

Table 2. PROMETHEE II - results.

Predictor	Criterion 1	Criterion 2	φ +	φ -	φ	Status
Age	58.3%	0.16	0.469	0.227	0.242	*Rejected*
Reason for disability	41.7%	−0.26	0.085	0.543	−0.457	*Rejected*
FL – Spine/Back	58.3%	−0.05	0.298	0.324	−0.026	*Rejected*
FL – Trunk	50.0%	−0.13	0.176	0.423	−0.247	*Rejected*
FL – Neck	91.7%	0.45	0.703	0.072	0.631	*Accepted*
FL – Right upper arm	50.0%	−0.05	0.247	0.378	−0.131	*Rejected*
FL – Right hand and forearm	58.3%	0.03	0.424	0.283	0.141	*Rejected*
FL – Eyesight	83.3%	0.45	0.661	0.080	0.582	*Accepted*
Experience with hand controls	50.0%	−0.09	0.201	0.400	−0.199	*Rejected*
Average annual mileage	50.0%	0.07	0.396	0.314	0.082	*Rejected*
Driving lecture on HCs vehicle	33.3%	−0.18	0.082	0.606	−0.524	*Rejected*
Driving – unfamiliar destinations	25.0%	−0.51	0.003	0.810	−0.807	*Rejected*
Driving – long distances	33.3%	−0.34	0.034	0.652	−0.618	*Rejected*
Driving – bad weather	58.3%	−0.09	0.252	0.346	−0.094	*Rejected*
Driving – peak hours	41.7%	−0.43	0.048	0.578	−0.530	*Rejected*
Driving – night conditions	50.0%	−0.01	0.330	0.360	−0.030	*Rejected*
Seat belt usage	33.3%	−0.42	0.019	0.663	−0.644	*Rejected*
Speeding	83.3%	0.75	0.696	0.021	0.675	*Accepted*
Traffic lights – yellow light	66.7%	0.25	0.546	0.176	0.370	*Rejected*
Alcohol consumption	100.0%	1.08	0.827	0.000	0.827	*Accepted*
Mobile phone usage	100.0%	0.75	0.782	0.010	0.772	*Accepted*
Fatigue	83.3%	0.75	0.696	0.021	0.675	*Accepted*
Vehicle age	33.3%	−0.59	0.008	0.697	−0.689	*Rejected*

recognised as significant by over 50% of experts, and only two predictors (Alcohol consumption and Mobile phone usage) were recognised by all experts. According to the measure that shows the relative importance of the predictor compare to other predictors (Criterion 2), eleven predictors had a positive value. According to this criterion, Alcohol consumption was recognised as the most important predictor. Based on two defined criteria and set requirements, the number of predictors was reduced from twenty-three to six. Based on the values of both criteria, the predictor Alcohol consumption was highlighted as the most dominant predictor. The results obtained using the PROMETHEE II method are presented in Table 2.

The PROMETHEE II method showed that two of the six dominant predictors were related to the medical status of DwD who use HC (FL – Neck and FL – Eyesight). The remaining four dominant predictors were related to risky behaviour in traffic. In addition to the predictor Alcohol consumption, the PROMETHEE II method identified Mobile phone usage, Speeding, and Fatigue as dominant predictors.

3.2. Research with DwD who use HC

The research was carried out on the territory of Serbia, and a sample of 65 DwD who use HC was collected. The research was conducted in the period from September to October 2020. Considering that the approximate number of drivers who use hand controls in Serbia is about 250 (RTSA, 2021),

Table 3. Sample profile.

	Frequencies	Percentage
Gender		
Female	8	12.3%
Male	57	87.7%
Age		
Mean	42.9	
Standard deviation	10.5	
Median	40.0	
Residence type		
Urban	33	50.8%
Suburban	12	18.5%
Small town	11	16.9%
Rural	9	13.8%
Monthly income (€)		
<500	37	56.9%
500-750	18	27.7%
750-1000	5	7.7%
>1000	5	7.7%
Education		
High school graduate or lower	44	67.7%
Bachelor's degree or higher	21	32.3%
Employment status		
Unemployed	43	66.2%
Employed	22	33.8%
Reasons for disability		
Road accident	32	49.2%
Consequence of disease	7	10.8%
Injury at work	6	9.2%
Wounding from a weapon	5	7.7%
Diving	4	6.2%
Innate	4	6.2%
Other	6	9.2%
Driving experience with hand controls		
Mean	12.4	
Standard deviation	8.8	
Median	11.0	
% novice drivers (<5 years)	14	21.5%
% experienced drivers (>20 years)	12	18.5%
Average annual mileage (km)		
Mean	13,752	
Standard deviation	7,611	
Median	14,000	
Road accidents experience		
Yes	18	27.7%
No	47	72.3%

about 25-30% of DwD who use HC from the population participated in the survey.

The elementary sociodemographic characteristics of the respondents are shown in Table 3. According to the obtained results, males more often than females use HCs. This fact indicates the gender bias of the sample. The average age of the respondents was 42.9 years. The DwD most often lived in urban areas, had low monthly incomes (below €500), had a high school diploma or lower education, and were unemployed. The most common cause of disability among DwD who use HC was road accidents. The average driving experience among DwD who use HC was 12.4 years, and a similar number of novice and experienced drivers were interviewed. The

Table 4. Functional limitations of parts of the body.

Parts of the body	Functional limitation	Full function
Spine/Back	76.9%	23.1%
Trunk	15.4%	84.6%
Abdominal muscles	66.2%	33.8%
Neck	6.2%	93.8%
Left upper arm	4.6%	95.4%
Right upper arm	3.1%	96.9%
Left hand and forearm	10.8%	89.2%
Right hand and forearm	9.2%	90.8%
Left thigh	96.9%	3.1%
Right thigh	98.5%	1.5%
Left foot and lower leg	98.5%	1.5%
Right foot and lower leg	98.5%	1.5%
Sense of hearing	4.6%	95.4%
Eyesight	13.8%	86.2%

average annual mileage was about 13,752 kilometres. Regarding participation in road accidents, 27.7% of DwD who use HC stated that they had been involved in a road accident.

Table 4 presents the functionality of the most critical parts of the body in terms of driving. As observed, the highest degree of functional limitation was present in respondents' lower extremities (left/right thigh, lower leg, and foot). Also, a significant number of respondents had certain functional limitations of the spine/back and abdominal muscles.

The procedure of selection of dominant predictors identified four risky behaviours in traffic. The answers to these questions are shown in Figure 2. A significant number of DwD who use HC had exceeded the speed limit, had used a mobile phone, and had driven the vehicle despite fatigue. On the other hand, most drivers had never driven a vehicle after alcohol consumption.

3.3. Bayesian logistic regression models

3.3.1. Prior distributions

Prior distributions were defined in three ways. The first approach used the non-informative prior distributions, which are based on the assumption that there is no knowledge about the impact of dominant predictors on the dependent variable (Model_NIP). This approach is common when creating Bayesian regression models in road safety studies (Afghari, Haque, Washington, & Smyth, 2019; Farid, Abdel-Aty, Lee, & Eluru, 2017). The second approach proposed by Yu and Abdel-Aty (2013) assumes that for prior distributions of each coefficient next to the predictor, is chosen normal distribution with mean and variance equal to the maximum likelihood estimator obtained in the logistic regression model with just that predictor (Model_MLE). Prior distributions in the last model (Model_EP) were created based on expert knowledge. The parameters of the prior normal distributions used in the models are shown in Table 5.

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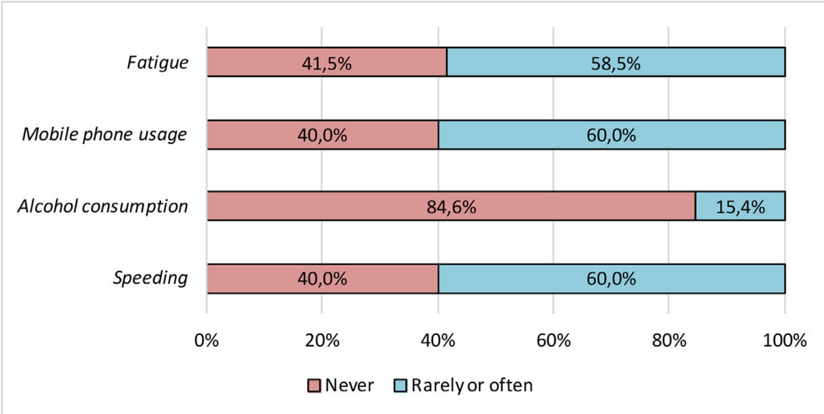

Figure 2. Dominant predictors - respondents' answers.

Table 5. Prior distributions.

	Model_NIP		Model_MLE		Model_EP	
Predictors	Mean	Variance	Mean	Variance	Mean	Variance
FL – Neck			−0.147	1.415	0.564	0.201
FL – Eyesight			0.312	0.591	0.693	0.241
Speeding	0	10000	0.268	0.356	0.374	0.035
Alcohol consumption			1.034	1.085	0.665	0.111
Mobile phone usage			0.611	0.313	0.556	0.104
Fatigue			1.308	0.349	0.518	0.117

3.3.2. Creating models

Based on the defined prior distributions, three Bayesian logistic regression models were created. The acceptance rates were between 0.434 and 0.446, following the recommendations of Gelman et al. (2004). A visual check ensured fair values of all observed parameters. Diagrams of autocorrelation, trace, histogram, and density for dominant predictors are given in Appendix 1. Finally, based on the model's quality parameter (DIC), the best model was created based on expert knowledge (Table 6).

All risky behaviours in traffic showed a statistically significant impact in a model based on expert prior distributions (Model_EP). The regression coefficients were positive, which indicates a positive correlation between these predictors and the participation in road accidents of DwD who use HC. For example, the driver who consumed alcohol more frequently was involved in road accidents more often than a driver who consumed alcohol less frequently. In the remaining two models (Model_NIP and Model_MLE), the only predictor of risky behaviour that showed a significant impact was Fatigue. As with Model_EP, the value of the regression coefficient of this predictor was positive. On the other hand, medical predictors (FL – Neck, and FL – Eyesight) did not show a statistically

Table 6. Bayesian logistic regression models.

	Model_NIP			Model_MLE			Model_EP		
Predictors	B	90% BCI		B	90% BCI		B	90% BCI	
FL – Neck	−0.977	−3.383	1.550	−0.673	−2.247	0.875	0.431	−0.258	1.122
FL – Eyesight	0.209	−1.311	1.756	0.230	−0.773	1.245	0.601	−0.056	1.295
Speeding	−0.120	−1.270	1.114	−0.059	−0.904	0.775	**0.349**	**0.069**	**0.651**
Alcohol consumption	0.143	−2.075	2.319	0.154	−1.183	1.570	**0.641**	**0.125**	**1.161**
Mobile phone usage	0.264	−0.893	1.360	0.265	−0.471	1.037	**0.519**	**0.058**	**0.990**
Fatigue	**1.332**	**0.063**	**2.606**	**1.245**	**0.452**	**2.044**	**0.599**	**0.124**	**1.112**
Intercept	−1.595	−2.454	−0.746	−1.567	−2.311	−0.873	−1.711	−2.271	−1.115
DIC	86.4			80.0			77.2		

significant impact in the models. Based on the obtained results, risky behaviours in traffic (especially Fatigue) have a significant influence on the participation of DwD who use HC in road accidents.

4. Discussion

The expert research identified twenty-three significant predictors that potentially impact the participation of DwD who use HC in road accidents. Two medical and four risky behaviour predictors were identified as dominant based on PROMETHEE II analysis. In terms of medicine, the experts especially pointed out the functional limitations of the neck and eyesight. In general, the more fragile the health status of drivers, the more likely it is to influence road safety (Anstey, Wood, Lord, & Walker, 2005), especially the problems with the neck (Marottoli et al., 1998) and eyesight (Ball, Owsley, Sloane, Roenker, & Bruni, 1993). With regards to that, Greve, Santos, Alonso, and Tate (2015) considered driving evaluation methods for DwD and recommended using driving simulators (assessing functional limitations) and functional tests (evaluating motor performance). In addition, speeding, alcohol consumption, mobile phone usage, and fatigue have been identified as risk factors for participating in road accidents (Bucsuházy et al., 2020; Naevestad, Phillips, & Elvebakk, 2015; Petridou & Moustaki, 2000). Wiacek, Roth, Rush, Toth, and Williams (2019) analysed 31 road accidents that involved vehicles equipped with HC. They found that alcohol consumption and distraction contributed to over 15% of these accidents. Sociodemographic, driving habits, and vehicle characteristics predictors were not recognised as dominant. This finding indicates that in order to ensure a safe traffic environment for DwD who use HC, it is imperative for the vehicle to be adapted to the physical needs of the driver. Even if DwD who use HC have certain physical limitations, this problem can be significantly reduced by adapting the vehicle. For example, the functional limitations of the neck (in terms of rotation) can be effectively overcome by installing additional mirrors (Bouman & Pellerito, 2006).

Three models of Bayesian logistic regression were created to identify the most significant predictors that affect the participation of DwD who use HC in road accidents. The models have different prior distributions (non-informative prior, maximum likelihood estimation, and expert prior). By comparing the DIC values, the best model was created based on the prior distributions obtained by the experts' knowledge. Thus, it confirmed the usefulness of including experts' knowledge in analysing specific phenomena in road safety (small sample size and a small number of the previous studies). This conclusion is in concordance with some previous findings (Schlüter et al., 1997; Washington & Oh, 2006; Yu & Abdel-Aty, 2013).

Proposed models did not show a statistically significant impact at two medical predictors. A possible reason for this finding is that DwD who use HC, with certain functional limitations of the neck or eyesight, had adapted the driving conditions to their specific needs. Potentially, this group of drivers participates in traffic more cautiously. This behaviour is also known as risk compensation. Namely, the more inferior the health status of drivers, the more likely they are to compensate for those limitations with a more careful driving style. Risk compensation has also been noted in previous road safety studies (Bergel-Hayat, Debbarh, Antoniou, & Yannis, 2013; Phillips, Fyhri, & Sagberg, 2011). Although functional limitations of the neck and eyesight have a very significant impact according to expert assessments, in practice, they do not have a significant impact on participation in road accidents.

Predictor Fatigue showed a statistically significant impact in all models. Namely, DwD who use HC who sometimes or frequently drive despite fatigue, were significantly more likely to participate in road accidents. However, by comparing the experts' prior distribution for the predictor Fatigue and the results obtained in the model, it can be noted that the experts underestimated the importance of this predictor. In many previous studies, fatigue was a significant predictor of road accidents (Das, Dutta, & Rahman, 2021; Davidović, Pešić, & Antić, 2018; Kim & Oh, 2021; Kwon, Kim, Kim, & Cho, 2019; Liu & Wu, 2009). According to the ESRA (E-Survey of Road users' Attitudes) questionnaire for Serbia (Vias institute, 2021), non-disabled drivers were less tired – 13.9%, compared to DwD who use HC – 58.5% (Figure 2). Considering this fact, this predictor was more pronounced in DwD who use HC. The present finding may be due to the following assumptions. The first assumption is insufficient awareness of DwD who use HC about starting to drive despite fatigue and the relationship between fatigue and participation in road accidents. This fact is recognised as a problem in the general population (Nordbakke & Sagberg, 2007; Smith, Carrington, & Trinder, 2005). Also, more demanding driving with HC (Benoit et al., 2009) can cause drivers to get tired faster. In addition, Bascom and Christensen (2017) reported vehicle access problems among PwD. Namely, DwD who use HC wasted more energy when arriving at the vehicle and while entering the vehicle. This situation potentially affects the higher level of fatigue in DwD who use HC.

The remaining three predictors of risk behaviours showed significant impact only in the model created based on expert knowledge. According to the model, DwD who use HC who are more likely to exceed speeding limits, consume alcohol, and use a mobile phone, are more likely to be involved in road accidents. Although these predictors had proven to be significant, it can be noted that experts had somewhat overestimated the impact of these predictors in this population. Compared to the non-disabled drivers, DwD who use HC have similar behaviours related to these predictors (Vias institute, 2021). In this research, the self-reported speeding of non-disabled people is 44.5-64.5% depending on the road type compared to 60.0% of DwD who use HC. Small differences were observed in the percentage of drivers who had driven after alcohol consumption: non-disabled drivers – 19.4%, and DwD who use HC – 15.4%. Also, the frequency of mobile phone usage was similar, 54.9% among non-disabled drivers and 60.0% among DwD who use HC. These predictors showed a very significant impact on the participation in road accidents and road safety in previous research among non-disabled drivers: speeding (Abdel-Aty & Radwan, 2000; Adanu, Agyemang, Islam, & Jones, 2021; Clarke, Ward, Bartle, & Truman, 2010; Shaaban, Gharraie, Sacchi, & Kim, 2021), alcohol consumption (Clarke et al., 2010; Das et al., 2021; Híjar, Carrillo, Flores, Anaya, & Lopez, 2000; Padilla, Doncel, Gugliotta, & Castro, 2018; Shaaban et al., 2021), and mobile phone usage (Gariazzo, Stafoggia, Bruzzone, Pelliccioni, & Forastiere, 2018; Lipovac, Đerić, Tešić, Andrić, & Marić, 2017; Nasr Esfahani, Arvin, Song, & Sze, 2021). However, these predictors are not so emphasised among DwD who use HC. There are several reasons for this conclusion. First, when DwD who use HC exceed the speed limit, it can be assumed that speeding is not significantly high. Cooper (1997) pointed out that the increased risk of participating in road accidents increased when there was "excessive" speeding compared to the exceeding speed limit. Additionally, the alcohol consumption among DwD who use HC may not be not large enough to significantly increase the risk of participating in road accidents. However, what was common among this group of drivers, was that mobile phones had been used with more caution or with a hands-free device, which had been proven to be safer (Törnros & Bolling, 2005).

5. Conclusion

The application of expert knowledge in creating a model that describes the participation of DwD who use HC in road accidents proved to be helpful.

This approach enables the elimination of numerous shortcomings that may be encountered in the analysis of road safety of specific categories of traffic participants. In addition, this approach solves the problems of a small sample and a lack of prior knowledge about a specific topic.

In this research, a unique procedure was used for identifying the contributing predictors using expert knowledge, the multicriteria decision-making method (PROMETHEE II method), and the Bayesian approach. A multidisciplinary team of experts identified twenty-three predictors that impact the participation of DwD who use HC in road accidents. The six most prominent predictors were recognised according to expert estimates: FL – neck, FL – eyesight, Speeding, Alcohol consumption, Mobile phone usage, and Fatigue. Research among the population of DwD who use HC and the creation of three models of Bayesian logistic regression showed that the most influential predictors are related to risky behaviour in traffic. Speeding, alcohol consumption, mobile phone usage, and especially fatigue were identified as risky behaviours.

The primary focus should be on eliminating risky behaviour in traffic. Raising awareness among DwD who use HC about risky behaviours in traffic is the most critical task in achieving this goal. This task can be accomplished by educating DwD who use HC about risky behaviours during driver training and active driving experience. A special topic that should be emphasised is the impact of fatigue on road safety. Considering the severity of fatigue, measures that will prevent the onset of, and facilitate the driving process itself should be created. The proposed measures would significantly improve road safety of DwD who use HC. These measures would encourage PwD who are able to drive a vehicle with HC to start participating in traffic as drivers. Consequently, the measures would positively impact mobility and improve the quality of life of PwD (better social life, greater economic activity, better access to health services, more accessible education, etc.). Outstanding results can be expected in countries and regions with lower levels of PwD inclusion.

During the research, certain limitations were noticed. The first limitation was the assumption that all experts were equally weighted. However, this shortcoming was somewhat overcome because experts had given their assessments primarily in the areas for which they are specialists. Another limitation was the non-recognition of PwD as categories of traffic participants in statistical reports. Therefore, the data about the number of DwD who use HC, road accidents in which they had been involved in, etc., were not available. This problem was solved by researching within the population of DwD who use HC. On the other hand, this type of research brings a risk of socially acceptable answers by the respondents. Gender bias of the sample was another limitation. The higher share of males in the sample could indicate a problem of female inclusion in society and the gender inequality problem.

This research provides a good basis for future research on the road safety of PwD. In the future, the research focus should be placed on other predictors that have not been analysed in detail by this research. As one of the useful tools for this purpose, Ledesma et al. (2021) recommend exploratory factor analysis. Although risky behaviours predictors showed impacts among both DwD and non-disabled drivers, future research should explore differences in predictor's effect size between these groups to understand better and prevent road accidents among DwD. Special emphasis should be placed on the relationship between traffic fines and the participation of DwD who use HC in road accidents. Moreover, an in-depth study of road accidents in which DwD who use HC participated should be performed. It is essential to point out that this research analysed only DwD who use HC who represent one group of PwD. In the future, the emphasis should be on road safety for PwD who are non-drivers and who predominantly use other modes of transport (public transport). Special attention should be paid to procedures for safe participation in traffic for different health conditions (e.g., cerebrovascular accident or stroke). Gender inequality among PwD and the specific problems faced by females need to be further explored.

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References

Abdel-Aty, M. A., & Radwan, A. E. (2000). Modeling traffic accident occurrence and involvement. *Accident; Analysis and Prevention*, *32*(5), 633–642. doi:10.1016/s0001-4575(99)00094-9

Adanu, E. K., Agyemang, W., Islam, R., & Jones, S. (2021). A comprehensive analysis of factors that influence interstate highway crash severity in Alabama. *Journal of Transportation Safety & Security*, *0*(0), 1–25. doi:10.1080/19439962.2021.1949414

Afghari, A. P., Haque, M. M., Washington, S., & Smyth, T. (2019). Effects of globally obtained informative priors on bayesian safety performance functions developed for Australian crash data. *Accident; Analysis and Prevention*, *129*(January), 55–65. doi:10.1016/j.aap.2019.04.023

Q2 ANED. (2018). *European Semester 2018/2019 shadow fiche on disability Republic of Serbia*.

Anstey, K. J., Wood, J., Lord, S., & Walker, J. G. (2005). Cognitive, sensory and physical factors enabling driving safety in older adults. *Clinical Psychology Review*, *25*(1), 45–65. doi:10.1016/j.cpr.2004.07.008

Ball, K., Owsley, C., Sloane, M. E., Roenker, D. L., & Bruni, J. R. (1993). Visual attention problems as a predictor of vehicle crashes in older drivers. *Investigative Ophthalmology & Visual Science*, *34*(11), 3110–3123.

Bascom, G. W., & Christensen, K. M. (2017). The impacts of limited transportation access on persons with disabilities' social participation. *Journal of Transport & Health*, *7*(January), 227–234. doi:10.1016/j.jth.2017.10.002

Benoit, D., Gelinas, I., Mazer, B., Porter, M. M., & Duquette, J. (2009). Drivers' perceived workload when driving using adaptive equipment: A pilot study. *Physical & Occupational Therapy in Geriatrics*, *27*(4), 277–297. doi:10.1080/02703180902768650

Bergel-Hayat, R., Debbarh, M., Antoniou, C., & Yannis, G. (2013). Explaining the road accident risk: Weather effects. *Accident; Analysis and Prevention*, *60*, 456–465. doi:10.1016/j.aap.2013.03.006

Bouman, J., & Pellerito, J. M. (2006). Preparing for the on-road evaluation. In J. M. Pellerito (Ed.), *Driver rehabilitation and community mobility* (pp. 239–253). Elsevier Mosby.

Q3 Brans, J.-P., & De Smet, Y. (2016). PROMETHEE methods. In S. Greco, M. Ehrgott, & J. R. Figueira (Eds.), *Multiple criteria decision analysis: State of the art surveys* (pp. 187–219). Springer. doi:10.1007/978-1-4939-3094-4_6

Brumbaugh, S. (2018). *Travel patterns of American adults with disabilities*. U.S. Department of Transportation. (Issue September).

Bucsuházy, K., Matuchová, E., Zůvala, R., Moravcová, P., Kostíková, M., & Mikulec, R. (2020). Human factors contributing to the road traffic accident occurrence. *Transportation Research Procedia*, *45*(2019), 555–561. doi:10.1016/j.trpro.2020.03.057

Chu, W., Wu, C., Atombo, C., Zhang, H., & Özkan, T. (2019). Traffic climate, driver behaviour, and accidents involvement in China. *Accident; Analysis and Prevention*, *122*(1178), 119–126. doi:10.1016/j.aap.2018.09.007

Clarke, D. D., Ward, P., Bartle, C., & Truman, W. (2010). Killer crashes: Fatal road traffic accidents in the UK. *Accident; Analysis and Prevention*, *42*(2), 764–770. doi:10.1016/j.aap.2009.11.008

Cochran, A. L. (2020). Impacts of COVID-19 on access to transportation for people with disabilities. *Transportation Research Interdisciplinary Perspectives*, *8*, 100263. doi:10.1016/j.trip.2020.100263

Cooper, P. J. (1997). The relationship between speeding behaviour (as measured by violation convictions) and crash involvement. *Journal of Safety Research*, *28*(2), 83–95. doi:10.1016/S0022-4375(96)00040-0

Dahuri, M. K. A. M., Hussain, M. N., Yusof, N. F. M., & Jalil, M. K. A. (2017). Factors, effects, and preferences on vehicle driving modification for the malaysia independent disabled. *Journal of the Society of Automotive Engineers Malaysia Volume 1*, *1*(2), 103–110.

Das, S., Dutta, A., & Rahman, M. A. (2021). Pattern recognition from light delivery vehicle crash characteristics. *Journal of Transportation Safety & Security*, *0*(0), 1–19. doi:10.1080/19439962.2021.1995800

Davidović, J., Pešić, D., & Antić, B. (2018). Professional drivers' fatigue as a problem of the modern era. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 199–209. doi:10.1016/j.trf.2018.03.010

Di Stefano, M., Stuckey, R., Macdonald, W., & Lavender, K. (2015). Vehicle modifications for drivers with disabilities: developing the evidence base to support prescription guidelines, improve user safety and enhance participation.

European Commission. (2010). European disability strategy 2010-2020: A renewed commitment to a barrier - Free Europe.

European Commission. (2021a). Disability statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Disability_statistics

European Commission. (2021b). Union of equality: strategy for the rights of persons with disabilities 2021-2030. In *European Union*. doi:10.2767/31633

Farid, A., Abdel-Aty, M., Lee, J., & Eluru, N. (2017). Application of Bayesian informative priors to enhance the transferability of safety performance functions. *Journal of Safety Research*, *62*, 155–161. doi:10.1016/j.jsr.2017.06.005

Gariazzo, C., Stafoggia, M., Bruzzone, S., Pelliccioni, A., & Forastiere, F. (2018). Association between mobile phone traffic volume and road crash fatalities: A population-based case-crossover study. *Accident; Analysis and Prevention*, *115*(January), 25–33. doi:10.1016/j.aap.2018.03.008

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2004). *Bayesian data analysis* (C. Chatfield, M. Tanner, & J. Zidek (Eds.)). Chapman & Hall/CRC.

Greve, J. M. D., Santos, L., Alonso, A. C., & Tate, D. G. (2015). Driving evaluation methods for able-bodied persons and individuals with lower extremity disabilities: A review of assessment modalities. *Clinics (Sao Paulo, Brazil)*, *70*(9), 638–647. doi:10.6061/clinics/2015(09)08

Grujičić, D., Ivanović, I., Jović, J., & Đorić, V. (2014). Customer perception of service quality in public transport. *Transport*, *29*(3), 285–295. doi:10.3846/16484142.2014.951685

Henly, M., & Brucker, D. L. (2019). Transportation patterns demonstrate inequalities in community participation for working-age Americans with disabilities. *Transportation Research Part A: Policy and Practice*, *130*(September), 93–106. doi:10.1016/j.tra.2019.09.042

Henriksson, P., & Peters, B. (2004). Safety and mobility of people with disabilities driving adapted cars. *Scandinavian Journal of Occupational Therapy*, *11*(2), 54–61. doi:10.1080/11038120410020511

Híjar, M., Carrillo, C., Flores, M., Anaya, R., & Lopez, V. (2000). Risk factors in highway traffic accidents: a case control study. *Accident Analysis & Prevention*, *32*(5), 703–709. doi:10.1016/S0001-4575(99)00116-5

Hu, J., Orton, N., Manary, M. A., Boyle, K., & Schneider, L. W. (2020). Should airbags be deactivated for wheelchair-seated drivers? *Traffic Injury Prevention*, *21*(sup1), S37–S6. doi:10.1080/15389588.2020.1778676

Hutchinson, C., Berndt, A., Cleland, J., Gilbert-Hunt, S., George, S., & Ratcliffe, J. (2020). Using social return on investment analysis to calculate the social impact of modified vehicles for people with disability. *Australian Occupational Therapy Journal*, *67*(3), 250–210. doi:10.1111/1440-1630.12648

Jansuwan, S., Christensen, K. M., & Chen, A. (2013). Assessing the transportation needs of low-mobility individuals: case study of a small urban community in Utah. *Journal of*

Urban Planning and Development, *139*(2), 104–114. doi:10.1061/(ASCE)UP.1943-5444.0000142

Kim, S., & Oh, C. (2021). Freeway crashes involving drowsy driving: Crash characteristics and severity in South Korea. *Journal of Transportation Safety & Security*, *13*(1), 93–107. doi:10.1080/19439962.2019.1605641

Knol, A. B., Slottje, P., Van Der Sluijs, J. P., & Lebret, E. (2010). The use of expert elicitation in environmental health impact assessment: A seven step procedure. *Environmental Health: A Global Access Science Source*, *9*(1), 19–16. doi:10.1186/1476-069X-9-19

Kwon, S., Kim, H., Kim, G. S., & Cho, E. (2019). Fatigue and poor sleep are associated with driving risk among Korean occupational drivers. *Journal of Transport & Health*, *14*(May), 100572. doi:10.1016/j.jth.2019.100572

Ledesma, R. D., Ferrando, P. J., Trógolo, M. A., Poó, F. M., Tosi, J. D., & Castro, C. (2021). Exploratory factor analysis in transportation research: Current practices and recommendations. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 340–352. doi:10.1016/j.trf.2021.02.021

Lipovac, K., Đerić, M., Tešić, M., Andrić, Z., & Marić, B. (2017). Mobile phone use while driving-literary review. *Transportation Research Part F: Traffic Psychology and Behaviour*, *47*, 132–142. doi:10.1016/j.trf.2017.04.015

Liu, Y. C., & Wu, T. J. (2009). Fatigued driver's driving behavior and cognitive task performance: Effects of road environments and road environment changes. *Safety Science*, *47*(8), 1083–1089. doi:10.1016/j.ssci.2008.11.009

Lourens, P. F., Vissers, J. A. M. M., & Jessurun, M. (1999). Annual mileage, driving violations, and accident involvement in relation to drivers' sex, age, and level of education. *Accident; Analysis and Prevention*, *31*(5), 593–597. doi:10.1016/s0001-4575(99)00015-9

Marottoli, R. A., Richardson, E. D., Stowe, M. H., Miller, E. G., Brass, L. M., Cooney, L. M., Jr,., & Tinetti, M. E. (1998). Development of a test battery to identify older drivers at risk for self-reported adverse driving events. *Journal of the American Geriatrics Society*, *46*(5), 562–568.

Naevestad, T. O., Phillips, R. O., & Elvebakk, B. (2015). Traffic accidents triggered by drivers at work - A survey and analysis of contributing factors. *Transportation Research Part F: Traffic Psychology and Behaviour*, *34*(0349), 94–107. doi:10.1016/j.trf.2015.07.024

Nasr Esfahani, H., Arvin, R., Song, Z., & Sze, N. N. (2021). Prevalence of cell phone use while driving and its impact on driving performance, focusing on near-crash risk: A survey study in Tehran. *Journal of Transportation Safety & Security*, *13*(9), 957–977. doi:10.1080/19439962.2019.1701166

Nordbakke, S., & Sagberg, F. (2007). Sleepy at the wheel: Knowledge, symptoms and behaviour among car drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *10*(1), 1–10. doi:10.1016/j.trf.2006.03.003

Norweg, A., Jette, A. M., Houlihan, B., Ni, P., & Boninger, M. L. (2011). Patterns, predictors, and associated benefits of driving a modified vehicle after spinal cord injury: Findings from the national spinal cord injury model systems. *Archives of Physical Medicine and Rehabilitation*, *92*(3), 477–483. doi:10.1016/j.apmr.2010.07.234

Padilla, J.-L., Doncel, P., Gugliotta, A., & Castro, C. (2018). Which drivers are at risk? Factors that determine the profile of the reoffender driver. *Accident; Analysis and Prevention*, *119*, 237–247. doi:10.1016/j.aap.2018.07.021

Petridou, E., & Moustaki, M. (2000). Human factors in the causation of road traffic crashes. *European Journal of Epidemiology*, *16*(9), 819–826. doi:10.1023/A:1007649804201

Petrović, Đ., Pešić, D., & Mijailović, R. M. (2020). Modes to improve the road safety of people with disabilities as drivers (On serbian: Начини унапређења безбедности особа са инвалидитетом у саобраћају у својству возача). IX International Conference “Road Safety in Local Communities, 81–90.

Phillips, R. O., Fyhri, A., & Sagberg, F. (2011). Risk compensation and bicycle helmets. *Risk Analysis: An Official Publication of the Society for Risk Analysis*, *31*(8), 1187–1195. doi: 10.1111/j.1539-6924.2011.01589.x

Pilkey, W., Thacker, J., Shaw, G. (2001). *Hand control usage and safety assessment*. http://www.nhtsa.dot.gov/people/injury/olddrive/modeldriver/volume_ii.htm#Table of Contents

Pyer, M., & Tucker, F. (2017). With us, we, like, physically can’t’: Transport, mobility and the leisure experiences of teenage wheelchair users. *Mobilities*, *12*(1), 36–52. doi:10.1080/17450101.2014.970390

Royall, R. M. (1986). The effect of sample size on the meaning of significance tests. *The American Statistician*, *40*(4), 313–315. doi:10.1080/00031305.1986.10475424

RTSA. (2021). *Data on vehicles with implemented hand controls for the drivers with disabilities*.

Sagberg, F., Amundsen, A. H., & Glad, A. (2003). *Trafikksikkerhet for spesialtilpassede biler for førere med fysisk funksjonshemning Forord*.

Santos, S., Brech, G. C., Alonso, A. C., & Greve, J. M. D. (2021). Brake response time between male drivers with and without paraplegia: Association between sociodemographic, motor and neurological characteristics. *Traffic Injury Prevention*, *22*(3), 207–211.

Schlüter, P. J., Deely, J. J., & Nicholson, A. J. (1997). Ranking and selecting motor vehicle accident sites by using a hierarchical Bayesian model. *Journal of the Royal Statistical Society: Series D (the Statistician)*, *46*(3), 293–316. doi:10.1111/1467-9884.00084

Schneider, L. W., Manary, M. A., Orton, N. R., Hu, J., Klinich, K. D., Flannagan, C. A., Moore, J. L. (2016). *Wheelchair Occupant Studies*. https://deepblue.lib.umich.edu/handle/2027.42/122860

Shaaban, K., Gharraie, I., Sacchi, E., & Kim, I. (2021). Severity analysis of red-light-running-related crashes using structural equation modeling. *Journal of Transportation Safety & Security*, *13*(3), 278–297. doi:10.1080/19439962.2019.1629137

Smith, S., Carrington, M., & Trinder, J. (2005). Subjective and predicted sleepiness while driving in young adults. *Accident; Analysis and Prevention*, *37*(6), 1066–1073. doi:10.1016/j.aap.2005.06.008

Törnros, J. E. B., & Bolling, A. K. (2005). Mobile phone use-effects of handheld and hands-free phones on driving performance. *Accident; Analysis and Prevention*, *37*(5), 902–909. doi:10.1016/j.aap.2005.04.007

United Nations. (2019). Disability and development report. In *United Nations*. doi:10.4337/9781847202864.00035

Vias institute. (2021). *Serbia – ESRA2 country fact sheet. ESRA2 survey (E-Survey of Road users’ Attitudes)*.

Wagenmakers, E. J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review*, *25*(1), 35–57. doi:10.3758/s13423-017-1343-3

Washington, S., & Oh, J. (2006). Bayesian methodology incorporating expert judgment for ranking countermeasure effectiveness under uncertainty: Example applied to at grade railroad crossings in Korea. *Accident; Analysis and Prevention*, *38*(2), 234–247. doi:10.1016/j.aap.2005.08.005

Wiacek, C. J., Roth, J., Rush, C., Toth, A., & Williams, V. (2019). *Analysis of real-world crashes where involved vehicles were equipped with adaptive equipment (Report No. DOT HS 812 752)*.

World Health Organization. (2021). *Disability and Health - Key facts*. https://www.who.int/news-room/fact-sheets/detail/disability-and-health

Yu, R., & Abdel-Aty, M. (2013). Investigating different approaches to develop informative priors in hierarchical Bayesian safety performance functions. *Accident; Analysis and Prevention*, *56*, 51–58. doi:10.1016/j.aap.2013.03.023