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# Factors Impacting the Choice of Seatbelt Use, Accounting for Complexity of Travelers' Behaviors

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**Abstract:** Wyoming has one of the highest fatality rates, and a significantly lower rate of seatbelt use in the United States. Thus, this study was conducted with the objective to investigate contributory factors to the choice of drivers' seatbelt use. Various environmental factors and drivers' characteristics were considered as it is expected that they account for unseen factors that impact drivers' choice of buckling up. Although the mixed model has been used extensively for studying the impacts of seatbelt use on the severity of crashes, not many studies have been conducted regarding factors contributing to the choice of seatbelt use itself. In this study, the standard logit model is extended to the mixed model to account for heterogeneity across drivers' observations. In addition, the standard mixed model was extended to incorporate the random parameters' heterogeneity in taste based on the means of other observed variables. The results highlighted that moving from the standard logit model to the mixed model, considering heterogeneity in tastes, results in a gain in the model fit, and also an adjustment for the model's parameters' estimates. The findings indicated that some of factors impacting the choice of wearing seatbelt include gender, road classification, weather condition, vehicle types, time of driving, vehicle registration and day of the week. Those factors are mainly related to unobserved factors impacting the drivers' behaviors. For instance, drivers with particular characteristics are expected to own particular vehicle types or drive their vehicles under a particular weather condition.

**Keywords:** seatbelt usage; mixed model; choice modeling; heterogeneity in taste; traffic safety

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## 1. Introduction

Annually, about 50% of vehicle occupants who are killed in vehicle crashes in the U.S. are unrestrained drivers and passengers [1]. This is despite the importance of buckling up, as seatbelt usage could reduce front seat fatalities by as much as 60% [2]. If all front-seat occupants in the US used their seatbelt, this is expected to have a 41% reduction in fatalities [3]. Although seatbelt use in the U.S. has reached about 89% [4], the number of buckled drivers in Wyoming is only about 79%. Over the years, an increase in the number of vehicle miles traveled per year has underlined the importance of identifying factors that impact seatbelt use.

Buckling up is mainly a result of factors such as attitudes and behaviors of drivers, which might result from various individual-specific demographic and background characteristics. Some drivers view buckling up as an inconvenience, whereas others might view that as a discomfort with no reward. Given the importance of buckling up, extensive efforts have been already made to identify factors in seatbelt choice, and how those factors increase the propensity of seatbelt usage. For instance, self-reported seatbelt use among front-seat passengers was evaluated in past studies [5]. It was found that attitudes and the subjective norm have a positive relation with the intention of seatbelt use for both urban and rural roads.

Various factors have been linked to the choice of not buckling up in the literature reviewed. For instance, the psychological consideration of seatbelt use was evaluated in terms of experience and cognition [6]. It was found that the decision of not buckling up might be related to the belief that it is irrational to bear the slight cost of buckling up for the reward of partial protection. Additionally, when drivers experience repeated safe trips, they might believe that crashes occasionally happen to others, which might contribute to the lack of seatbelt usage. For instance, the psychological aspect of driving indicates that each safe trip reinforces the non-use of seatbelts [6].

A past study was conducted to investigate seatbelt wearing compliance across road users in Malaysia. Gender, time of the day and type of vehicles were some of the factors impacting seatbelt use [7]. It should be noted that the study was cross-sectional, and just a descriptive summary of recorded observations was presented. The impact of demographic factors on seatbelt use by injured adults in crashes was reported [8]. The data used in that study were from injured adults who were admitted to a trauma center. Standard logistic regression was used for the purpose of the analysis. The results indicated that those drivers making more yearly income, female and white drivers are more likely to have their seatbelts on while involved in crashes.

Occupation, education, driver age, gender, type and make of vehicles, road surface condition and type of roadway were some of the factors which were found to impact the likelihood of seatbelt use in another study [9]. The collected data included a total of 1427 motor vehicles, and a descriptive summary of the data was presented in the study. In another study, occupant seatbelt use in Ghanaian University campus was recorded [10]. The data were collected by an unobstructive survey by collecting the information from 5589 vehicles. It was found that vehicle type and gender were two factors that impact the usage of seatbelts. In that study, the chi-squared test was used to establish the relationship between seatbelt use and vehicle type. The results of a study conducted in Tennessee implied that seatbelt users can be heavily impacted by type, sex and belted driver status [11].

A comprehensive evaluation of the front seat passenger seatbelt use was evaluated in another study [12]. Various techniques such as the mixed model, accounting for scale and taste heterogeneity, were considered and compared. It was found that time of travel, vehicle type, and drivers' gender are some of factors impacting the choice of passengers' seatbelt use. Additionally, other studies used seatbelt datasets as a case study to evaluate the applicability of various advanced statistical techniques in modeling individual-specific observations [13–15].

Given the sparse literature on the choice of seatbelt use, and the continuing rise in the number of vehicles, there is a need for safety engineers and decision makers to understand factors impacting the choice of seatbelt use so that appropriate countermeasures could be taken to tackle them. Despite the importance of buckling up, the majority of past studies mainly used traditional methods, which cannot account for the data heterogeneity, and consequently might result in biased or even erroneous point estimates.

Although the mixed model gives a higher flexibility to the estimation of model parameters, compared with the standard logit model, the mixed model might still be considered as a poor option for some drivers based on their gender: for example, they care less or more about seatbelt use. Here, to capture the possible heterogeneity based on the observed variables, the mixed model is extended to allow the means of the random coefficients to depend on other observed characteristics of drivers.

The focus of this study is only on seatbelt use in the state of Wyoming, located in the western and mountainous area in the U.S. To answer the question of factors impacting the choice of seatbelt use, the data regarding various sociodemographic characteristics of drivers and environmental and vehicle characteristics were used for the analysis. It should be reiterated that various vehicles and environmental characteristics were incorporated into the analysis as they could account for unseen factors that were not recorded at the time of the crashes. For instance, vehicle type might provide information regarding the incomes or personalities of drivers.

## 2. Data

The dataset used in this study was collected in 2019 in Wyoming. The observers, who collected the data, were trained before data collection to be conformed to the criteria highlighted for the state observational seatbelt issued in 2011 by the National Highway Traffic Safety Administration [16]. The trained observers were placed in 289 sites within 17 counties in Wyoming, where they collected data related to a total of 18,286 vehicles.

The dependent variable in this study corresponds to the status of drivers' seatbelt use at the time of data collection. The seatbelt usage in the state varies from a low of 63.5% belted in Sweetwater County to a high of 97.8% belted in Niobrara County. The dataset contains information regarding the drivers' characteristics such as gender and various weather and roadway characteristics that are collected by the observers.

A set of dummy variables indicating various drivers, vehicles and weather characteristics were created and used. While creating dummy variables, we made sure that the $n$-1 rule for the number of dummy variables is fulfilled. The data were collected by the observers within the span of two hours from 7:30 a.m. to 5:30 p.m. (e.g., 7:30–9:30 a.m. to 3:30–5:30 p.m.). Various dummy variables of vehicle types include auto, sport utility vehicle (SUV), van and pickup truck.

Weather condition was recorded at the time of data collection by the observers. Those include weather conditions such as rain, snow, heavy rain or occasional rain. For instance, as can be seen from Table 1, the majority of the data were collected in rural areas (mean = 1.7), and a significant proportion of the vehicles were pickup trucks (mean = 0.41).

**Table 1.** Descriptive summary of important variables and response.

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| Response | | | | |
| Seatbelt condition, not belted (vs. belted *) | 0.212 | 0.409 | 0 | 1 |
| Predictors | | | | |
| Van (vs. others *) | 0.29 | 0.455 | 0 | 1 |
| SUV (vs. others *) | 0.055 | 0.229 | 0 | 1 |
| Time of data collection as 3:30–5:30 0 (vs. others *) | 0.257 | 0.437 | 0 | 1 |
| Lanes, 2 lanes (vs. single lane *) | 1.442 | 0.496 | 1 | 2 |
| Random parameter | | | | |
| Gender, female (vs. male *) | 1.318 | 0.465 | 1 | 2 |
| Roadway classification, rural (vs. urban *) | 1.741 | 0.437 | 1 | 2 |
| Sunny condition (vs. others *) | 0.709 | 0.453 | 0 | 1 |
| Pickup truck (vs. others *) | 0.405 | 0.490 | 0 | 1 |
| Time of drive: 1:30–3:30 (vs. others *) | 0.153 | 0.360 | 0 | 1 |
| Others (vs. Wyoming plate *) | 1.429 | 0.775 | 1 | 2 |
| Day of a week, weekdays (vs. weekend *) | 0.85 | 0.348 | 0 | 1 |
| Driver gender: male * (vs. female) | 1.318 | 0.465 | 1 | 2 |

* Reference category.

## 3. Methodology

The logit model is a traditional method, which has been mostly used to model the choice of seatbelt use [17]. However, one of the main shortcomings of the standard logit model is its inability to capture the possible unobserved heterogeneity across individual observations.

The random parameter binary logit model, on the other hand, assumes that the coefficients vary across individual drivers based on some continuous distribution [18]. Here, the interests of the random parameters model are the first moment of the distribution, or the means of the parameters, and finding the second moment of distribution, or standard deviation, for capturing the unobserved factors.

This study evaluates the choice among drivers for a binary alternative of buckling up or not. To explain the mixed model, first we present the formulation of the standard logit model, and then its modification to the mixed model estimation.

The mixed model is a generalization of the standard logit model, by allowing the preference parameter to vary across each individual [18]. The standard logit model could be written as [19]:

$$y_i = \beta_i x_i + \varepsilon_i \tag{1}$$

where $x_i$ is observed characteristics of observer $i$, $\varepsilon_i$ is the i.i.d error term and $\beta_i$ is a fixed coefficient. Now, the mixed logit could be extended from the standard logit model by letting $\beta_i$ to vary across individuals of the population based on the continuous density of $f\ (\beta_i|\theta)$, where $\theta$ is some parametric distribution.

It should be noted that the above formulation assumes constant random $\beta$s for all observations based on preassigned continuous distribution. The above discussion could be modified to relax the restriction by considering the heterogeneity in means as follows [20]:

$$y_i = (\beta_i + \eta_i)x_i + \varepsilon_i \tag{2}$$

where $\eta_i$ is the vector of observation $i$ deviating from the mean, being based on an observed attribute. Additionally, $\eta_i$ is assumed to be normally distributed.

This simulated maximum likelihood (SML) is used for the parameters' estimates of the model. This is similar to the maximum likelihood with the difference that for estimating the random parameter coefficients, random draws are considered. The inference of the mixed model could be written as:

$$f(y_i|x_i,\gamma) = \int f(y_i|x_i,\beta_i)g(\beta_i,\gamma)d\beta_i \tag{3}$$

From the above, $\beta_i$ has a conditional density of $f(y_i|x_i,\beta_i)$, and density of $g(\beta_i,\gamma)$. After assuming the random parameter follows normal distribution as $\beta_i \sim N(\mu,\sigma)$, we have:

$$\begin{aligned} P_i(\theta) = f(y_i|x_i,\gamma) &= \textstyle\int_{-\infty}^{\infty} f(y_i|x_i,\ \mu,\sigma)PDF_N \\ &= \textstyle\int_{-\infty}^{\infty} f(y_i|x_i,\ \mu,\sigma)\ \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\nu^2\right)d\nu \end{aligned} \tag{4}$$

where $\nu_i \sim N(0,I)$, and $\gamma$ includes parameters $\mu$ and $\sigma$ of preassigned distribution, and the second part of the above equation is probability distribution function (PDF) of normal distribution. As the above equation has no close-form solution, an approximation of $f$ could be obtained by random draws and the results would be summarized as follows:

$$\hat{P}_i(\theta) = \frac{1}{R}\sum_{r=1}^{R} f(y_i|x_i,\beta_{ir},\gamma) \tag{5}$$

The maximum likelihood, then, is employed to maximize the log of the above expression as [21]:

$$\gamma_{MSL} = argmax\sum_{i=1}^{N}\log(\frac{1}{R}\sum_{r=1}^{R} f(y_i|x_i,\beta_{ir},\gamma)) \tag{6}$$

To summarize the implementation of the model parameters, the estimation of the mixed model with heterogeneity in taste is:

$$\beta_i = \beta + \nabla \times s_i + \sigma.\omega_{ir} \tag{7}$$

where $\beta$ is the initial values of random parameters, which might be set by employing the standard logistic regression, $\beta_i$ is a matrix including the random parameters to be estimated, $s_i$ is a covariate of a parameter that changes the mean of a random parameter, and $\nabla$ is a matrix of parameters to be estimated. On the other hand, $\omega_{ir}$ are random draws based on the normal distribution or random numbers based on some prime values, Halton draws.

For instance, if the mean of random parameters of gender is changed based on the mean of vehicle type, then $s_i$ is vehicle type. $\nabla$ is a parameter which is estimated for a random parameter, when heterogeneity is considered, e.g., gender and vehicle type.

It should be noted for just considering the standard mixed model, items of $\nabla \times s_i$ in Equation (7) would be ignored.

## 4. Results

The mixed model with heterogeneity in taste, standard mixed model, and standard logit model are considered and presented in Table 2. The results of the best performed model, or the mixed model with heterogeneity in taste are presented in three subsections: fixed, random parameter and random parameters with heterogeneity in taste.

**Table 2.** Estimation results of three considered models.

| | Mixed Model with Heterogeneity in Taste | | | Standard Mixed Model | | | Standard Logit Model | | |
|---|---|---|---|---|---|---|---|---|---|
| **Coef.** | **Est.** | **St. Err** | ***p*-value** | **Est.** | **St. Err** | ***p*-Value** | **Est.** | **St. Err** | ***p*-Value** |
| Constant | 2.63 | 0.977 | 0.007 | 2.13 | 0.721 | <0.005 | 0.013 | 0.145 | 0.927 |
| Van | −0.47 | 0.137 | <0.005 | −0.49 | 0.142 | <0.005 | −0.26 | 0.054 | <0.005 |
| SUV | −0.55 | 0.211 | 0.010 | −0.57 | 0.213 | 0.01 | −0.32 | 0.097 | <0.005 |
| 3:30–5:30 | 0.46 | 0.128 | <0.005 | 0.37 | 0.119 | <0.005 | 0.19 | 0.044 | <0.005 |
| Number of Lanes | 0.24 | 0.095 | 0.011 | 0.25 | 0.097 | 0.01 | 0.09 | 0.038 | 0.018 |
| **Point Estimates of Random Parameters** | | | | | | | | | |
| Gender | −0.54 | 0.332 | 0.107 | −1.21 | 0.392 | <0.005 | −0.28 | 0.045 | <0.005 |
| Roadway Classification | −1.92 | 0.572 | <0.005 | −1.64 | 0.405 | <0.005 | −0.79 | 0.041 | <0.005 |
| Weather Condition: Sunny | 0.43 | 0.142 | <0.005 | 0.09 | 0.176 | 0.63 | 0.14 | 0.043 | <0.005 |
| Vehicle Type: Pickup Truck | −0.13 | 0.255 | 0.609 | 0.25 | 0.195 | 0.19 | 0.37 | 0.049 | <0.005 |
| Time of Data Collection: 1:30–3:30 | 0.92 | 0.266 | <0.005 | 0.26 | 0.167 | 0.12 | 0.19 | 0.054 | <0.005 |
| Vehicle Registration | −0.63 | 0.386 | 0.102 | −0.99 | 0.278 | <0.005 | −0.11 | 0.028 | <0.005 |
| Day of a week | −2.14 | 0.596 | <0.005 | 0.21 | 0.138 | 0.13 | 0.17 | 0.058 | <0.005 |
| **Heterogeneity in Taste** | | | | | | | | | |
| $\beta_{roadwat\ classification_i} = \beta + \nabla \times s_{gender} + \sigma\ \omega_i$ | −0.34 | 0.213 | 0.100 | - | - | - | - | - | - |
| $\beta_{roadwat\ classification_i} = \beta + \nabla \times s_{day} + \sigma\ \omega_i$ | 1.35 | 0.350 | <0.005 | - | - | - | - | - | - |
| $\beta_{vehicle\ registration_i} = \beta + \nabla \times s_{road\ classification} + \sigma\ \omega_i$ | 0.42 | 0.195 | 0.034 | - | - | - | - | - | - |
| $\beta_{vehicle\ registration_i} = \beta + \nabla \times s_{pickup\ truck} + L\ \omega_i$ | −0.40 | 0.200 | 0.047 | - | - | - | - | - | - |
| $\beta_{sunny_i} = \beta + \nabla \times s_{1:30-3:30} + L\ \omega_i$ | −0.90 | 0.293 | 0.002 | - | - | - | - | - | - |
| **Standard Deviation of Random Parameters** | | | | | | | | | |
| $\sigma_{gender}$ | 1.10 | 0.391 | 0.005 | 1.26 | 0.406 | <0.005 | - | - | - |
| $\sigma_{roaday\ classification}$ | 0.89 | 0.343 | 0.010 | 0.63 | 0.364 | 0.08 | - | - | - |
| $\sigma_{\text{sunny}}$ | 0.83 | 0.549 | 0.131 | 1.26 | 0.629 | 0.05 | - | - | - |
| $\sigma_{\text{Pickup truck}}$ | 1.71 | 0.614 | 0.006 | 2.14 | 0.682 | <0.005 | - | - | - |
| $\sigma_{1:30-3:30}$ | 0.78 | 0.537 | 0.145 | 0.97 | 0.601 | 0.11 | - | - | - |
| $\sigma_{vehicle\ registration}$ | 1.13 | 0.332 | 0.001 | 0.98 | 0.274 | <0.005 | - | - | - |
| $\sigma_{day}$ | 0.54 | 0.476 | 0.255 | 0.81 | 0.465 | 0.08 | - | - | - |
| Log Likelihood = −8964<br>AIC = 17,976<br>BIC = 18,164 | | | | Log Likelihood: −8993<br>AIC:18,023<br>BIC:18,171 | | | Log Likelihood: −9024<br>AIC:18,071<br>BIC: 18,165 | | |

### 4.1. Fixed Effects

Types of vehicles including van and SUV, time of the data collection of 3:30–5:30, and number of lanes were some of the factors that found to be fixed across the population which are outlined in the next paragraphs.

#### 4.1.1. Vehicle Types

Various types were converted into dummy variables, and those variables were found to be important to be considered in the final analysis. It was found that the drivers who drive SUVs and vans are less likely to be unbuckled, compared with other vehicles such as passenger cars. It should be noted that the effect of the SUV predictor on the reduction in being unbuckled is slightly higher, $\hat{\beta}_{SUV} = -0.55$, than the van, $\hat{\beta}_{Van} = -0.47$. The findings somehow oppose the previous study that teenagers who drive SUVs and vans are less likely to be buckled up [22]. However, that study only considered the data related to fatally injured teenage drivers.

#### 4.1.2. Time of Data Collection: 3:30–5:30

We found that the drivers who drive their vehicles from 3:30 to 5:30 are more likely to be unbuckled, compared with drivers in other times. The result is somehow in line with the previous study that the later time of a day is negatively correlated with seatbelt usage [23].

#### 4.1.3. Number of Lanes

Number of lanes is another factor that was found to have a fixed effect on the seatbelt usage. The results indicate that when there are more lanes, drivers are more likely to wear their seatbelts. The impact might be related to the fact that often the roadways with less traffic and lanes are associated with lower enforcement, or possibly while traveling on roadways with lower traffic, drivers might think it is ok to be unbuckled.

### *4.2. Random Parameters*

This section presents random parameters that were found to change across the population without any observed heterogeneity. The way that the random sampling is incorporated in the analysis is by the cross product of standard deviation (SD) of random parameters by Halton draws and summing the two matrices by the initial value of random parameters, as shown in Equation (8):

$$\beta_{ir} = \beta + L\omega_{ir} \tag{8}$$

where $\beta_{ir}$ is the points' estimates of random parameters, and $L$ is a diagonal matrix including starting values of the random parameters' standard deviation. The values of random parameters estimate, and their standard deviations are estimated by the maximum likelihood process, and the $p$-value is estimated from coefficients and standard error. Recall that for this random parameters' deterministic taste, variations are constant across the population and do not change based on other observed variables.

#### 4.2.1. Gender

The predictor of drivers' gender indicates whether an observed driver was male as 1 or female as 2. The estimated normal distribution has a mean of −0.535 and standard deviation of 1.088. The cumulative density function (CDF) has an associated estimate of 0.69, indicating that almost 70% of male drivers are unbuckled compared with their female counterparts. This is in accordance with previous studies, which found that male drivers are more likely to be unbuckled compared with their female counterparts [16]. However, that study did not account for the heterogeneity across observations.

#### 4.2.2. Pickup Truck

This attribute highlights whether the drivers were driving a pickup as 1, versus others as 0. This random parameter has a mean of −0.13 and SD of 1.702, associated with CDF of 0.531. The results indicated that a slight majority of non-pickup drivers are more likely to be unbuckled. The result is in line with the previous studies that the pickup truck drivers have a lower seatbelt use compared with van and auto vehicles [4].

#### 4.2.3. Time of Data Collection: 1:30–3:30

The predictor of time of a day indicates whether drivers were observed to be buckled or unbuckled during 1:30–3:30 as 1, versus others. The estimated normal distribution has a mean of 0.43 with a standard deviation of 0.830. The associated CDF is 0.303, indicating that about 70% of the drivers during the times of 1:30–3:30 are likely to be unbuckled.

#### 4.2.4. Day of a Week

The predictor of day of a week indicates whether seatbelt status was collected during weekdays as 1 versus weekend as 0. Almost 100% of the drivers during weekends were buckled up. The results are in line with the previous study that seatbelt usage is higher in weekends compared with weekdays [24]. However, that study did not account for heterogeneity in the dataset. Results of a higher seatbelt usage might be attributed to a higher presence of cops on the roads or the fact that some drivers are accompanied by family members.

## 5. Heterogeneity in Tastes

The observed heterogeneity could be considered in the random parameter model by the inclusion of individual specific covariates [21,25]. The way that the heterogeneity in tastes work is similar to the standard random model (see Equation (2)) with the difference that the cross product of matrix parameter and vector of covariates of another of the observed variables, $\nabla \times s_i$, is included in the equation (see Equation (7)).

The following sections present the parameters that heterogeneity in tastes were considered. Three random parameters were found to vary based on the means of other variables. Those random parameters include roadway classification, vehicle registration and sunny weather condition. The following sections outline those variables. It should be noted that all variables were tested for the consideration of heterogeneity in means of random parameters, but only the below variables were considered due to their significance.

### *5.1. Road Classification*

The means of this random parameter of road classification variy based on the tastes' means of gender, day of a week and road classifications. This random parameter has a mean of −1.92 and SD of 0.887, with CDF of 0.98. This indicated that 98% of the drivers in urban areas are expected to be unbuckled.

#### 5.1.1. $\beta_{roadwatclassification_{\mathrm{i}}} {\sim} \mathrm{s}_{\mathrm{gender_i}}$

It is found that the mean of random parameter of road classification changes based on the mean of variable of gender. This indicated that the heterogeneity of road classification is varied based on gender across the population for status of seatbelt use. In other words, the higher the value of gender category of females ($\hat{\beta} = 0.34$), the lower the impact of road classification of rural areas ($\hat{\beta} = -1.92$) and, consequently, the less likely the drivers are to be wearing their seatbelts. The impact of the gender mean on road classification is expected, as female drivers are less likely to drive in rural areas compared with their male counterparts, and, consequently, are more likely to wear their seatbelts.

#### 5.1.2. $\beta_{roadwatclassification_i} {\sim} \mathrm{s}_{\text{day of a week}_{\mathrm{i}}}$

The mean of the day of the week is another factor that is found to impact the road classification taste heterogeneity. The results indicated that the weekday as 1 ($\hat{\beta} = 1.35$) increases the means of road classification as drivers are possibly more likely to use rural areas during the weekdays for careers. Additionally, the rural road classification ($\hat{\beta} = -1.92$) decreases the odds of being unbuckled.

### *5.2. Vehicle Registration*

It is found that road classification and pickup trucks are determinants of vehicle registration, and they play a significant role in drivers' decision-making process. The heterogeneity in mean of vehicle registration is varied based on the mean of two variables. This random parameter has a mean of −0.63, and SD of 1.128, with a CDF of 0.71. This indicates that 71% of drivers, with non-Wyoming vehicle registration, are more likely to be unbuckled.

This might be related to the fact that the out-of-state travelers are less likely to be buckled compared with the state drivers that drive for work or other nearby businesses.

The results are somehow in line with the previous studies that seatbelt usage changes based on various traveling conditions [26].

Additionally, as discussed by the previous study, the impact might be mainly related to the level of perceived risk for traveling condition. For instance, when state drivers, due to being experienced, consider the risk of traveling to be high due to nighttime or adverse weather conditions, they are more likely to be buckled.

#### 5.2.1. $\beta_{vehicleregistration_i} \sim s_{roadwat}$ classification$_{\mathrm{i}}$

Rural types of road classification $\left(\hat{\beta} = 0.42\right)$ are found to increase the mean of non-Wyoming vehicle registration ($\hat{\beta} = -0.63$). Consequently, the lower mean of vehicle registration results in a lower CDF and lower number of unbuckled non-Wyoming drivers.

#### 5.2.2. $\beta_{vehicleregistration_i} \sim s_{vehicle}$ type of pickup$_{\mathrm{i}}$

The type of vehicle, (pickup truck) $\hat{\beta} = -0.40$, is found to impact the mean of vehicle registration ($\hat{\beta} = -0.63$). In other words, driving a pickup truck was found to decrease the mean of non-Wyoming vehicle registration. Consequently, that effect decreases the impact of the non-Wyoming vehicle registration and the likelihood of being unbuckled.

#### 5.2.3. $\beta_{weathersunny_i} \sim s_{\mathrm{time:1:30-3:30_i}}$

The time of 1:30–3:30 is found to be the only indicator that significantly impacts the heterogeneity in the mean of random parameters of sunny weather conditions. Sunny-weather condition has a mean of 0.43 and SD of 0.830, with CDF of 0.30. The value of CDF indicates that in 30% of non-sunny condition cases, the drivers are unbuckled. The impact might result from the fact that the drivers consider non-sunny weather conditions to be riskier, and are thus less likely to be unbuckled. The uncertainty in the significance of SD of sunny weather conditions should be taken into consideration ($p$-value = 0.1).

### *5.3. Models Comparison*

For comparison purposes, in addition to the mixed model with heterogeneity in tastes, models including the standard mixed model, and the standard logit model were included (see Table 2). From Table 2, the mixed model with heterogeneity in taste (Akaike information criterion (AIC) = 17,976) has a better fit compared with the standard mixed model (AIC = 18,023) and the standard logit model (AIC = 18,071).

Based on the results, accounting for heterogeneity is important, moving to the more advanced technique of mixed model with heterogeneity in taste from the standard logit model. That is expected as the choice of seatbelt use involved a more complex relationship across various variables. AIC and Bayesian information criterion (BIC) were used due to reliabilities by penalizing for the number of included predictors.

A question arises: Why does the mixed model with heterogeneity in taste perform better compared with the standard mixed model? This might result from complexity of the choice that drivers make regarding the seatbelt usage, which the mixed model could only account for inefficiently. This complexity might end up in error terms, and decrease the goodness of fit, if they are not accounted for. This could be observed in the variation of the point estimates, and even the significance of the variables.

This is despite the fact that for fixed parameters in standard mixed, and mixed models, accounting for heterogeneity in taste, point estimates of fixed effects are almost identical. The standard deviation for the standard mixed model is significant for some random variables, e.g., sunny weather conditions, whereas they are not for the mixed model with heterogeneity in taste. That implies that those coefficients varying across observations based on some observed attributes, and thus the constant distribution mean might provide biased point estimates regarding the impacts of those variables.

Finally, considering the standard mixed model and mixed model with heterogeneity in tastes, the percentage of unbuckled male drivers changes from 69% to 83% for the mixed model with heterogeneity in taste and the standard mixed model, respectively. This is an indication that there are differences in the magnitudes of effects for various approaches.

## 6. Discussion

A lack of seatbelt usage is a major safety concern for policy makers. Thus, this study employed three methods of the standard logit, mixed model and the mixed model with heterogeneity in taste to explore the determinants of drivers' choice of bucking up in a less-biased way. The response variable is whether drivers were buckled, as a reference category, or not. In the mixed approach, heterogeneity is accounted for by assuming that parameters (or the tastes of the individuals) vary across the population based on some pre-specified continuous distribution, which defines continuous segmentation of preferences.

Although the standard mixed model helps to capture the unobserved heterogeneity, the mixed model, accounting for the heterogeneity in tastes, could also help to capture observed heterogeneity [27]. Based on the obtained results, we found that moving from the standard logit model to the standard mixed model and the mixed model, with heterogeneity in taste, allows new insights to emerge, and also results in an enhancement of the model's overall fit.

The results indicated that the choice of seatbelt usage is a complex task, which depend on a number of factors. For instance, vehicle types, time of a day and number of lanes were some of the fixed factors that were found to impact the drivers' choice of seatbelt usage. We found that SUV and vans drivers are less likely to be unbuckled. That result is against the previous study that those drivers are less likely to be buckled up [22]. Again, the reason for the impacts might be due to many unseen factors that were not recorded at the time of data collection.

For instance, the reason why SUV users have higher seatbelt use might be due to a possible reason that those vehicles are primarily used by families. Another reason could be that factor highlights drivers with other specific characteristics that were not recorded at the time of data collection. For instance, it was highlighted in the literature that 80% of SUV owners live in urban areas [28]. Additionally, it was discussed that women carry out one-third of all SUV purchases [28], and that SUV drivers are less likely to be frustrated and those are overrepresented across highly educated individuals with higher income [29]. More studies are needed to highlight the underlying factors behind the impact.

In addition, although the impact of gender was found to be random, the distribution of that variable highlighted the fact that male drivers are less likely to be buckled. The impact might be due to risk aversion between genders as various genders are expected to have different approaches toward risk-taking behaviors. The variation across genders in risk-taking behavior were explored in different contexts, e.g., investment [30]. The difference has been linked to cognitive and noncognitive traits on which men and women differ [31]. However, it should be noted that the impact for gender in risk-taking behaviors in the majority of past studies was considered as fixed.

Few variables were found to have unobserved heterogeneities in their means across the drivers' population. Those include gender, time of a day, day of a week and type of vehicles. Most of the outcomes are in line with the previous studies. For instance, as expected, females in general are more inclined to be buckled [32].

However, it is found that for some variables, heterogeneities are not constant across the population, and their means change across the population based on some observed heterogeneities. These include sunny weather conditions, road classification and vehicle registration. For instance, observed heterogeneity exists in the road classification: the heterogeneity of the mean of road classification is a function of gender and day of the week. Variation across gender in terms of the use of various road types and the complexity of travel behavior were discussed in the literature [33]. It was found that women have lower levels of individual access to urban opportunities.

Finally, it should be reiterated that the inclusion of various environmental and vehicle types was considered in the analysis as they account for unobserved factors that the observers failed to record. For instance, the choice of drivers in buckling up in various days or environmental conditions or even type of vehicles they own, could provide information regarding the psychology and drivers' attributes that we could not, or at least, would be very challenging, to record.

## 7. Recommendations

The findings of this study have important implications for the policy makers in the state. The results show that the governmental bodies should pay more attention to the underlying impact of the discussed variables. For instance, it was found that various demographic and environmental conditions impact the use of seatbelts. It is expected that the impacts of those factors are related to the psychology of drivers and how drivers are influenced by various environmental and drivers-related characteristics.

For instance, the fact that drivers in rural areas are more likely to be unbuckled is expected to be related to the drivers with non-Wyoming plate registration. This could be an indication that travelers from outside the state that come to Wyoming for a possible reason of leisure, are more prone to be unbuckled. Therefore, more attention should be given to the seatbelt use of outside-the-state travelers by placing billboards about seatbelt use at state borders. The importance of the role of communication by factors such as billboard, and media were discussed in the past study [34].

One of the most effective population-based interventions for improving seatbelt use is seatbelt laws and the related enforcement [35]. For instance, the literature review highlighted the importance of primary enforcement of seatbelt laws, where the officers stop drivers who are not wearing seatbelt and ticket them compared with the time the ticket issuance is after vehicle was stopped for other reasons [36]. Thus, the highway patrol in the state could have an influential impact on the use of seatbelts, especially by targeting the right group.

Additionally, research suggests that enhanced enforcement through communication and outreach is associated with higher seatbelt usage [37]. Educational programs are recommended for nonresident travelers of the state, especially regarding the danger of driving in a mountainous area with adverse conditions such as Wyoming.

Educational programs are especially important as it is expected that many road users might not be fully aware of the importance of the seatbelt use in prevention of crash fatalities and injuries. More education programs and training are needed to provide the drivers with the information regarding the importance of seatbelt use. The importance of education programs has been discussed extensively in the past studies. For instance, the impact of early elementary school safety education was evaluated and found to be successful on family seatbelt use [38].

Educational programs are especially important as many drivers might not be fully aware of the importance of seatbelt use in reduction in crash severity. That could especially be employed by the DOT while training and issuing the driver's license.

It is expected that the seatbelt policy and program initiatives will be associated with a reduction in occupant fatalities, especially in Wyoming, with one of the highest fatalities rates in the states. Especially the changes of regulations are important as highlighted that the importance of governmental legislation within each state in the reduction in related seatbelt injuries [39]. More studies are needed to highlight the effectiveness of various possible countermeasures.

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