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Understanding and modeling willingness-to-pay for public policies to enhance road safety: A perspective from Pakistan

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ABSTRACT

Evaluating road safety improvements becomes important because it can assist policymakers in allocating economic resources to improve safety and implementing effective policy interventions. As such, this study aims to estimate the value of road safety risk measures using a new modeling approach for willingness-to-pay (WTP). Specifically, this study integrates a machine learning technique (decision tree) with a correlated random parameters Tobit with heterogeneity-in-means model. The decision tree identifies a *priori* relationships for higher-order interactions, while the model captures unobserved heterogeneity and the correlation between random parameters. The proposed modeling framework examines the determinants of public WTP for improving road safety using a sample of car drivers from Peshawar, Pakistan. WTP for fatal and severe injury risk reductions is estimated and used to calculate the values of corresponding risk reductions, which can be used for monetizing the cost of road traffic crashes in the country. Modeling results reveal that most respondents are willing to contribute to road safety improvement policies. Further, the model also uncovers significant heterogeneity in WTP corresponding to the safer perception of the overall road infrastructure and perceived risk of accident involvement. Systematic preference heterogeneity is also found in the model by including higher-order interactions, providing additional insights into the complex relationship of WTP with its determinants. Further, the marginal effects of explanatory variables indicate different sensitivities toward WTP, which can help to quantify the impacts of these variables on both the probability and magnitude of WTP. Overall, the proposed modeling framework has a twofold contribution. First, the modeling framework provides valuable insights into the determinants of public WTP, mainly when the heterogeneous effects of variables are interactive. Second, its implementation and consequent findings shall help prioritize different road safety policies/projects by better understanding public sensitivity to WTP.

1. Introduction

Road safety projects (and policies) are necessary to lessen the number of road traffic crashes and their adverse outcomes on human health and the economy. Road crashes are estimated to cost around 1–3% of the gross national product of a country and result in 1.36 million fatalities every year (WHO, 2009; 2018). Preventing road crashes requires developing and implementing interventions/policies and involves the expenditure of public resources. This expenditure significantly burdens society as there are many competing needs for sustainable development in low- and middle-income countries (Svensson and Johansson, 2010). To ensure efficient resource allocation, cost-benefit analyses are conducted to understand the benefits and costs of public investment, thereby justifying public investments and ensuring transparency of policy decisions. It is commonly acknowledged that monetary valuation is required to compare road safety policy's benefits regarding traffic crashes and their outcomes with its costs (Wijnen and Stipdonk, 2016). Monetizing the benefits expected from road safety measures is a practical tool that helps increase transport investment projects' efficiency and equity (González et al., 2018).

The monetized benefit of improved traffic safety, as perceived by each individual in society, can be evaluated through their willingness-

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to-pay (WTP) (Svensson, 2009). Microeconomic theory suggests that individuals' choices are the basis for economic welfare (Nicholson and Snyder, 2012). Therefore, the societal losses resulting from road crashes should be valued according to the WTP of those affected. WTP is the additional amount that individuals (or road users) are willing to pay for a road safety measure/policy intended to decrease (non-) fatal traffic crash rate. As such, WTP allows the valuation of (non-) fatal risk reduction and signifies the monetized benefits of improved road traffic safety. Further, this approach thoroughly explains the factors associated with their financial contribution towards road safety improvement programs. Identifying the factors that affect public WTP can assist policymakers in initiating road safety campaigns to elicit their monetary contribution to road safety policies, significantly reducing the burden of road traffic crashes on the country's economy.

Several studies have used WTP for road safety improvements for developed countries, such as Norway (Flügel et al., 2019), Spain (González et al., 2018), and Australia (Hensher et al., 2009). WTP has become an institutionally accepted means for deriving monetary values using individual's stated and revealed preferences. Unfortunately, in many developing countries like Pakistan, the cost-benefit analysis of road safety programs is highly unreliable due to the unavailability of quality data. It has been well established that there is a need to improve data quality and implement typical road safety methodologies in low- and middle-income (developing) countries (Haghani et al., 2022). Road safety benefits in these countries are not officially added to other benefits and safety value, instead of WTP to value road crash fatalities and injuries, is based on the human capital approach (Hensher et al., 2009), which rests on accounting principles (Ashenfelter, 2006). A plausible concern could be understating the benefits obtained from improvements in road traffic safety, and as such, many potential investments in improving road safety may not deem cost-effective. As a result, road safety improvements in these countries are lacking compared to that of developed countries. A better understanding of individual's WTP for improved road traffic safety in these countries is clearly missing in the literature, which can provide better information from an end-user perspective. Further, developing countries cannot rely on research conducted in developed countries as individual's WTP for improved road traffic safety is directly associated with personal characteristics, perceptions, and situational variables, which vary across jurisdictions (Andersson and Lindberg, 2009). Therefore, a better understanding of individuals' preferences for road safety improvement at a national level can help to prioritize road safety interventions and reduce policy resistance in the communities (Andersson and Lindberg, 2009), which hinders the applicability of road pricing policies (Langmyhr, 1997; Pronello and Rappazzo, 2014). Road safety measures should be personalized to increase acceptability among target groups (Zhang et al., 2013). Also, comparisons of road crash risk reduction valuations across countries with varying levels of development in the transport system are not possible (Wegman, 2017). Therefore, to fill this gap in the literature, the present investigation examines the determinants of WTP for road safety improvement and evaluates road crash risk reductions at a country level (in the context of developing countries).

Examining WTP for road safety improvement involves many factors and complex interactions among them. Specifying potential interactions among the main factors heavily depends on the analysts' domain knowledge, which induces subjectivity during the model development. Currently, the WTP model development does not follow a systematic approach, which can compromise the replicability of the findings. Additionally, most studies have examined the relationship between individuals' WTP and contributing factors by solely applying conventional statistical models that do not account for interaction effects (second- and higher-order) among explanatory variables (personal characteristics, perception, and situational variables). A possible reason for not considering these interaction effects might be that these interactions often require an analyst to specify *a priori* second- and higher-order interaction effects. Further, these interaction effects grow geometrically and exponentially by adding ordinal and nominal variables, respectively (Ali et al., 2020a). Although a few studies have used interaction effects (up to second-order only), these studies failed to find significant interaction effects (e.g., see González et al. (2018)) with a few exceptions (Bhattacharya et al., 2007; Flügel et al., 2019). A possible reason for non-influential interaction effects could be the unsystematic specification in the model. The problem becomes more complicated and may lead to omitted variable bias affecting model estimates and inferences when significant higher-order interactions are not considered during the model development (Mannering et al., 2016). The present study also addresses this methodological limitation in the published literature (irrespective of developing/developed countries context).

The majority of past studies (e.g., see Wenge and Shengchuan (2013) and Mon et al. (2018)) used conventional fixed-effect models, which are unsuitable for capturing and explaining unobserved heterogeneity associated with WTP. Using stated choice surveys, some recent studies tried to capture unobserved heterogeneity in WTP using random parameter (or mixed logit) models (González et al., 2018; Flügel et al., 2019). However, these studies assumed the independence of unobserved heterogeneity by allowing their distribution to be independent. However, correlation is likely to exist between different sources of unobserved heterogeneity because of the complicated interactive effects of unobserved characteristics. Overlooking such potential unobserved heterogeneity caused by correlation between or among random parameters may lead to biased estimations and restricted inferences. Therefore, understanding the complex relationship between public WTP and its determinants remains elusive, and the interactive effects of heterogeneity are relatively less explored. As such, there is a growing need to simultaneously consider higher-order interactions and unobserved heterogeneity during model development to comprehensively understand individuals' WTP for improved road safety. Motivated by this critical research gap, this study aims to investigate public WTP for road safety improvement through an integrated modeling framework of machine learning and advanced econometric methods to simultaneously capture unobserved heterogeneity arising from preference heterogeneity and interactions of different behaviors (possible correlations among random parameters). As the WTP variable is considered a continuous variable and has a positive density at zero (i.e., high frequency of zero observations) (Guo and Mcdonnell, 2013), the WTP variable is left censored (at zero). To this end, a Tobit regression framework is employed to cater for the skewed nature of the data without omitting observations by censoring the analysis at a specific value (i.e., zero in our case) (Washington et al., 2020).

The contribution of this study is threefold. First, this study demonstrates the application of machine learning for better understanding WTP, uncovering complex relationships, which may not be possible through conventional models. Along this line, machine learning models often overcome data inaccuracies or unavailability problems — some common issues faced by developing countries. As such, utilizing machine learning models, this study provides insights into enhancing road safety by understanding community perceptions that can be used to reduce policy resistance. Further, machine learning models divide the entire population into smaller groups based on the willingness towards financial contribution for road safety policies. The identification of such smaller groups can help policymakers to devise policies for different groups and overcome distributive issues. Second, the impact of influential factors on the probability of participation and the expected value of WTP for road safety improvement policies is investigated with the help of a new modeling framework proposed in this study. Further, leveraging the benefits of the framework, monetary values for fatal and severe injury risk reductions are estimated for a developing country. Finally, this study, for the first time, proposes a new modeling framework for estimating and understanding WTP that simultaneously accounts for higher-order interactions using a machine learning technique and unobserved heterogeneity using a correlated random parameters Tobit with heterogeneity-in-means model. Utilizing the proposed framework, heterogeneous effects arising from multiple sources of different determinants of public WTP for improved road safety are identified. Such findings will help policymakers to account for heterogeneity among groups of individuals and devise policies tailored for heterogeneous groups, which can provide valuable insights into how small groups perceive and react to WTP for road safety improvement.

2. Methodological approach

An integrated modeling framework is proposed to model public willingness-to-pay (WTP) for road safety improvement. This modeling framework involves a decision tree (i.e., a machine learning technique) and a correlated random parameters Tobit with heterogeneity-in-means (CRPTHM) model (i.e., an advanced econometric modeling technique). The decision tree determines the potential higher-order interaction effects among explanatory variables. These higher-order interactions serve as an input to the CRPTHM model and provide more insights into WTP, whereas the CRPTHM model captures the unobserved heterogeneity associated with WTP. As previously mentioned, WTP is generally clustered at zero (i.e., left-censored). Several techniques can model such type of left-censored dependent variable. The most popular among them is Tobit regression that qualitatively differentiates between limit (zero) and non-limit (above zero) observations (Tobin, 1958). These characteristics and the ability to capture unobserved heterogeneity using random parameters motivated us to use the integrated modeling framework.

First, a fixed parameters Tobit (FPT) model is developed. The response variable in the model is the WTP (stated amount) that individuals are prepared to contribute to road safety improvement programs/policies. The explanatory variables are the respondents' sociodemographic, perception, and situational variables. Mathematically, the generic Tobit model can be written as (Washington et al., 2020)

$$Y_i^* = \boldsymbol{\beta} \boldsymbol{X}_i + \varepsilon_i, \tag{1}$$

$$Y_i = \begin{cases} Y_i^* & if Y_i^* > L \\ 0 & if Y_i^* \leq L \end{cases}, \tag{2}$$

Where Y_i^* is an implicit and stochastic index that is observed only when greater than zero, Y_i is the WTP for the respondent i (=1, …N, where N is the total number of respondents), $\boldsymbol{X}_i$ is a vector of explanatory variables with parameter $\boldsymbol{\beta}$, L refers to the value at which the model is censored, and ε_i is the error term following the normal and independent distribution with zero mean and constant variance σ^2.

In Eq. (1), only main effects are considered, whereas interaction effects are often omitted or considered as per analyst's domain knowledge, leading to subjectivity in model development process. To overcome the problem of subjective bias in selecting some interactions and leaving out others, leading to omitted variable bias and model misspecification issues (Mannering et al., 2016; Washington et al., 2020), a machine learning (decision tree) technique is employed to systematically obtain potential higher-order interactions. A decision tree is a non-linear discrimination method that splits an entire dataset into progressively simple and smaller groups of explanatory variables using various cut-off values. The procedure is iterative at every single split in a tree structure as it chooses the explanatory variable that is strongly associated with the response variable (WTP in this study) based on a predefined criterion (Michael and Gordon, 1997).

A number of algorithms can be used to construct decision trees. These algorithms include classification and regression tree (CART), Chi-Squared Automatic Interaction Detection (CHAID), and Quick, unbiased, efficient, and statistical tree (QUEST), among others. CART is a recursive splitting method used for both classification and regression. Its goal is to split the entire dataset into homogeneous subsets in accordance with the response variable (Breiman et al., 2017). On the other hand, QUEST is a binary-split method used for classification, and it has a negligible bias in selecting the attributes (Loh and Shih, 1997). Finally, the CHAID algorithm uses a chi-square test. A CHAID (decision) tree is constructed by dividing the entire dataset into numerous subsets. This process is repeated to further split each subset into several nodes. The best split at any subset is determined by merging any pair of categories of the explanatory variables until the variation within that pair in accordance with the target variable is not significant (Michael and Gordon, 1997). This method naturally provides interactions among explanatory variables, which can be directly examined from the tree.

All the aforementioned decision tree methods have their pros and cons (Hastie et al., 2009; Lee and Park, 2013). Previous studies found comparatively higher accuracy for the CHAID method (Lee and Park, 2013). Therefore, this study applied the CHAID decision tree method to respondents' WTP for improved safety. More specifically, a decision tree analysis is used to obtain interaction effects that can be used as explanatory variables in the Tobit model. Let $\boldsymbol{W}_i$ be a vector of interaction effects among explanatory variables obtained using the decision tree analysis. As such, Eq. (1) can be re-written as

$$Y_i^* = \boldsymbol{\beta} \boldsymbol{X}_i + \boldsymbol{\gamma} \boldsymbol{W}_i + \varepsilon_i, \tag{3}$$

where, γ is a vector of estimable parameters corresponding to interaction effects. The model formulation, in Eq. (3), indicates that the effects of covariates (both main and interaction effects) remain the same for all the sampled individuals, imposing an unrealistic assumption that every individual (road user in our case) is likely to have the same preferences towards road safety (improved through the implementation of different safety measures). However, different individuals perceive and react to safety improvement projects differently, leading to preference heterogeneity. If unobserved heterogeneity is overlooked (i.e., assuming effects of explanatory variables to be constant across all individuals), the developed model will be mis-specified resulting in biased and inefficient parameters, which could in turn lead to erroneous model inferences (Mannering et al., 2016).

To account for unobserved heterogeneity and fill the methodological weakness of traditional fixed parameter models, recent advancements in econometric modeling, such as a random parameter modeling approach, could be helpful that enabling the estimated parameters to vary across the observational units systematically. As such, random parameters are included in the Tobit model (Eq. (4)), where $\boldsymbol{\beta}_i$ indicates a vector of the individual-specific random parameters. The random parameters vector can be expressed as

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \Omega \mu_i, \tag{4}$$

where, β and $\Omega\mu_i$ respectively denote the deterministic component and stochastic terms, with Ω being a lower triangular Cholesky matrix that contains information about the variances and covariances and accounts for potential correlations in random parameters, and μ represents a randomly distributed term with mean and variance equal to zero and one, respectively. Several distributions are used for random parameters, including uniform, triangular, normal, log-normal, and Weibull. However, this study finds a normal distribution for random parameters to provide a statistically better fit and intuitive interpretation, which is also aligned with the existing literature (Ali et al., 2022a).

Further, the heterogeneity in a random parameter can be explained as

$$\beta_i = \boldsymbol{\beta} + \boldsymbol{\delta} z_i + \Omega \mu_{i,} \tag{5}$$

where, $\boldsymbol{\beta}_i$ follows a multivariate normal distribution with $\boldsymbol{\beta} + \boldsymbol{\delta} z_i$, where $\boldsymbol{\delta}$ and z_i are a matrix of coefficients and a column vector of explanatory variables to describe heterogeneity across individuals.

Past studies demonstrate that the sources of unobserved heterogeneity may be correlated (Mannering et al., 2016; Ali et al., 2020b) because of the complex interactive effects between unobserved characteristics. Therefore, the effects of unobserved characteristics on WTP are likely to be correlated. As this study finds two statistically significant random parameters (after testing for several random parameters), the correlation between them is also considered using the unrestrictive form of the Cholesky matrix (non-zero below diagonal elements in Ω). This results in a modeling framework called a correlated random parameters (Tobit) model, which is expected to capture the heterogeneous effects of observed factors and the potential interactions between unobserved characteristics. The correlation coefficient between a pair of random parameters is expressed as (Ali et al., 2022b)

$$Corr(\beta_k, \beta_l) = cov(\beta_k, \beta_l) \Big/ \sqrt{var(\beta_k) var(\beta_l)}, \tag{6}$$

where, k and l indicate rows in $\boldsymbol{\beta}_i$. For a correlated random parameters model, the diagonal elements of Ω denote the squared values of the mixing distributions for the correlated random parameters. The standard deviation of the correlated random parameters is based on the diagonal and off-diagonal elements of Ω, and can be defined as (Ali et al., 2020c, 2021; Washington et al., 2020)

$$\sigma_k = \sqrt{\sigma_{k,k}^2 + \sigma_{k,k-1}^2 + \sigma_{k,k-2}^2 + \ldots + \sigma_{k,1}^2}, \tag{7}$$

where σ_k represents the standard deviation, $\sigma_{k,k}$ is the diagonal element of Ω, and $\sigma_{k,k}, \sigma_{k,k-1}, \sigma_{k,k-2}, \ldots, \sigma_{k,1}$ represent the below-diagonal elements. The statistical significance of these standard deviations can be computed as (Ali et al., 2020c, 2021)

$$SE_{\sigma k} = \frac{S_{\sigma k,i}}{\sqrt{N}}, \tag{8}$$

$$Z_{\sigma k} = \frac{\sigma_k}{SE_{\sigma k}}, \tag{9}$$

where σ_k denotes the distributional standard deviation of a random parameter k, $SE_{\sigma k}$ represents the standard error of the standard deviation specific to an observation, $\sigma_{k,i}$ denotes the standard deviation of the random parameter for observation i (generated by the software), $S_{\sigma k,i}$ denotes the observation-specific $\sigma_{k,i}$ standard deviation, N denotes the number of observations, and $Z_{\sigma k}$ represents the corresponding z-statistic.

Since estimating the (traditional) maximum likelihood of a random parameters model is computationally cumbersome, a simulation-based maximum likelihood (Greene, 2016) method is employed using Halton draws. More specifically, Monte Carlo simulation with 1000 quasi-random Halton draws is used for estimating model parameters.

Concerning the overall goodness-of-fit of Tobit regression, the Maddala pseudo-R^2 (Maddala, 1983) is frequently used to assess the statistical performance. Moreover, the Akaike information criterion (AIC) is employed to evaluate the overall fit of the Tobit models and model comparison. Furthermore, likelihood ratio tests are conducted for testing the statistical superiority of the developed model over its competing models. Note that a 95% confidence level is assumed in this study.

The change in the expected value for positive cases (quantitative WTP) and the cumulative probability of being above zero (categorical WTP) for each explanatory variable are calculated to obtain the marginal effects of explanatory variables on WTP. These changes are derived by quantifying the impact of a small increase/decrease in a continuous variable from its mean value or a category change for a categorical variable while keeping other variables at mean values and reference categories.

3. Data collection

3.1. Questionnaire design

The most critical part of the willingness-to-pay (WTP) questionnaire is to elicit the individuals' WTP for road traffic safety improvement programs. Here, the respondents express the maximum additional amount they are prepared to contribute to lessening the rate of (non-) fatal road traffic crashes. In previous studies, the value of road crash risk reduction based on WTP was estimated initially using stated preference contingent valuation (CV) (Beattie et al., 1998) and stated choice survey (Rizzi and Ortúzar, 2003). The CV approach is useful for evaluating traffic crash risk reduction (Elvik, 1995). Also, previous studies (Bateman et al., 2002; Guo and Mcdonnell, 2013) have shown that the payment card eases the valuation process for respondents and results in more certain WTP values. Therefore, a WTP-CV with a payment card approach was deemed more appropriate for Pakistani drivers, who are less educated and unaware of road crash risk reduction valuations.

The designed questionnaire comprised four sections: (1) introducing a new road safety improvement policy to mitigate the increasing rate of road traffic crashes and minimize the risk associated with it, (2) general socio-economic characteristics and travel patterns, (3) history of road traffic crashes, perception of road infrastructure and overall travel, and perceived risk of road traffic crashes, and (4) a WTP valuation question to reduce (non-) fatal traffic crash risk.

3.2. Study area and survey details

Data were collected at selected locations in a metropolitan city of Pakistan, Peshawar, in 2020. Peshawar is a highly motorized city with a population of over 2.2 million. During 2018, 356 fatalities and 870 severe injuries occurred due to road traffic crashes in Peshawar. These figures were shown to the respondents to inform them about the risk of traffic crashes and the need for road safety improvement.

A traffic crash is a common tragedy with numerous consequences for individuals and society. However, as many individuals often think that the government, rather than the general public, should finance road safety improvement measures, a brief description to the respondents about the public benefits of road safety policy implementation was still needed. Further, being the first study in the country, we deemed it more appropriate to target one particular group of road users, i.e., car drivers.

As the road users in Pakistan were unaware of WTP and risk reduction valuation concepts, online and post-mail surveys were unsuitable. As such, respondents were interviewed face-to-face by trained undergraduate university students to ensure that they understood the questionnaire and chose an appropriate WTP amount. The social impact of road traffic crashes and the contribution of the study to this problem were explained to the potential participants. The road safety improvement program was described as a new public policy that would lessen the number of traffic crash fatalities/severe injuries in the study area. We thoroughly monitored the field surveys and promptly clarified any confusion or misunderstanding in interpreting the questionnaire.

A pilot test with 67 respondents, including university students and staff members, was conducted to confirm the participant's understanding of the questionnaire. The questionnaire was then revised according to their feedback. Furthermore, car drivers with at least 10th grade education (and over 18 years) and who resided for over a year in the study area were interviewed, as they could easily recognize the traffic crash risk and the information provided. After excluding erroneous responses, the final sample size used in the study was 653.

To reduce the common problem of respondents' judgment of (small) probabilities of the risk of crash involvement and to make the road safety policy more comprehensible, the safety improvement program was presented as a reduction in the number of road traffic crash fatalities/severe injuries (Andersson and Lundborg, 2007). To test for scope bias (Hultkrantz et al., 2006), some respondents were presented with fatal risk reduction while others had non-fatal (severe injury) risk reduction. Also, the severity of each type of non-fatal (severe and less severe) crashes was explained in the questionnaire to mitigate the problem of collinearity (Viscusi and Aldy, 2003). Finally, a 50% reduction in fatalities and severe injuries was set according to National Road Safety

Strategy 2018–2030, which aims to reduce traffic-related fatalities and injuries by 50% in 2030 (Ministry of Communications, 2018).

The road traffic safety program was presented as an unspecified safety program[1]. Respondents were informed that their answers would not affect their choice of transport mode, trip quality, speed, or the overall urban environment. Further, respondents were clarified that the payment would be an annual fee allocated for road safety improvement funds throughout the city. It was further emphasized that all other city residents also had to contribute equally to the road traffic safety improvement program. The respondents were then given the payment card (depicted in Fig. 1) and asked about their financial contribution to the road traffic safety improvement program as (Persson et al., 2001); "*How much would you be willing to pay each year for the road traffic safety improvement program that reduces the number of road traffic crash fatalities/severe injuries by one half (50%) in Peshawar?*". The respondents indicated the maximum amount of money they would contribute from the payment card.

In addition, a provision condition was presented to the respondents. This program was described as follows:

> "A requirement for the road traffic safety program to be initiated is that at least 70% of the inhabitants in Peshawar pay for a new road traffic safety program. If sufficiently many inhabitants do not pay, the traffic safety program will not be initiated, and your payment will be returned."

In addition, the road traffic safety improvement program was framed using the "community analogy" concept that was deemed appropriate to increase the respondents' feeling of participation (Calman and Royston, 1997). To reduce the hypothetical bias and highlight the budget constraint, respondents were asked to carefully consider their other daily living expenses along with the budgets.

3.3. Participants

Table 1 presents the descriptive statistics for the respondents. The lower proportion (17%) of females in the sample represents the population of female drivers in the study area and the country, which is aligned with previous studies conducted (Subhan et al., 2021). Most respondents (75%) were aged above 30 years and stated an income within the high-income level range (41%). Table 1 indicated that over half (59%) of the respondents noted that road infrastructure and overall city travel were unsafe. In line with the previous studies (e.g., Haddak et al. (2016)), the majority of the respondents (67%) stated a higher perceived risk of traffic crash involvement. Most (71%) respondents

Please tick (✓)/write the amount (in PKR) that you are willing to contribute.

0	25	50	75	100	150	200
250	300	400	500	600	800	1000
1250	1500	1750	2000	2500	3000	4000
5000	6000	8000	10000	12000	14000	16000
More than 16000						
OR, Any other amount (not mentioned above), please specify ☐ ___________						

Fig. 1. Payment card format.

[1] During the pilot survey, respondents suggested different road safety measures. Specifying all those road safety measures in the questionnaire was difficult, if not impossible, as different respondents preferred different road safety measures. Therefore, we presented the road safety improvement program as unspecified and we informed the respondents about the different safety measures to be implemented after their queries during the interviews.

Table 1
Sample characteristics.

Variable	Description	Mean	SD	Count	Percentage
Dependent Variable					
WTP (1000 PKR)		1.44	1.46		
Independent Variables					
Driver's age (years)	Age of the respondent	36.48	8.26	–	–
Young drivers	age ≤30 years	25.19	3.47	162	24.81
Middle-aged drivers	>30–40 years	36.70	2.46	302	46.25
Older drivers	> 40 years	46.20	3.69	189	28.94
Gender					
Male		–	–	541	82.8
Female		–	–	112	17.2
Family Status					
Unmarried		–	–	213	32.62
Married		–	–	440	67.38
Education					
Completed Matric (Grade 10) and above		–	–	117	17.92
Completed Higher Secondary (Grade 12) and above		–	–	204	31.24
Completed Bachelor's Degree and above		–	–	227	34.76
Above Bachelor's Degree		–	–	105	16.08
Occupation					
Student		–	–	158	24.20
Private Employee		–	–	155	23.74
Government Employee		–	–	179	27.41
Other		–	–	161	24.65
Personal Monthly Income (1000 PKR)		70.82	48.63	–	–
0–30000		–	–	170	26.03
>30000–100000		–	–	217	33.23
>100000		–	–	266	40.74
Sole Earner					
Yes		–	–	160	24.50
No		–	–	493	75.50
Travel Characteristics and Car Ownership					
Do not have a Personal Car		–	–	239	36.60
Have a Personal Car		–	–	414	63.40
Monthly Travel Cost (1000 PKR)		14.65	5.27	–	–
Work/Study Trip		–	–	463	70.90
Recreational Trip		–	–	190	29.10
Direct/indirect Crash History (last three years)					
Yes		–	–	273	41.81
No		–	–	380	58.19
Risk Perception					
Higher	= 1 if respondent stated that their own risk is higher than the average in Peshawar	–	–	435	66.62
Lower	= 1 if respondent stated that his/her own risk is lower than the average in Peshawar	–	–	159	24.35
Road Infrastructure Safety Perception					
SPRI	= 1 if respondent stated that the road infrastructure	–	–	267	40.89

(*continued on next page*)

Table 1 (*continued*)

Variable	Description	Mean	SD	Count	Percentage
	and overall travel is safe in Peshawar				
UPRI	= 0 if the respondent stated that the road infrastructure and overall travel is unsafe in Peshawar	–	–	386	59.11
Risk Type					
Fatal	= 1 if respondent is presented with fatal risk reduction	–	–	346	52.99
Severe Injury	= 0 if respondent is presented with severe injury risk reduction	–	–	307	47.01

Note: SPRI: Safe perception of road infrastructure; UPRI: Unsafe perception of road infrastructure. Sample size = 653.

traveled for work/study, and less than half (42%) had a (direct/indirect) traffic crash history in the last three years.

4. Results

4.1. Rate of willingness-to-pay

Among the 653 respondents interviewed, 233 stated a zero willingness-to-pay (WTP), making the overall refusal rate around 32.62%. Approximately 12% and 55% of participants are unwilling to contribute financially to the fatal and severe injury risk reduction programs, respectively, by stating zero WTP. The higher percentage of respondents stating zero WTP corroborates previous studies conducted in the field of road pricing (Li and Hensher, 2012; Grisolía et al., 2015). A thorough analysis of the motivations underlying the refusal to contribute confirmed this reasoning. For either of the road safety improvement programs, there are three main reasons for refusal: "*I do not feel concerned by the safety program*", "*I don't have the financial means to contribute*", and "*The safety program looks impractical*". Note that these responses vary between the road safety programs. Most respondents stated "*not having the financial means for contribution*" for both the road safety programs. The proportion of participants unwilling to contribute to the fatal risk reduction program by lack of financial means is higher than the severe injury risk reduction program. The proportion of respondents stating the uselessness of road safety improvement programs is higher for severe injury risk reduction programs than for the fatal risk reduction program.

To further compare differences between WTP distributions for fatal and severe injury crash risk reductions, the kernel density plots of the stated WTP values are shown in Fig. 2. The following observations can be made. First, a two-sample Kolmogorov-Smirnov test suggests that the WTP for fatal and severe injury risk reduction programs is significantly different (p-value <0.001), implying significant heterogeneity in WTP. Second, a Levene's test suggests that the WTP for both risk reduction programs have an equal spread ($F_{345,\ 306}$ = 1.053, p-value >0.05), implying homogeneity (equality of variances) in WTP for two road safety programs. Third, in the case of fatal risk reduction, zero WTP proportion is lower than severe injury risk reduction. Fourth, the WTP values for both risk reduction types mainly lie in the lower range (below PKR 4000). Finally, the higher WTP values (i.e., above PKR 4000) are similar for both types of crash risk reduction, with a longer right tail (representing a higher upper range) for fatal crash risk reduction. For the positive contributions (above zero values), the Kolmogorov-Smirnov test and Levene's test indicate that the WTP for both the road safety

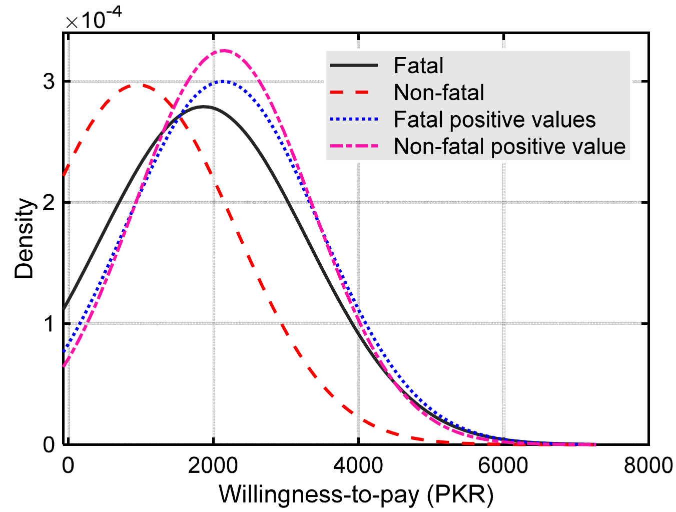

Fig. 2. Distribution of WTP values.

improvement programs follow the same distribution (p-value >0.05) and possess an equal spread ($F_{302,\ 136}$ = 0.0838, p-value >0.05), respectively, suggesting uniformity in WTP for their positive contributions in road safety programs.

4.2. Quantitative willingness-to-pay and values of risk reductions

Table 2 presents the mean WTP values for both crash risk reduction programs. A two-sample independent samples test suggests a statistically significant difference between the mean WTP for fatal and severe injury risk reductions (z-value = 8.384; p-value <0.001). On average, an individual is willing to contribute more (almost double) for fatal risk reduction than for severe injury risk reduction program. On the other hand, there is no statistical difference between the mean of the positive WTP (values above zero) for both road safety improvement programs (z-value = 0.076; p-value >0.05).

Individuals' WTP reflects their preferences for the reduction of the risk of either fatalities or severe injuries resulting from road traffic crashes. These values can be converted to the value of a fatal risk reduction (or value of a statistical life) and the value of a severe injury risk reduction (or value of a statistical severe injury) by dividing the WTP values for the road safety improvement programs with the corresponding risk reductions (i.e., 50% fatal or severe injury risk reductions). The estimated values of both fatal and severe injury risk reductions based on mean WTP values are presented in Table 2. On average, if each individual in the study area (Peshawar city) is willing to contribute PKR 1864 for a road safety project that will lessen road traffic fatalities into half, the total WTP for the population, i.e., the value of fatal risk reduction, is PKR 23.07 million (0.597 million purchasing

Table 2
Mean WTP and risk reduction values.

Crash risk reduction	Mean WTP	95% Confidence Interval	
		Lower	Upper
Fatal	1864	1713	2015
Severe injury	954	803	1105
Value of fatal risk reduction (in millions)[a]	23.065 (0.597)	21.194 (0.548)	24.935 (0.645)
Value of severe injury risk reduction (in millions)[a]	4.287 (0.111)	3.591 (0.093)	4.983 (0.129)

[a] Purchasing power parity or PPP$ in brackets; *Note: the value of (non-) fatal risk reduction is calculated by dividing the mean WTP with the corresponding risk reduction.*

power parity or PPP$). The WTP for severe injury risk reduction and the corresponding value of severe injury risk reduction can be interpreted similarly. Further, the value of fatal risk reduction is around five times higher than that of severe injury risk reduction, which is close to the estimates provided by previous studies (Svensson, 2009; Flügel et al., 2019) using the death-risk equivalent.

The values of risk reductions can be used to estimate the economic losses due to traffic crashes and to understand the extent of national road safety problems. These values can be used as benchmarks for selecting improved road safety measures/interventions. Further, the benefits obtained from reduced fatalities and severe injuries resulting from these crashes can be estimated using risk reduction values. This estimation will increase transparency in the cost-effectiveness and help in the efficacy and equity of safety-enhancing interventions in the transport sector.

4.3. Decision tree analysis

The first part of the proposed integrated modeling framework determines potential higher-order interaction effects that can be used in the model. As such, this study used a machine learning technique to obtain these interaction effects systematically. Using a Chi-Squared Automatic Interaction Detection algorithm (Ramotowski and Fitzgerald, 2020), a decision tree is constructed with several possible combinations and splits using chi-square tests with corresponding thresholds (p-value < 0.05). The input variables are respondents' sociodemographic, situational, and perception-related variables (shown in Table 1). To prevent overfitting, k-fold cross-validation is performed. The dataset is divided into ten unique subsets ($k = 10$). The tree structure is assessed using each subset of the data. Nine-tenths of the subset is utilized for training the decision tree, while the remaining subset is used to evaluate its performance. The decision tree accurately classified 75% of the cases using 55 terminal nodes (presented in Table 3) that serve as potential interaction effects to be included in the proposed modeling framework (Eq. (3)).

The decision tree classified the respondents' willingness (not) to contribute to the road safety improvement programs by segmenting the entire dataset into smaller, homogenous groups including 45 internal and 55 terminal nodes (see the decision tree diagram in Appendix B for corresponding statistics within each node). Each terminal node presents the statistics corresponding to the respondents' willingness (not) to contribute to road safety improvement programs. For instance, terminal node 10 implies that 100% of respondents presented with fatal risk reduction, having a higher risk perception of crash involvement, with a monthly travel cost of ≤ PKR 14699, stated income falling within the middle-income level range, and with a direct/indirect road traffic crash history are willing to contribute to road safety improvement programs. Terminal node 22 indicates that 50% of young respondents with a bachelor's degree, with no direct/indirect crash history, and presented with severe injury risk reduction are willing to pay and contribute to road safety improvement programs. All the other nodes can be interpreted similarly. These findings confirmed the clustering of the individuals based on their sociodemographic, perceptions, past experiences (crash history), and financial contribution towards road safety improvement programs (Pronello and Rappazzo, 2014).

Further, a decision tree pools the variables in an ordered manner such that the foremost variable is placed at the root of the tree. In this study, the type of risk (fatal and severe injury) reduction is the most significant factor in determining WTP and contribution towards road safety improvement programs, followed by the perceived risk of road traffic crash involvement (in case of fatal risk reduction) and crash history (in case of severe injury risk reduction). More specifically, given that an individual is presented with a deadly crash risk reduction program, the perceived risk of traffic crash involvement plays the next major role in their decision on a financial contribution to the road safety improvement programs. Similarly, for an individual presented with a

Table 3
Interaction effects obtained from the decision tree analysis.

No.	Description	WTP frequency	
		Yes	No
1	FRR, RP higher, and TC > 14699	156	0
2	FRR, RP higher, TC ≤ 14699, and high-income	38	0
3	FRR, RP higher, TC ≤ 14699, low-income, and female	2	2
4	FRR, RP higher, TC ≤ 14699, low-income, male, and above bachelor	2	0
5	FRR, RP higher, TC ≤ 14699, low-income, male, and bachelor	8	0
6	FRR, RP higher, TC ≤ 14699, low-income, male, intermediate, and with no crash history	2	1
7	FRR, RP higher, TC ≤ 14699, low-income, male, intermediate, and with crash history	6	0
8	FRR, RP higher, TC ≤ 14699, low-income, male, and matric	1	0
9	FRR, RP higher, TC ≤ 14699, middle-income, and with no crash history	5	7
10	FRR, RP higher, TC ≤ 14699, middle-income, and with crash history	5	0
11	FRR, RP lower, middle-aged, married, TC > 14699, and above bachelor or intermediate	10	0
12	FRR, RP lower, middle-aged, married, TC > 14699, and bachelor	6	1
13	FRR, RP lower, middle-aged, married, and TC ≤ 14699	23	0
14	FRR, RP lower, middle-aged, unmarried, and above bachelor or intermediate	2	0
15	FRR, RP lower, middle-aged, unmarried, and bachelor	1	1
16	FRR, RP lower, older or young, and high-income	8	0
17	FRR, RP lower, older or young, low-income, and with no crash history	8	11
18	FRR, RP lower, older or young, low-income, and with crash history	3	0
19	FRR, RP lower, older or young, middle-income, and employed	3	5
20	FRR, RP lower, older or young, middle-income, and unemployed	0	9
21	SIRR, middle-aged, above bachelor, and with no crash history	10	0
22	SIRR, young, above bachelor, and with no crash history	1	1
23	SIRR, RP higher, high-income, bachelor, and with no crash history	10	0
24	SIRR, RP higher, middle-aged, low-income, bachelor, and with no crash history	2	0
25	SIRR, RP higher, young, low-income, bachelor, and with no crash history	3	2
26	SIRR, RP higher, middle-aged, middle-income, bachelor, and with no crash history	0	3
27	SIRR, RP higher, older or young, middle-income, bachelor, and with no crash history	2	4
28	SIRR, RP lower, middle-aged, bachelor, and with no crash history	0	5
29	SIRR, RP lower, older, bachelor, and with no crash history	2	1
30	SIRR, RP lower, young, bachelor, and with no crash history	0	5
31	SIRR, RP higher, middle-aged, TC > 14699, intermediate, and with no crash history	2	0
32	SIRR, RP higher, older or young, TC > 14699, intermediate, and with no crash history	3	6
33	SIRR, RP higher, middle-aged or young, TC ≤ 14699, intermediate, and with no crash history	1	12
34	SIRR, RP higher, older, TC ≤ 14699, intermediate, employed, and with no crash history	3	2
35	SIRR, RP higher, older, TC ≤ 14699, intermediate, unemployed, and with no crash history	1	3
36	SIRR, RP lower, high-income, intermediate, and with no crash history	1	1
37	SIRR, RP lower, middle-aged, middle- or low-income, intermediate, and with no crash history	0	3
38	SIRR, RP lower, older, middle- or low-income, intermediate, and with no crash history	0	13
39	SIRR, RP lower, young, middle- or low-income, intermediate, and with no crash history	1	17
40	SIRR, RP higher, TC > 14699, matric, and with no crash history	4	5
41	SIRR, RP lower, TC > 14699, matric, and with no crash history	1	8
42	SIRR, TC ≤ 14699, high- or middle-income, matric, and with no crash history	0	42
43	SIRR, RP higher, TC ≤ 14699, low-income, matric, and with no crash history	1	1

(*continued on next page*)

Table 3 (*continued*)

No.	Description	WTP frequency	
		Yes	No
44	SIRR, RP lower, TC ≤ 14699, low-income, matric, and with no crash history	0	5
45	SIRR, RP higher, high-income, above bachelor, and with crash history	2	16
46	SIRR, RP higher, high-income, bachelor or intermediate or matric, and with crash history	34	0
47	SIRR, RP higher, TC > 14699, middle- or low-income, female, and with crash history	9	0
48	SIRR, RP higher, TC > 14699, middle- or low-income, male, and with crash history	16	3
49	SIRR, RP higher, middle-aged, TC ≤ 14699, middle- or low-income, and with crash history	4	0
50	SIRR, RP higher, older or young, TC ≤ 14699, middle- or low-income, and with crash history	5	6
51	SIRR, RP lower, middle-aged, TC > 14699, high- or middle-income, above bachelor or bachelor, and with crash history	2	2
52	SIRR, RP lower, older or young, TC > 14699, high- or middle-income, above bachelor or bachelor, and with crash history	0	3
53	SIRR, RP lower, TC > 14699, high- or middle-income, intermediate, or matric, and with crash history	2	0
54	SIRR, RP lower, TC ≤ 14699, high- or middle-income, and with crash history	0	4
55	SIRR, RP lower, low-income, and with crash history	2	0

Note: FRR: Fatal Risk Reduction; SIRR: Severe Injury Risk Reduction; TC: Travel Cost; RP: Risk Perception.

severe injury risk reduction program, the direct/indirect traffic crash history plays the next major role in determining their WTP decision and contribution to the road safety improvement programs. A similar interpretation can be made for all other variables in the decision tree. Such hierarchies indicate the common points in different groups of individuals, which can be helpful for policymakers in devising policies tailored to smaller and homogeneous groups (Pronello and Rappazzo, 2014).

4.4. Model comparison

The following four models are developed: a fixed parameters Tobit (FPT) model, an uncorrelated random parameters Tobit with heterogeneity-in-means (URPTHM) model, a correlated random parameters Tobit with heterogeneity-in-means (CRPTHM) model without interaction effects, and a CRPTHM model with interaction effects. A comparative analysis of these models is presented in Table 4, and some noteworthy observations are as follows. First, the random parameters Tobit models outperformed the fixed parameters model, as indicated by their lower AIC and higher Maddala Pseudo-R^2 values. In addition, the likelihood ratio tests confirmed the difference between these models (Table 4). Second, capturing the correlation between random parameters resulted in lower AIC and higher Maddala Pseudo-R^2 values as the correlated random parameters Tobit models outperformed its counterpart. Finally, likelihood ratio tests suggest that these models are not the same. A comparison of models with and without interactions is performed to validate further the inclusion of higher-order interactions in the developed model. The model with interaction effects resulted in lower AIC and higher Maddala Pseudo-R^2 than the model without interaction effects. Also, likelihood ratio tests suggest that these models are different. As such, this study selects a CRPTHM model considering interactions, which is further elaborated below.

Table 4
Model comparison and summary of statistical fits of the developed models.

Candidate model	*LL* (0)	*LL* ($\hat{\beta}$)	*df*	χ^2	AIC	Maddala pseudo-R^2
FPT model	−1122	−915	12	414	1854	0.469
URPTHM model	−1122	−801	16	642	1634	0.626
CRPTHM without interaction effects	−1122	−789	14	666	1606	0.639
CRPTHM with interaction effects	−1122	−758	17	728	1550	0.672

Comparisons (H_0 = models are equal)	*df*	χ^2	*p*-value	Remark
FPT model versus URPTHM model	4	228	<0.001	URPTHM model is superior
FPT model versus CRPTHM model	6	318	<0.001	CRPTHM model is superior
CRPTHM model versus URPTHM model	2	86	<0.001	CRPTHM model is superior
CRPTHM model with Interactions effects versus CRPTHM model without interactions effects	3	62	<0.001	CRPTHM model with Interactions effects is superior

4.5. Model interpretation

Table 5 presents the estimation results for the selected model fitted to the respondents' WTP and contribution to road safety improvement programs. The parameters for the dummy variables for the safe perception of road infrastructure and higher risk perception of crash involvement are random and normally distributed, which is aligned with previous studies (Fountas et al., 2019; Ali et al., 2020c). The fixed parameters in the model are travel cost, dummy variables for gender, young and older drivers, lower risk perception, risk type, trip purpose, and sole earner in the household. The final model is specified as

Table 5
Estimation results of the CRPTHM model.

Variable	estimate	*s.e.*	*z*-value	*p*-value	95% CI of estimated parameter	
					lower	upper
Non-random parameters						
Constant	−0.683	0.242	−2.82	0.005	–	–
Young drivers	−0.149	0.032	−4.66	<0.001	−0.212	−0.086
Older drivers	−0.377	0.111	−3.41	<0.001	−0.595	−0.159
Sole earner (= 1 if yes)	−0.040	0.012	−3.20	<0.001	−0.063	−0.017
Trip purpose (= 1 if work/study)	1.029	0.118	8.71	<0.001	0.798	1.260
Travel cost (in 1000 PKR)	0.070	0.009	7.31	<0.001	0.052	0.088
Risk type (= 1 if fatal)	0.461	0.107	4.31	<0.001	0.251	0.671
Lower RP	−0.279	0.085	−3.25	<0.001	−0.446	0.112
Interaction term 9	−1.464	0.179	−8.17	<0.001	−1.815	−1.113
Interaction term 29	2.311	0.185	10.89	<0.001	1.948	2.674
Interaction term 45	−0.846	0.129	−6.53	<0.001	−1.099	−0.593
Random parameters						
SPRI (mean)	−1.482	0.296	−5.01	<0.001	−2.062	−0.902
SPRI [SD]	1.113	0.350	3.17	<0.001	–	–
Higher RP (mean)	0.540	0.175	3.09	<0.001	0.197	0.883
Higher RP (SD)	0.849	0.100	8.49	<0.001	–	–
Heterogeneity in mean of SPRI						
Female	0.760	0.288	2.64	0.008	0.195	1.325

LL ($\hat{\beta}$) = −758; *LL* (0) = −1122; Likelihood ratio = 728 (*p*-value <0.001); Sigma: 0.947 (*p*-value <0.001); Maddala pseudo-R^2 = 0.672; AIC = 1550; No. of observations = 653.

$$WTP = -0.683$$
$$-0.149 \times young\ drivers - 0.377 \times old\ drivers - 0.040 \times sole\ earner$$
$$+1.029 \times compelling\ trip + 0.070 \times travel\ cost$$
$$-\beta_{SPRI} \times SPRI - 0.279 \times lower\ risk\ perception + \beta_{HRP} \times higher\ risk\ perception$$
$$+0.461 \times fatal\ risk$$
$$-1.464 \times interaction\ term\ 9 + 2.311 \times interaction\ term\ 29 - 0.846 \times interaction\ term\ 45 \quad (10)$$

where, the first three lines, respectively, contain the constant, socio-demographic, and travel-related variables. The fourth line indicates the perception-related variables (i.e., perception of road infrastructure and crash involvement). Similarly, the fifth line indicates the presented risk reduction scenario (type of risk), while the sixth line indicates the interaction terms in the model obtained from the decision tree. The correlation structure between the random parameters can be specified as

$$\begin{pmatrix} \beta_{SPRI} \\ \beta_{HRP} \end{pmatrix} = \begin{pmatrix} -1.482 \\ 0.540 \end{pmatrix} + \begin{pmatrix} 0.760 \\ 0 \end{pmatrix} \times Female + \begin{pmatrix} 1.0129 & 0 \\ -0.335 & 0.781 \end{pmatrix} \begin{pmatrix} \varphi_{SPRI} \\ \varphi_{HRP} \end{pmatrix} \quad (11)$$

where, φ_{SPRI} and φ_{HRP} are the independent standard normally distributed random variables.

4.5.1. Main effects

The model suggests that dummy variables related to age groups are significantly associated with WTP for improved road safety. Compared to middle-aged drivers, young and older drivers have a lower propensity for WTP for road safety improvement programs. Further, WTP is significantly lower for individuals who stated themselves to be the sole earners in their households compared to their counterparts. The negative and significant coefficient of lower risk perception suggests that respondents with a lower perceived risk of traffic crash involvement are less willing to pay and contribute to road safety improvement programs.

Trip purpose and *travel cost* are significantly associated with WTP for improved road safety. Individuals who travel for work/study are willing to contribute more than those who travel for recreational reasons. Similarly, travel cost increases the respondents' WTP for road safety improvement programs. A similar interpretation can be made for other main effects in the model (Table 5).

4.5.2. Interaction effects

The developed model also includes three interaction terms (Table 5). *Interaction term 9* reveals that more than 50% of middle-income people whose monthly travel cost is ≤ PKR 14699, have a higher perceived risk of traffic crash involvement, have no (direct/indirect) traffic crash history, and are presented with fatal risk reduction are less likelier to contribute to road safety improvement programs. *Interaction term 29* suggests that two-third of the older individuals having an education level up to bachelor, with a lower risk perception of road crash involvement, with no direct/indirect traffic crash history, and presented with severe injury risk reduction are more willing to contribute to the road safety improvement program. Similarly, *interaction term 45* shows that about 89% of individuals with high-income levels, having an education level up to bachelor or above, with a higher risk perception of traffic crash involvement, with a direct/indirect traffic crash history, and presented with severe injury risk reduction are less willing to financially contribute to the road safety improvement program. These interaction effects explain heterogeneity in preferences of individuals belonging to different groups and indicate the complex relationships between observable characteristics that are typically poorly understood. Further, including higher-order interactions in the model provides micro-level information about WTP, which is otherwise not accounted for by traditional models with main effects only (Boxall and Adamowicz, 2002).

Further, the higher-order interaction effects identified significant associations of explanatory variables with WTP, whose main effects are insignificant in the final model. For example, none of the main effects of the dummy variables related to education groups is significant in the model. However, the effects of education are evident in the model through higher-order interaction terms (29 and 45). Similarly, the dummy variable for crash history is not a significant main effect in the model. At the same time, its impact is evident in the model through three higher-order interaction effects (interaction terms 9, 29, and 45). This finding reflects one of the advantages of using higher-order interactions: when the main effects are insignificant in the model, their effects can be implicitly captured through higher-order interactions.

The parsimonious model includes only three significant interaction effects. The significance of these interaction effects in the developed model implies that the relationship between WTP and interactive effects of explanatory variables exists and is evident in the model. Whereas for all other interaction effects, although their relationship with WTP exists (as illustrated by the decision tree analysis), the Tobit model failed to capture that relationship due to several reasons, such as small sample size, implicitly capturing that effect by other variables, and main effects are dominant in the model. Nevertheless, these interaction effects indicate critical theoretical aspects of the relationship between WTP and explanatory variables.

4.5.3. Unobserved heterogeneity

Table 5 reveals statistically significant mean and standard deviation of the *safe perception of road infrastructure*. The distribution of the coefficients of the safe perception of road infrastructure variable (Fig. 3 (a)) suggests significant heterogeneity in respondents' WTP for improved road safety. More specifically, WTP is lower for most respondents (95%), while higher for the rest, reflecting a non-monotonous attitude towards WTP for individuals having a safe perception of road infrastructure; this difference is found to be statistically significant as indicated by a paired t-test (t-statistics = 17.15, p-value <0.001). This finding implies that there are two groups of people who perceive the road infrastructure to be safe for traveling: one who are not/less willing to contribute to road safety improvement programs and one who are more inclined to contribute to them compared with individuals having an unsafe perception of road infrastructure. These two WTP behaviors can be explained as follows. Some respondents, who perceive the road infrastructure and overall travel to be safe, may consider the road infrastructure to play a less significant role in crash occurrence. As such, they contribute less to road safety improvement programs than those who perceive road infrastructure as unsafe. While others, who also perceive the existing road infrastructure to be safe, may still consider the road infrastructure to play a significant role in crash occurrence due to other unobserved factors. Therefore, these individuals are willing to contribute more to road safety improvement programs than their counterparts. A possible reason for the lower WTP of the first group of respondents might be that these individuals are more confident about their driving and are not concerned about the road infrastructure. As such, they consider avoiding crash involvement by driving safely on the existing (safe) road infrastructure.

The mean and standard deviation of the *higher risk perception* are also statistically significant (Table 5), indicating substantial heterogeneity in WTP for respondents having a higher perceived risk of a traffic crash involvement. As evident in Fig. 3 (b), the stated WTP is higher for some respondents (75%), but not for all. The positive coefficient of the higher risk perception suggests that the WTP is higher for individuals with a higher perceived risk of crash involvement, which is intuitive and aligned with previous studies (Haddak et al., 2016). Some individuals

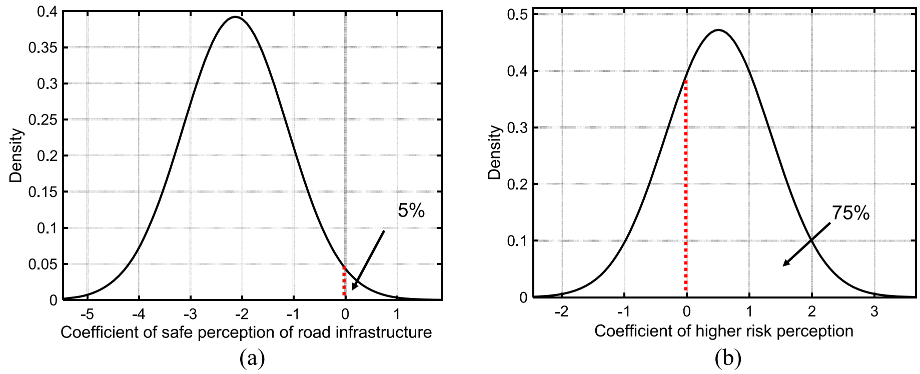

Fig. 3. Distribution of coefficients of random parameters. *Note that these distributions are obtained by fixing one of the two random parameters at its mean.*

with higher risk perception want to contribute more to road safety improvement programs to reduce their risk of crash involvement. While others, having the same higher level of risk perception, perhaps adopt safe driving behavior by themselves to reduce their risk of crash involvement and, therefore, are willing to contribute less to road safety improvement programs.

We also find that the parameter for the safe perception of existing road infrastructure has a significantly heterogeneous mean across observations, and the mean value is mainly related to *gender* (Table 5). This result indicates that compared to males, females reveal a higher WTP to travel on safer road infrastructure.

Further, the correlation between statistically significant random parameters is tested by the post-estimation technique proposed by Fountas et al. (2018). Table 6 presents the variance–covariance matrix results, correlation, and statistical analysis. Results indicate a significant correlation (−0.394) between the *safe perception of road infrastructure* and *higher risk perception* parameters (t-stats = 4.04; p-value <0.001) with a covariance of −0.339. The correlation between the random parameters uncovers the unobserved heterogeneity associated with the interactive effects of random parameters. The negative correlation between the random parameters implies a heterogeneous effect of unobserved characteristics on WTP for improved road safety. In other words, a safe perception of road infrastructure may decrease or increase the respondents' WTP and contribution to road safety improvement programs because of its unobserved heterogeneity associated with a higher perceived risk of crash involvement.

5. Discussion

Many developing countries face devastating social and economic effects due to the number of road crashes and injuries registered. Therefore, there is a need to support policy development and the allocation of resources to increase road safety with the community's support. In most developing countries, the prioritization of different road safety investments and consequent projects is based on cost-benefit analysis. This analysis often does not account for the multidimensional cost of road crashes due to the lack of quality data (e.g., social cost). Therefore, this study estimates public willingness-to-pay (WTP) for road safety improvement to be used in road safety appraisals in a country by considering the end users' perceptions of such a solution. A crucial benefit of this approach is that it can help reduce policy resistance, which has long been identified as a critical problem that reduces the effectiveness of road safety policy (Salmon et al., 2020).

Table 6
Variance–covariance matrix (t-stats in parentheses), and correlation coefficients [in square brackets] for the correlated random parameters.

Variable	Bid level	Subjective risk
Bid level	1.026 (2.47) [1.00]	–
Subjective risk	−0.339 (4.04) [-0.394]	0.722 (3.29) [1.00]

WTP is often modeled using various techniques, and several studies can be found in the literature in this direction. These studies, however, suffer from two major problems: ignoring higher-order interactions and monotonous WTP outcomes. Therefore, this problem is addressed in the present study by employing an integrated modeling framework comprised of machine learning and correlated random parameters Tobit with the heterogeneity-in-means (CRPTHM) model. The developed model identified significant higher-order interactions from the decision tree, which are discussed below.

5.1. Insights from higher-order interactions

Higher-order interactions heuristically provide information about unknown and complex relationships of explanatory variables with WTP. The different interaction effects in Table 5 detected the presence of systematic heterogeneity (Grisolía et al., 2015) in individuals' preferences for road safety improvement by estimating other specifications among the respondents' characteristics (i.e., socioeconomics, perception, and situational variables). Further, as different individuals' groups have different attitudes and opinions towards road pricing policies (Pronello and Rappazzo, 2014), the higher-order interactions provide micro-level information about the willingness of smaller groups, revealing the sensitivity of different and smaller cohorts on WTP. For example, the model results in Table 5 indicate that the separate impacts of income and higher risk perception on WTP are positive. However, as depicted in interaction term 45, the simultaneous effect of these variables on the probability of WTP is negative, implying that the effects of higher risk perception and personal income depend on the type of risk reduction. The negative parameter for the interaction term reveals that the impact of the kind of risk reduction on WTP is more prominent than that of personal income and higher perceived risk of accident involvement. This relationship shows that individuals in this group are more concerned about the type of risk reduction. Similarly, the negative parameter for interaction term 9 shows that a decrease in travel cost is negatively associated with WTP for respondents with higher risk perception of crash involvement and presented with a fatal risk reduction program. Lower travel cost indicates lesser traveling, reflecting lower traffic exposure and reduced probability of traffic accident involvement. Therefore, the negative parameter for this interaction term reveals that individuals in this group are more concerned about travel costs. Table 5 further shows that the separate impacts of the older age group, severe injury risk reduction, and lower risk perception on WTP are negative. However, the positive parameter for interaction term 29 reveals that the simultaneous impact of these variables combined with education (bachelor degree) on WTP is positive. This positive parameter implies that individuals with a bachelor degree are more willing to contribute to road safety improvement.

Individuals' WTP can be seen as the outcome of a decision process characterized by many interactions among different characteristics. Our integrated approach highlights the importance of modeling interactions by considering these characteristics in the form of interactions. From a perspective of policy implications, these results are much more informative as they can reveal additional insights into the complex relationship of WTP for road safety measures with its determinants. As policymakers are interested in framing policies for a target group (which is often a smaller cohort rather entire population, e.g., young male individuals with a bachelor's degree and high-risk perception compared to male individuals or young individuals) (Gehlert et al., 2011; Pronello and Rappazzo, 2014), interaction effects provide micro-level information to assist such initiatives. Understanding if and how individuals' WTP varies based on their sociodemographic, travel characteristics, and overall perceptions has implications for devising different road safety policy measures tailored to other cohorts. These interactions provide a more realistic insight into individuals' decisions to contribute financially to road safety improvement programs. The segmentation of the population provides input for the analysis of distributive issue, which arises from a new policy intervention (Anciaes et al., 2018). Many people in developing countries are not willing to contribute to government programs because of unawareness of the benefits of such programs. In this context, the decision tree analysis identified different groups of people who are (not) willing to contribute to road safety policies. Such information will help the policymakers to initiate road safety campaigns and design policies so that specific groups who are more likely to be unwilling to pay for road safety improvement programs understand the intentions and benefits of such policies. In general, adding interaction effects during the model development process greatly (i) expands the understanding of the non-linear relationships among the variables in the model, which is not considered in previous studies on WTP for improved road traffic safety, (ii) provides insights at a micro level and for smaller cohorts that are often overlooked, (iii) increases the model fit significantly (see Table 4), and (iv) impacts marginal impacts and corresponding interpretation (see Table 7 and Section 5.2).

The developed model can be applied to understand the effects of different determinants on WTP, as elaborated below.

5.2. Marginal effects of estimated parameters

The marginal effect of each variable on WTP is calculated using the partial derivative of WTP concerning that variable. For the variables with more than two categories (*age* in our case), the changes are computed based on category change from 0 to 1. In contrast, the other categories of this variable are fixed at 0 and all other variables at their mean values. For instance, the marginal effect of the *travel cost* on WTP is calculated by increasing its mean value by one percent while keeping all the other variables at their mean values (continuous variables) and reference categories (binary variables). Table 7 shows marginal effects reflecting the marginal change in the probability of being willing to pay and the expected value of the WTP conditioned on the change in a specific explanatory variable, keeping other variables constant. Although the following subsections describe marginal effects to understand WTP for different explanatory variables, the overall impact of considering interaction effects in the model on marginal effects is summarized below.

Table 7
Marginal effects of the model parameters.

Variable	With interaction effects		Without interaction effects	
	Zero sensitivity (%)[a]	Expected value sensitivity[b]	Zero sensitivity (%)[a]	Expected value sensitivity[b]
Female	6.87	−522.04	2.93	−911.15
Young drivers	−1.35	102.15	−0.96	298.16
Older drivers	−3.41	259.01	−0.30	934.73
Sole earner (= 1 if yes)	−0.04	2.72	−0.10	31.84
Trip purpose (= 1 if work/ study)	9.31	−707.09	9.40	−2923.37
Travel cost (in 1000 PKR)	0.63	−47.67	0.68	−210.67
Lower risk perception	−2.52	191.51	−1.03	321.76
Higher risk perception	4.89	−370.95	5.27	−1638.02
Safe perception of road infrastructure	−13.41	1018.20	−7.82	2432.21
Risk type (= 1 if fatal)	4.17	−316.64	4.04	−1257.67

[a] Change in the probability of being willing to pay (categorical WTP).
[b] Change in the expected value of WTP (quantitative WTP).

As shown in Table 7, the marginal effects of explanatory variables on the probability of being willing to pay and the expected value of WTP changed drastically when interaction effects were not considered in the model. Table 7 shows that, on average and without interaction effects, the WTP probability for females, compared to males, decreased from 6.87% to 2.93%. Also, their WTP difference is increased from PKR 655 to PKR 911. Although there is no ground truth to compare which is correct, this change in magnitude per se indicates the effects of interactions on the model output. Further, the zero value sensitivity for young and older individuals decreased from −1.35% and −3.41% to −0.96% and −0.30%, respectively. However, their expected value sensitivities increased from PKR 102 and PKR 259 to PKR 298 and PKR 935, respectively. The zero sensitivity for the travel cost is slightly increased, while a higher difference is observed in the expected value sensitivity. Similarly, the zero and expected value sensitivities are changed for other variables when interaction effects are omitted from the model, reflecting the impact of missing the interaction effects from the model.

5.2.1. Impact of sociodemographic on willingness-to-pay

The categorical WTP probability for females is 6.87% higher than for males. Females are more likely to pay, as observed in this study and other WTP studies (Haddak et al., 2016; Mon et al., 2019). Females are generally less likely to involve in risky behaviors (Oviedo-Trespalacios and Scott-Parker, 2018). Consequently, females could have less tolerance for risky behaviors, resulting in a higher perceived risk of traffic crash involvement and a higher willingness to support road safety improvement (Subhan et al., 2021). However, regarding the quantitative WTP, females have a lower WTP value than males. Among the individuals willing to pay for road safety improvement, the average contribution for females is PKR 522 less than that of males. This finding is aligned with a study on WTP for safety improvement in road transport (Svensson, 2009) that found a negative marginal effect of gender (female) on WTP. The difference in the signs of the zero and expected value sensitivities show that females are more willing to contribute to road safety improvement program than males. However, their average contribution is quantitatively less than those males willing to contribute.

Both *young* and *older* individuals are less willing to contribute to road safety improvement programs compared to middle-aged individuals, with about 1.35% and 3.41% lower probabilities of being willing to pay, respectively. These findings suggest that a lower proportion of young and older individuals are willing to contribute than middle-aged ones. These findings align with a study on WTP for improved road safety (Bhattacharya et al., 2007) that found a lower propensity of being willing to pay for young and older individuals. Young individuals possess a lower risk perception of traffic crash involvement (Delhomme et al., 2009), contributing to road safety improvement (Subhan et al., 2021). Similarly, many older individuals make fewer trips and are more cost-aware (Dominy and Kempson, 2006). As a result, older people may not consider road pricing an effective solution (Nikitas, 2010). However, their contributions in quantitative WTP are higher than that of middle-aged individuals (Table 7), suggesting that younger and older individuals willing to contribute to road safety improvement programs stated higher WTP values. Table 7 shows that the average contributions for young and older individuals, who are willing to contribute, are respectively PKR 102 and PKR 259 higher than that of middle-aged individuals. This behavior can be explained as follows. First, young individuals consider road pricing for safety improvement fair and are inclined to pay more, which is observed in this study. Second, older individuals have a higher perceived risk and a more positive attitude toward road safety (Subhan et al., 2021). Thus, they are more willing to contribute to road safety solutions. These observations and findings are consistent with other studies on WTP for improved road safety (Andersson, 2007; Mofadal et al., 2015). The difference between zero and expected value sensitivities shows that young and older individuals are less willing to contribute. However, those young and older individuals willing to contribute to the road safety improvement program stated higher WTP values.

People who indicated themselves as the household's sole earners are less willing to pay (participate) for improved road safety (Table 7). This finding aligns with studies on WTP for safety improvements in road transport (Bhattacharya et al., 2007). WTP is proportional to budget constraints (Smith and Richardson, 2005). People who are sole earners in the household have more financial responsibilities (due to the increased number of dependents (Bhattacharya et al., 2007)) and are more cost-aware than those with additional earners. They are less willing to participate in road safety improvement programs. On the contrary, those sole earners willing to participate in road safety improvement programs stated a higher quantitative WTP than their counterparts.

5.2.2. Impact of travel characteristics on willingness-to-pay

Individuals who travel for work/study have a higher propensity (9.3%) to pay and contribute to road safety improvement programs (categorical WTP) than those traveling for other reasons (shopping, leisure, visits, etc.). The work/study related travelers often travel more than recreational travelers, increasing their exposure to traffic and the risk of a crash. On the other hand, work/study related travelers are willing to pay less (quantitative WTP) than recreational travelers. On average, individuals who travel for work/study are willing to pay PKR 707 less than recreational travelers. Work related travelers are more cost aware and are therefore unwilling to contribute more. The opposite signs of zero and expected value sensitivities show that people who travel for work/study are more willing to participate in road safety improvement programs; however, their average quantitative contribution is less than their counterparts. These findings align with previous studies on WTP for improved road safety (Haddak et al., 2016) that found higher participation (categorical WTP) and lower quantitative WTP for road safety improvement for people who travel for work/study.

The probability of participation in road safety improvement programs increases with travel cost (probability increases by 0.63% with every 1% increase in travel cost). This is aligned with previous studies that found a positive impact of *travel cost* (proxied by travel time and exposure to traffic) on the probability of being willing to pay (Bhattacharya et al., 2007). However, results show a negative marginal effect of the travel cost on the quantitative WTP when other variables in the model are controlled. The respondents' WTP decreases by approximately 0.05 units (PKR) with every one unit increase in the monthly travel cost. This is in line with previous studies that found a negative association of *travel cost* (proxied by travel distance) with the acceptability of road pricing (Milenković et al., 2019). A higher travel cost indicates higher traveling, which can be indirectly linked to a more substantial driving experience. Drivers with higher experience are often confident about their driving and make safer decisions, thereby considering themselves as a safer component of the traffic stream (Ali et al., 2018). As such, these drivers assume that crash involvement is less likely to occur because they drive in a safer manner and are less likely to pay for road safety improvements.

A higher propensity (4.2%) of being willing to contribute (categorical WTP) and lower quantitative WTP is observed for individuals with fatal risk reduction compared to those with severe injury risk reduction. Further, higher and lower categorical and quantitative WTP are observed for people with higher and lower risk perception of traffic crash involvement and who have a safe perception of existing road infrastructure.

5.3. Comparison of risk reduction values

The risk reductions (both fatal and severe injury) values are calculated by averaging the corresponding WTP values across the population in the study area and dividing them by the respective risk reductions. This study estimated a value of fatal risk reduction from car drivers' road traffic crashes in Pakistan in 2021 at approximately 597,000 PPP$. For the value of severe injury risk reduction, it is 121,000 PPP$. Previous studies directly compared the values of risk reductions across countries with varying income levels (Jomnonkwao et al., 2021), indicating high values for high-income countries. WTP for road traffic safety improvement in each country depends on numerous factors, such as individuals' characteristics and their experiences, roadway characteristics and geometrics, per capita gross national income (GNI) (Niroomand and Jenkins, 2016), road user group (Flügel et al., 2019), and the magnitude of the risk reduction as well (Lindhjem et al., 2011). Further, it has been found that the income elasticity of risk reduction value is greater than 1 in lower-income countries (Milligan et al., 2014), implying that the value of risk reduction is a luxury good. A higher degree of risk reduction in a given community generally indicates higher values for the income elasticity of the risk reduction valuation (Andersson and Treich, 2011). Therefore, a lower risk reduction value in a community indicates that the individuals possess a lower degree of risk reduction. Consequently, it is essential to compare the normalized values of the same group of road users for countries with varying levels of development. Also, as non-fatal injuries have different definitions in different studies, most studies evaluate fatal risk reduction; therefore, using the values of fatal risk reduction for comparison across countries is suggested. Table 8 compares the values of fatal risk reduction for car drivers (same group of road users) across countries with different developmental levels and cultures. The countries' fatal risk reduction values were normalized based on GNI per capita in the respective years. The value for fatal risk reduction in Pakistan is lower than in many high- and middle-income countries. However, this value is higher after normalizing with the gross national income per capita.

5.4. Policy and practice implications

Valuing traffic crash risk reductions is a fundamental step in evaluating transport infrastructure and management projects, thereby valuable for policy formulation and decision-making. The estimated values of risk (both fatal and severe injury) reductions can be used in cost-benefit analysis of road safety appraisals in the country. These values can also be used as a benchmark to signify the benefits of preventing casualties from road traffic crashes in a road environment. Meanwhile, road authorities can allocate more budgets to improve road safety by evaluating the societal losses from road traffic casualties using the estimated risk reduction values. The findings of this study are helpful for policymakers for (i) evaluating the impact of road traffic crashes, (ii) allocating budgets, (iii) devising road safety improvement policies, and (iv) designing a possible tax for road safety improvement in the country.

Factors associated with WTP would assist in targeted public education and eliciting their support for road safety improvement programs. Further, disaggregated findings of this study are expected to provide project-specific inputs to initiate road safety campaigns. As individuals' attitudes towards road pricing vary with their overall characteristics (Odeck and Kjerkreit, 2010), the study findings will help determine specific groups of individuals likely to participate in improved road

Table 8
International comparison of values of fatal risk reduction.

Study	Country	Income Level	GDP	GNI per Capita	User Group	VFRR	VFRR/GNI
Mon et al. (2019)	Myanmar	Middle	327.63	4770	Car drivers	496,582	104.11
Flügel et al. (2019)	Norway	High	357.94	70,330	Car drivers	5,850,000	83.18
Hensher et al. (2009)	Australia	High	715.23	38,900	Car drivers	4,389,369	112.84
Rizzi and Ortúzar (2003)	Chile	Middle	124.25	10,180	Car drivers	1,271,184	124.87
Current study	Pakistan	Middle	1370	4710	Car drivers	597,000	126.75

VFRR: value of fatal risk reduction (PPP$); GDP in billion PPPS; GNI per capita in PPPS.

traffic safety. Additionally, identifying those groups that are disenfranchised can support the development of targeted educational initiatives that help them reduce resistance and increase support for road safety policies. Potentially, people with a lower willingness to pay lack a complete understanding of the impact of traffic crashes in society. Therefore, to increase public financial support for road safety improvement, road authorities should initiate more road safety campaigns to increase safety awareness by targeting specific road user groups from this study.

6. Conclusions and future research directions

This study proposed an integrated modeling framework of a decision tree and a correlated random parameters Tobit with heterogeneity-in-means (CRPTHM) model to investigate public willingness-to-pay (WTP) for road safety improvement. Using the proposed framework, this study estimated the values of fatal and severe injury risk reductions for Pakistan in road transport using a WTP approach. Data related to individuals' WTP and financial contributions to a road safety improvement program were obtained through face-to-face interviews using a stated preference contingent valuation payment card method. A decision tree algorithm was used to detect systematic heterogeneity in preferences for improved road safety across respondents by identifying potential higher-order interactions among explanatory variables. The CRPTHM model captured unobserved heterogeneity and the correlation between random parameters.

The developed model accounted for unobserved heterogeneity associated with WTP and the interactive effects of unobserved characteristics. Model results revealed that while most respondents who perceive a higher risk of traffic crash involvement were more willing to pay and contribute to the road safety improvement program, a class of respondents was less inclined to financially contribute. Results also suggest that a higher proportion of respondents with a safe perception of existing road infrastructure was less willing to pay. However, a small proportion of respondents with a similar perception was willing to contribute more to road safety improvement programs. Further, it was found that the mutually dependent unobserved characteristics uncovered by the two random parameters have heterogeneous effects on WTP. A safer perception of existing road infrastructure may increase or decrease the respondents' WTP for improved road safety because of its unobserved heterogeneity associated with a higher perceived risk of traffic crash involvement. The model also indicated that the heterogeneity in WTP is associated with gender, as females were more willing to pay than males. Further, variables such as sociodemographic (gender, age, and sole earner), travel characteristics (trip purpose and travel cost), perception of the existing road infrastructure and crash involvement, and the type of risk reduction were also significantly associated with WTP. In addition, the marginal effects of explanatory variables on the categorical WTP and the quantitative WTP revealed different possibilities of WTP.

WTP for fatal and severe injury risk reductions was estimated for Pakistan as the economic damages of a fatality and a severe injury. The higher value of fatal risk reduction than severe injury risk reduction ruled out scope bias. These findings can help in the policymaking process by providing information on road crash risk reduction valuation strategies. The estimated values of road crash risk reductions can be used as a benchmark for prioritizing road safety interventions in the country. Such information will be helpful in the decision-making process for allocating budgets and devising policies for improving road traffic safety in the country.

The study employed a decision tree to systematically obtain higher-order interactions that can significantly impact WTP and heuristically provide information about unknown relationships. Higher-order interaction effects indicate complexity in the relationships between individuals' WTP and drivers' age, education level, income, travel cost, risk perception, risk type, and crash history. The interaction effects provided insights into the relative importance of and interaction between/among the variables. The exchanges accounted for the higher-order interaction effects, which ultimately prevents over- or under-estimating the econometric model. In this study, the interaction effects segmented the road users into different groups and revealed their sensitivities toward WTP. This segmentation is particularly useful and interesting in the context of road safety policies, where decisions are taken into consideration by other groups of road users, as different individuals can have different opinions. Although the decision tree analysis employed in this study systematically obtained higher-order interactions, future research is needed to consider more complex interactions of respondents' sociodemographic, travel characteristics, and perceptions. Due to their insignificant impact, many potential interactions were excluded (except for three exchanges) from the final model. A possible reason for such insignificance could be that other explanatory variables in the model may implicitly capture the effect of these variables. Although our sample size is significantly larger than the minimum sample size required in this study (~385, see the calculations in Smith (2013)), we believe that a bigger sample size would provide more insights into public WTP.

The proposed framework is flexible, not country-specific, and can be applied to any country, and as a case study of its application, the findings obtained for Pakistan are presented. Further, with some adjustments to regional conditions, the transferability of findings to other developing countries with similar economic levels, socioeconomic characteristics, road users' attitude towards traffic safety improvement, roadway characteristics, and driving conditions is possible. However, one needs to re-estimate the model with new data and accordingly discussions can be made. The study presents an alternative approach for developing countries to devise road safety policies and estimate public WTP for enhanced road safety. It should also be noted that the results of this study indeed seem to be transferable to other developing countries; however, it is important to take local characteristics and social backgrounds into account when devising road safety policies based on public financing in developing countries. Before inferring the WTP relationship, the framework needs to be re-calibrated with new data. Finally, this study only focuses on car drivers, while other road users are not considered in the analysis. Because road users have different perceptions and attitudes towards road safety and its improvement, other road users should be included in future research.

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Fazle Subhan: Conceptualization, Methodology, Data collection, Formal analysis, Writing – original draft, Visualization. **Yasir Ali:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Shengchuan Zhao:** Conceptualization, Methodology, Visualization, Writing – review & editing, Supervision. **Oscar Oviedo-Trespalacios:** Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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