Injury

How Mode of Evacuation, Roadway Environment, and Traffic Conditions Relate to Injury Severity Score? Untangling the Role of Pre-hospital Time in Road Crashes

--Manuscript Draft--

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Abstract:	This study explores the effects of some of the key factors including emergency response measures, roadway and environment, traffic-related attributes, and crash-specific factors on the Injury Severity Score (ISS) of Road Traffic Crashes (RTCs) victims, both directly and through pre-hospital time (PHT) using rigorous path analysis. Data for 298,654 crashes, compiled by the Road Traffic Injury Research and Prevention Center (RTIRPC) in Karachi (Pakistan) was used for analyses. Owing to the corner-solution distribution of the response variables (PHT and ISS), two Tobit regression models are estimated after accounting for missing values through synthetic data generation. Marginal effects from these models are used in the path analysis. The findings suggest that ISS increases by 0.01 units with a unit increase in PHT, highlighting the critical need for rapid evacuation of crash victims to medical facilities. The mode of evacuation emerged as a crucial factor, with ambulances resulting in increased PHT and ISS compared to private or public transport, underscoring the improvement needed in the dedicated ambulance-based emergency response. PHT and ISS were found to be higher in nighttime crashes, necessitating better emergency medical services (EMS) response during the night. Intersection crashes were associated with lower PHT and ISS; whereas, crashes on undivided roads and those involving multiple or large vehicles increased PHT and ISS. The path analysis revealed that the overall effects of some of the key variables on ISS were higher than their direct effects – something that could not be explored without the path analysis. These insights can help policymakers develop strategies to improve emergency response and road safety, ultimately reducing the number of RTC-related injuries and fatalities.
Response to Reviewers:	Peter V Giannoudis, MD, FACS, FRCS Editor-in-Chief Injury Dear Peter V Giannoudis, We greatly appreciate the opportunity to submit a revised manuscript titled “How Mode of Evacuation, Roadway Environment, and Traffic Conditions Relate to Injury Severity Score? Untangling the Role of Pre-hospital Time in Road Crashes” for publication in the Journal of Injury. We have addressed the comments by the reviewers in the revised manuscript. In response to the comments, the revised paper has been enhanced through: •Better articulating and shrinking the introduction section (Reviewer 3) •Reducing the redundant texts in the literature review section (Reviewer 3) •Squeezing the methods section (specifically reducing the data cleaning portion) to make it more concise (Reviewer 3) •Modifying and better articulating the results section, especially the results for the two

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Point-by-point responses to each reviewer's comments are provided below. Revisions are colored red in the revised paper, and all pages, sections, tables, and figure numbers in our responses refer to the revised manuscript.
By responding to the reviewers' constructive comments and questions through the course of our revision, we believe we have produced an even stronger paper.
We sincerely appreciate you handling this paper.
Please feel free to contact us. Thank you.

EDITOR AND REVIEWER COMMENTS

Reviewer #1

After reading and studying the article, it is clear to me that the authors are not medical professionals. However, I believe that the article is extremely thorough and well-written in all its segments. I particularly like how they presented an overview of the literature published so far. For a large part of the written text, and especially the mathematical formulas presented, I am not qualified and competent enough to evaluate them. This is because I am not a civil engineer or mathematician to thoroughly analyze the written formulas and figures.
But still, I think that the paper is absolutely well written and that in this form as it is written, it is completely adequate for publication. The only thing I do not know is whether Injury, as a medical journal, is the best solution for publishing an article of this content, but there are certainly links to the medical profession in it. The assessment of whether the article is suitable for publication in Injury or not; or whether this article is "medical" enough or not, will ultimately be decided by the editor-in-chief.

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Reviewer #2

The incidence of traffic accidents has been increasing, especially in low-income countries. The method of rescuing victims is not always optimal, which can lead to a worsening of the patient's condition. The parameters analyzed in the study are interesting and can be addressed to improve rescue conditions for victims.

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Reviewer #3

Overview: This submission presents valuable insights into a significant issue, but it requires refinement to enhance clarity and focus.

Response: We appreciate the reviewer for his/her valuable input and the time spent reviewing our manuscript. In response, we have put sincere efforts to refine the manuscript to improve the readability and focus. A detailed point-by-point response to each of the reviewer's comments can be seen below. Please note that revisions are colored red in the revised paper, where the content was modified to shrink the content. Furthermore, some contents in several sections were removed to reduce the text and enhance clarity and focus.

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Literature Review: There is no need for a comprehensive literature review; this can be seamlessly integrated into the discussion section. It is important to remember that this is not a thesis.

Response: Point well taken – we reduced the literature review section by 338 words (from 1,284 to 946 words) in light of the reviewer’s comment.

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Discussion: The Discussion is also too lengthy and should be limited to two pages at most while remaining concise.

Response: For conciseness and brevity, we have reduced the Discussion section by 265 (from 1,619 to 1,354) words, to cover it in a maximum of two pages. Since the Discussion section is the core of the manuscript, only redundant and/or less vital content was excluded, whereas all critical details was cautiously maintained.

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Manuscript Number: JINJ-D-24-02294

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Dear Dr. Ahmad,

Thank you for submitting your manuscript to Injury.

I have completed my evaluation of your manuscript. The reviewers recommend reconsideration of your manuscript following major revision.

I invite you to resubmit your manuscript after addressing the comments below. Please resubmit your revised manuscript by 23 Jul 2025.

When revising your manuscript, please consider all issues mentioned in the reviewers' comments carefully: please outline every change made in response to their comments and provide suitable rebuttals for any comments not addressed.

Injury values your contribution and I look forward to receiving your revised manuscript.

Kind regards,

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Response to Review Comments on Manuscript JINJ-D-24-02294

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Highlights

- Evacuation mode, road environment, and traffic can influence pre-hospital time (PHT)
- The above factors can also affect injury severity score (ISS) via PHT in road crashes
- With hospital crash data, this study examines the above relations via path analysis
- Ambulance evacuation and nighttime significantly increase ISS directly and via PHT
- Overall effects on ISS surpass direct effects, stimulating debate on countermeasures

How Mode of Evacuation, Roadway Environment, and Traffic Conditions Relate to Injury Severity Score? Untangling the Role of Pre-hospital Time in Road Crashes

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1. Introduction

One person died in a car crash in the United States in 1899, while two people died in a similar road crash in Great Britain in 1896. Unfortunately, a string of casualties and injuries began with these seemingly minor episodes [1, 2]. With 20 to 50 million road traffic injuries (RTIs) and 1.19 million road traffic fatalities (RTFs) annually worldwide, road traffic crashes (RTCs) have become a serious public health concern [3]. By 2030, it is projected to be the fifth leading cause of death globally. The situation is severe especially in low- and middle-income countries, defined as those with a gross national income (GNI) per capita of $13,845 or less in 2022 [4]. Although these countries have just over 60% of all registered vehicles globally, they experience about 92% of all RTFs [3]. It is important to note that the fatality rate from RTCs in low- and middle-income countries is approximately twice that of their high-income counterparts [4].

The outcome for victims of RTCs largely depends on receiving timely and efficient medical care. One critical aspect of medical treatment is the time between the occurrence of a crash and the provision of proper medical care either on the spot or at hospitals/emergency units. If quick and effective pre-hospital care is provided, a significant number of the 1.19 million lives lost globally in RTCs each year could be significantly reduced, and a substantial amount of the resulting disabilities suffered by the 20-50 million injured people could be mitigated [5]. The total pre-hospital time (PHT), which encompasses the time between the occurrence of an RTC and the crash victim's arrival at the hospital, can be divided into multiple phases: response time, scene time, and transport time. The time between the emergency medical services (EMS) notification and their arrival at the RTC scene is usually termed the “response time”. “Scene time” refers to the duration between EMS arrival at the crash scene and their departure for the hospital. “Transport time” is the time it takes to travel from the crash scene to the hospital if additional medical treatment is needed [6]. Contrary to the developed countries, in low- and middle-income countries, crash victims are frequently transported to hospitals by family members, taxi drivers, truck drivers, police officers, or other road users, many of whom lack formal training. The dedicated (but limited) ambulance service is generally accessible only in urban areas. Many neurological injuries appear to be the consequence of inadequate immobilization or improper extraction procedures during the carriage of crash victims, which is frequently performed by individuals who lack adequate training. Past research suggests that the severe consequences of RTIs are predominantly attributable to inadequate public health infrastructure and limited access to (or poor) healthcare services [5]. The time to provide medical care to the victims of RTCs becomes more important in cases where the first medical aid is either unavailable or the victims need to be shifted to hospitals for extensive or additional treatment due to severe injuries. These situations are more critical as the PHT may significantly determine the final injuries and survival of the victims in RTCs who are to be shifted to the hospital(s) for extensive treatment.

Understanding the effects of the leading factors (i.e., roadway and environmental factors, traffic-related attributes, and response as well as evacuation-related factors) on injury outcome(s) of RTCs is significant and several past studies have analyzed these relationships via traditional modeling approaches usually capturing only the direct associations. However, we consider that in addition to the direct effects, the abovementioned factors can have significant association with the injury outcomes through some of the mediating variable (i.e., PHT in the present case) which if not captured, the overall relationships maybe overlooked. To the best of authors knowledge, none of the studies investigated how various roadway and environmental factors, traffic-related attributes, and response as well as evacuation-related factors relate to ISS (being a fine injury measure) both directly and via PHT. Furthermore, recognizing the crictial of PHT in determining the injury outcome(s) of RTCs, it is vital to understand how various roadway and environmental factors, traffic-related attributes, and response as well as evacuation-related factors relate to the PHT. For instance, the PHT for the victims in an RTC occurring on a roadway segment may significantly differ from that at intersections as the chance of being timely noticed and assisted can be higher in the latter case. Similarly, different roadway types, weather, light conditions, crash locations, time of the crash, etc. may have diverse effects on the PHT. While studies mostly investigated how various roadway and environmental factors relate to response time, the factors affecting the "pre-hospital" time (which mostly relate to more critical injuries to be treated at hospitals) are lightly researched. In particular, the association of some of the important factors e.g., roadway types (divided versus undivided, and number of lanes, etc.), visibility-related factors (weather and light conditions), crash locations (segments versus intersections), and time of the crash considering traffic flow (peak versus off-peak hours), etc. with the PHT needs an in-depth investigation. As discussed earlier, the above-mentioned factors may also significantly relate to the injury severity directly. To understand the overall effects of the aforementioned factors on injury severity, it is important to unveil the effects of these factors on injury severity (especially using hospital-based fine injury data and measures like Injury Severity Score "ISS") both directly and indirectly (via PHT) which are not well investigated to date. Referring to the injury/crash severity analyses, studies mostly rely on police-crash data which can be prone to subjectivity and underreporting. Unlike studies using police crash data which uses a coarser KABCO scale for classification of injury severity, this study uses an anatomical Injury Severity Scoring System to account for potential injuries to different body parts/regions.

In summary, understanding the factors that affect PHT and, in turn, their association with ISS is paramount not only for providing a safer transportation environment but also for improving EMS and trauma care systems. In the context of transportation engineering, the investigation of PHT and its associated factors represent a compelling area of research. Despite the acknowledged importance of PHT, factors influencing it, and more importantly, the subsequent indirect association of the determinants of PHT with the injury severity (using the finer injury scoring system i.e., ISS) is overlooked to the best of authors' knowledge. This research aims to bridge the aforementioned gaps by investigating how the above-mentioned factors relate to ISS both directly and indirectly (via PHT) using rigorous path analysis. In particular, complex pathways leading from diverse roadways and environments, and crash- as well as response-related factors to ISS are aimed to be explored in this study which can provide a more comprehensive and in-depth picture of the system.

The specific circumstances of Pakistan, a lower-middle-income country (with a GNI per capita ranging from $1,136 to $4,465 in 2022) are the primary focus of this research. The safety and efficacy of transportation systems are presented with both opportunities and challenges by the country's complex road networks, traffic patterns and healthcare infrastructure. Pakistan was rated first in the Asian region and had the highest number of RTFs worldwide [7]. Karachi, the country's largest metropolis, has been acknowledged as the fourth-largest contributor of RTFs globally [8]. These standings underscore Pakistan's significance as a compelling case study for the proposed research, particularly in Karachi where the latter is home to 17.6 million people [9]. The present research aims to provide useful insights that may help shape policies aimed at reducing unnecessary deaths and serious injuries in RTCs. The specific study objectives are listed below:

- To investigate the direct association of the roadway and environment, as well as crash- and response-related factors, with ISS of RTC victims
- To analyze the indirect (and overall) effects of the aforementioned factors on ISS through PHT
- To discuss and suggest potential measures that can help in improving the PHT, resulting in reduced RTIs and RTFs.

2. Literature review

Past research suggests that accurately evaluating and measuring the extent of injuries caused by RTCs is of utmost importance in the field of transportation engineering and public health. This is essential for conducting research, formulating policies, and enhancing trauma care systems. Several injury classification systems are employed to categorize the injuries experienced by roadway users involved in RTCs [10, 11]. The often-employed injury severity scales in transportation engineering include the KABCO Scale, Abbreviated Injury Scale (AIS), and Injury Severity Score, etc. The KABCO injury scale serves as the basis for injury data recorded in police crash reports. It involves a five-point scale (Fatal (K), Serious (A), Moderate (B), Minor (C), and None (O)) used by crash reporting officers to assess the severity of an RTC . In general, the KABCO scale offers a simple and easy-to-understand system for categorizing injuries. However, it also has obvious limitations [12, 13, 14, 15, 16, 17]. In contrast to the KABCO scale, the AIS is a global severity scoring system that is anatomically based, consensus-derived, and considers the relative significance of each injury in classifying it by body region on a six-point ordinal scale: 1 = Minor injury, 2 = Moderate injury, 3 = Serious injury, 4 = Severe injury, 5 = Critical injury, and 6 = Un-survivable (fatal) injury. The AIS assigns a numerical value to each injury based on its level of severity. Based on the anatomical structure, the human body can be categorized in nine body parts, such as the head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and whole body (external) to each of which the AIS score is assigned as shown in Figure-1 [18, 19]. Although the AIS describes anatomical injuries, it lacks internal consistency. Nevertheless, the anatomical-based AIS has served as the foundation for various anatomical assessments of injury severity, such as the ISS [14, 20, 21]. The ISS is a well-established medical scoring system and is considered the leading and most reliable system for assessing injuries [19, 21]. The ISS is highly pertinent to evaluating the severity of injuries in RTCs as it enables the assessment of multiple injuries in several body regions. Specifically, the ISS is determined by the AIS scores of the three most serious injuries in three distinct anatomical locations. Past research shows that ISS has a high level of proficiency in forecasting mortality, morbidity, and the duration of hospitalization [14, 22, 23, 24].

PASTE FIGURE 1 HERE

Previous research has found a wide range of factors that are associated with RTCs of different levels of injury severity. The investigation largely considered the impact of driver demographics and behavior, crash characteristics, roadway features, and environmental variables. The literature consistently identifies factors such as excessive speed, older age of the driver or rider, driving while intoxicated, road alignment, low visibility, crashes involving large commercial vehicles and motorcycles, and head-on collisions as frequent causes associated with greater severity of injuries in RTCs [25]. Research also indicated that there are three main elements that have an impact on RTCs: traffic characteristics, road network and infrastructure, and demographic and environmental features [26]. It is also highlighted that several factors significantly influence road traffic casualties including gender, vehicle condition, safety status, overloading, street lighting, weekends, type of vehicle, driver experience, morning rush hours, and severe weather conditions [27].
The idea of the "Golden Hour" emphasizes the significance of the period before arrival at the hospital in providing care for trauma patients. Most trauma experts believe that the initial 60 minutes following a crash, commonly known as the "golden hour," are crucial for maximizing the chances of preserving lives. Following this period, there is a substantial increase in the likelihood of fatality or the severity of injuries [28]. An effective and timely provision of emergency medical care during the PHT, combined with trauma care services at the hospital, is crucial in minimizing the negative outcomes of RTCs. According to the World Health Organization (WHO), a significant number of individuals may perish unnecessarily at the location of the crash or in the initial hours after sustaining an injury because of inadequate care provided before reaching a hospital [29].

Unfortunately, the quality of pre-hospital care in many low- and middle-income countries is inadequate, resulting in a significant number of deaths during the pre-hospital stage [28]. Due to the absence of established EMS systems in most of these countries, most crash victims are rescued by bystanders at the crash scene. Moreover, many of these bystanders rely on commercial vehicles to transport the crash victims to a healthcare facility [29]. Consequently, a considerable number of neurological injuries appear to occur due to the procedure of extrication or shifting the crash victims without appropriate immobilization, which is frequently carried out by inexperienced persons [28]. Furthermore, the occurrence of RTFs before reaching the hospital in these nations can be partially attributed to the absence of prompt post-crash interventions and limited hospital accessibility. Additionally, the healthcare facilities within these countries may lack the necessary resources and expertise to provide comprehensive care for severely injured patients with head and torso injuries accompanied by significant bleeding. These types of injuries are major contributors to fatalities in the immediate aftermath of a crash.

Studies show that several socio-demographic characteristics are strongly linked to various aspects of response time, such as geographical regions, types of crash, age, gender, and nationality. Gaining a comprehensive understanding of these elements is crucial for maximizing efficiency during the period spent before reaching the hospital [30]. Furthermore, places exhibit pre-hospital delays that are correlated with criteria such as older age, living in rural areas, and level of consciousness of crash victims [31]. Environmental and infrastructural variables, such as the day of the week, whether the site is urban or rural, the exact details of the crash, and the time it takes for emergency response, have a considerable impact on the time it takes to clear the scene and the total duration during peak traffic hours. The delays in transferring crash victims to hospitals are sometimes caused by the unavailability of specialized transportation, communication difficulties, and a lack of awareness regarding nearby medical services [4, 32]. The EMS play a vital role in minimizing the duration of care provided before a patient reaches the hospital. Problems related to quick response include the cooperation of the public, the distribution of EMS facilities, the availability of ambulances, and the resources. The timely arrival of EMS has a direct impact on the time interval between an RTC and the provision of medical care, which in turn affects the pace at which victims are transported to hospitals [33].

The association between prehospital time and injury severity has primarily been studied in developed countries. However, it is still uncertain whether these findings can be applied to developing countries, particularly in low-resource settings, due to the existing status of pre-hospital and in-hospital care [34]. Therefore, it is necessary to conduct research that is specifically concentrated on the distinctive prevailing environment of these countries. Moreover, the available literature clearly shows that both the direct effects of PHT and factors (i.e. environmental, highway, and crash-related elements) affecting it can have a significant influence on injury outcomes. Hence, in order to comprehend the comprehensive impact of the aforementioned elements on ISS, it is crucial to uncover their direct and indirect effects on ISS, particularly via PHT. Although the literature has documented the direct impact of the aforementioned factors (including PHT) on ISS, gaining an understanding of the indirect effects of these factors on ISS (via PHT) can offer valuable insights for developing or improving a comprehensive strategy to enhance road safety and decrease injury severity for victims of RTCs. For a summary of the relevant past literature, please refer to Table 1.

PASTE TABLE 1 HERE

3. Methodology

3.1 Data Source

This study analyzes the RTCs data acquired from the Road Traffic Injuries Research and Prevention Center (RTIRPC), for a period of nine years (2007 to 2015) focused on Karachi, Pakistan. The dataset contains details about 298,654 crashes and includes extensive information such as demographic, socioeconomic, roadway and environmental, and crash-related aspects. The presence of extensive injury data categorized by specific body parts enables more accurate injury assessment using reliable injury rating systems, such as the ISS [14]. Considering the present constraints on the availability and handling of the RTC data in Pakistan, this dataset is possibly one of the most reliable and extensive sources accessible in the country. For details about the RTIRPC and data collection protocols, please refer to [35, 36].

During the data cleaning process, we noticed that 160,365 entries (which accounted for approximately 54% of the total) had missing or improper values for one or more variables. For instance, there were ~7% (N=20,465) cases in which no AIS score was assigned to any of the nine body parts. Given that the data concerns individuals who attended or were taken to the hospital after the crash, it is anticipated that they would have suffered injuries. Hence, it was highly unlikely for there to be no AIS scores or scores of zero for all body parts. Furthermore, in 37% (N=110,479) crashes, several body parts were assigned AIS ratings that surpassed the established maximum of 6, resulting in difficulties in interpretation. Other variables of importance, especially those related to the time or date, etc. had similar issues i.e. lacking a consistent or standardized pattern or containing implausible values in ~10% (N=29,421) cases. This resulted in 138,289 entries (approximately 46%), having complete and accurate information for all the variables of interest. Although the sample size of 138,289 obtained from accurate entries was still substantial for analyses, excluding all entries with missing or incorrect values (for one or more variables of interest) would have led to the loss of a considerable amount of data (~ 54%). It is important to note that entries with problems in certain variables often included accurate data for several other variables. Hence, if those entries had been discarded, valuable information pertaining to those particular crashes would have been lost. To address this problem, synthetic data generation techniques were used to account for the missing or incorrect values by generating 160,365 entries, using the distribution of the key variables of interest (along with their correlation with each other), from the cleaned data (N = 138,289). Subsequently, the cleaned dataset with a sample size of 138,289 and the synthetic dataset with a sample size of 160,365 were combined to get the original sample size of 298,654. This enabled the preservation of the maximum possible quantity of accessible information while ensuring the accuracy and reliability of the data, facilitating the most efficient utilization of the information while retaining data integrity.

3.2 Synthetic Data Generation

The employment of synthetic data in this context is relevant, as it guarantees the optimal utilization of vital information that could otherwise be lost owing to improper or missing inputs arising from data entry errors. The "synthpop" program in R software was utilized to generate a synthetic dataset for the key variables based on the complete observed data. The "synthpop" technique involves the selection of an initial variable (by the user) to be synthesized, followed by the generation of values randomly using a method that samples with replacement from the observed data with complete information [38]. Then, a parametric or non-parametric approach can be selected in the synthpop technique to predict the values of subsequent variables, utilizing the previously synthesized variables as predictors [37]. This study used a non-parametric classification and regression tree (CART) approach for synthetic data generation. The selection of the CART method, whether it is regression or classification, was determined by the nature of the variable, such as whether it is continuous, binary, or categorical. This method generated a synthetic data clone which was similar to the original data in terms of distribution of variables and correlation among them, therefore maintaining the accuracy and usefulness of the dataset [37]. In-depth analyses and illustrations of the process of creating synthetic data may also be found in several research publications [39, 40, 41, 42, 43].

3.3 Classification of Injury Severity Using Injury Severity Score

To calculate the ISS for a particular crash victim, the nine body parts (head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and external) are classified into six ISS body regions, ranked in descending order of significance: head or neck including the cervical spine, face including the facial skeleton (ears, nose, eyes, and mouth), chest, abdomen, extremities/pelvic girdle, and external as shown in Figure-1. The injury is evaluated at each specific anatomical location, and a severity score based on the AIS is assigned to each individual injury. Then the highest severity code (AIS) for each of the three most severely injured body regions is squared and then summed to obtain the ISS score for a crash victim, which can be shown below:

$$\text{ISS} = X^2 + Y^2 + Z^2 \tag{1}$$

Where X, Y, and Z represent the AIS scores of the three body regions with the most serious injuries according to the ISS scale.

The ISS scores span a range of 1 to 75. If any of the three AIS scores is 6, indicating an injury that cannot be survived, the ISS is automatically assigned a value of 75. Given that an AIS score of 6 signifies that further medical care would not be effective in saving a person's life, it is possible that a crash victim with a score of 6 in any of the three categories may not receive additional medical care. Furthermore, studies have categorized ISS into four levels which include: minor (ISS of 1-8); moderate (ISS of 9-15); severe (ISS of 16-24); and very severe (ISS of 25)[a].

3.4 Conceptual Framework

This research aims to examine the relationships of various factors including roadway and environmental factors, and crash- and response-related aspects with the ISS of the victims in RTCs both directly and through PHT. The motivation for this research is based on our hypotheses that various factors, including the characteristics of the road (such as the presence of a median, number of lanes in each direction, etc.), the location of the crash (at an intersection or on a straight portion), the time of day (day or night), and the volume of traffic (during peak or off-peak hours), can have statistically significant effects on the PHT where the latter may significantly relate to the ISS. For example, during peak hours, congested undivided roadway portions may have prolonged PHT for RTCs due to the complex road network and dense traffic, which may hinder the prompt arrival of emergency personnel. In contrast, RTCs occurring on uncongested divided roadway segments during non-peak hours may encounter faster response times, resulting in shorter pre-hospital durations. Furthermore, we consider that there can be potential direct association of roadway and environmental conditions, and crash- and response-related factors with ISS. In order to systematically approach the research objectives, this study uses a two-stage path analysis (as depicted in Figure 2) to understand the overall effects of the key variables on the ISS while accounting for indirect pathways from these factors to ISS via PHT.

[a]VanDerHeyden, N., & Cox, T. B. (2008). Trauma scoring. In *Current therapy of trauma and surgical critical care* (pp. 26-32). Mosby.

PASTE FIGURE 2 HERE

3.5 *Modelling Framework*

The study aims to develop two separate models for each response variable: PHT and ISS. This modeling approach is specifically designed to account for any relationships among unobserved factors that could have a major impact on the outcomes of the two responses. This study used the Tobit model due to the continuous nature and distribution of the response variables (PHT for Model 1 and ISS for Model 2) in our data. The Tobit model is appropriate for addressing the corner-solution problem, which occurs when the dependent variable shows clustering or a spike at its lowest extreme value [37, 12]. This characteristic was observed in both ISS and PHT in this study. A brief description of the Tobit model can be found below:-

3.5.1 *Tobit Regression*

In the statistical literature, truncation and censoring are regarded as distinct phenomena; however, they both pertain to data observability concerns [38, 39, 40]. Censoring refers to a situation when a significant proportion of observations exceed the censoring threshold or events are not recorded for a considerable number of observations. Alternatively, truncation happens when a substantial amount of observations surpasses the maximum observable range. Even without any censoring or truncation, the dependent variable can exhibit a cluster at the lowest extreme value (spike at 0 or 1), which is referred to as a corner-solution problem. In our case, we observed that both the distribution of ISS and the PHT exhibit a left spike indicating corner-solution problems. It is important to highlight that there is no issue with data observability in our case. To fully incorporate and take into account all observations, research indicates that Tobit regression can be employed for all three phenomena [37, 38, 39, 40]. Thus, in this study, Tobit regression is used to estimate the ISS and PHT because of the corner-solution setup seen in the ISS and PHT:-

$$Yi^* = \beta 1Xi + \varepsilon 1, (i = 1, 2, 3, \dots, N) \tag{2}$$

$$Yi = Yi^* \ (if\ Yi^* > \tau) \tag{3}$$

$$Yi = \tau_Y \ (if\ Yi^* \leq \tau) \tag{4}$$

In equation (2), the latent variable (stochastic index) is denoted as $Yi*$, the observed dependent variable is Yi, $\boldsymbol{\beta 1}$ represents a set of estimable parameters associated with independent variables ($\mathbf{X}\boldsymbol{i}$), N represents the number of observations, and $\varepsilon 1$ represents residuals that are assumed to follow a normal distribution with $\mathbf{N}(\mathbf{0}, \boldsymbol{\sigma}\mathbf{1}^2)$. The log-likelihood function for Tobit regression can be derived as follows:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset (\frac{Y-\mu}{\sigma})]^{di} [1 - \emptyset (\frac{\mu-\tau}{\sigma})]^{1-di} \tag{5}$$

In equation (5), τ represents the threshold in the data where a corner-solution (left-spikes) is observed, $\emptyset$ denotes the standard cumulative normal distribution function, and $\emptyset$ represents the standard normal density function. By setting $\tau = 0$ and expressing μ as a function of observed variables and their estimated parameters ($\beta 1\mathrm{X}i$), the log-likelihood function for the Tobit model can be obtained:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset (\frac{Yi-\beta 1Xi}{\sigma})]^{di} [1 - \emptyset (\frac{\beta 1Xi}{\sigma})]^{1-di} \tag{6}$$

By further expanding equation (6), the log-likelihood functions can be expressed as:

$$lnL = \sum_i^N \{di\,(-ln\sigma + ln\emptyset (\frac{Yi-\beta 1Xi}{\sigma})) + (1 - di)ln\,(1 - \emptyset (\frac{\beta 1Xi}{\sigma}))\} \tag{7}$$

The equation (7) comprises two components: 1) the standard regression for uncensored observations and 2) the probability of censoring for specific observations. Marginal effects (MEs) can be calculated to see the impact of a unit increase in a specific continuous variable (or a transition from 0 to 1 in an indicator) on the response variable while holding all other variables in the model at their average values. Three distinct forms of MEs can be determined in Tobit regression, based on different predicted values of the dependent variable [41]. It should be noted that depending on the extent, one or more of these MEs can be utilized. With that being stated, we calculate and furnish all three MEs for this research. However, we eventually utilize and interpret ME-1. It should be noted that ME-1 is calculated using both uncensored and censored observations. In our scenario, the ISS and PHT suggest a situation where the lowest limits are reached, known as a corner solution with left spikes [37, 41]. However, there is no actual censorship, as previously mentioned. Therefore, we employ ME-1, taking into account both censored and uncensored data, as shown below:-

$$\frac{\partial E[Yi]}{\partial Xi} = \varphi\left(\frac{\beta 1 Xi}{\sigma}\right) \beta 1 \tag{8}$$

To calculate the chance of an observation being uncensored, ME-2 can be determined using the following method:-

$$\frac{\partial Pr[Yi>1|Xi]}{\partial Xi} = \varphi\left(\frac{\beta 1 Xi}{\sigma}\right) \frac{\beta 1}{\sigma} \tag{9}$$

The equation (10) provided below can be utilized for MEs (ME-3) that rely solely on unfiltered observations of response variables:-

$$\frac{\partial E[Yi|Yi>0]}{\partial Xi} = \beta i \left\{1 - \lambda(\alpha)\left[\frac{\beta 1 Xi}{\sigma} + \lambda(\alpha)\right]\right\} \tag{10}$$

Where, $$\lambda(\alpha) = \frac{\emptyset\left(\frac{\beta 1 Xi}{\sigma}\right)}{\varphi\left(\frac{\beta 1 Xi}{\sigma}\right)} \tag{11}$$

It is important to mention that the ME-3 is more applicable in situations of "true censoring," which is not the case in this study.

In summary, we employed the ME-1 method, which incorporates both censored and uncensored observations, from the Tobit model in our final path analysis. This allowed us to assess the indirect and total effects of PHT and other important factors on ISS [37, 42].

3.6 Path Analysis

Within the path analysis framework, the MEs obtained from the individual models are utilized to ascertain the direct, indirect, and overall effects of relevant factors on the ultimate response variable (ISS), as depicted in Figure 1 [43, 44]. The impact of various factors related to roadway conditions, environmental factors, and crash and response-related factors on the severity of injuries (ISS) is determined by multiplying the estimated effects (MEs) obtained from the PHT model (Model 1) with the ME of PHT obtained from the ISS model (Model 2). It should be noted that the "ISS model" quantifies the direct impact of road conditions, environmental factors, crash, and response-related factors, post-crash health conditions, and PHT on the severity of injuries sustained by a crash victim. When combined with the indirect effect, these factors provide the overall impact of a specific explanatory variable on ISS. The equations for calculating the indirect and total impacts of certain explanatory variables are provided below [17, 45, 46]:-

Indirect MEs = (MEs from PHT model) *(MEs of PHT from ISS model) (12)

Total MEs = Direct MEs + Indirect MEs (13)

While consistent estimates can be obtained via standard path analysis (i.e., independent estimation of models), studies suggest to achieve more efficient results if potential correlation between the unobserved factors exist and is taken into account via joint estimation[b,c]. To account for potential correlation between the unobserved factors which can be associated with both PHT and ISS, we used the limited information maximum likelihood procedure for the estimation of the two models jointly via Conditional Mixed Process (CMPT) where the later is a user-written STATA routine[d]. The joint estimation considers the two error terms ($\varepsilon 1$ and $\varepsilon 2$), associated with PHT and ISS, to have multivariate normal distribution[d].

[b]Ahmad, N., Arvin, R., & Khattak, A. J. (2023). How is the duration of distraction related to safety–critical events? Harnessing naturalistic driving data to explore the role of driving instability. *Journal of safety research*, *85*, 15-30.
[c]Ahmad, N., Arvin, R., & Khattak, A. J. (2023). Exploring pathways from driving errors and violations to crashes: The role of instability in driving. *Accident Analysis & Prevention*, *179*, 106876.
[d] Roodman, D., 2009. Mixed-process models with CMP. In: Proceedings of the DC09 Stata Conference.

4 Results

4.1 Actual Versus Synthetic Data

The cleaned RTIRPC data, which consisted of 138,289 observations, were employed to produce a synthetic dataset with 160,365 observations, as previously mentioned. Subsequently, these datasets were merged to produce a combined sample size that was equivalent to the original RTIRPC data (N=298,654). The distribution of key variables in both the actual and synthetic datasets is compared in Figure 3. The synthetic data's distribution of all variables appears to be reasonable when compared with the actual (observed) data. Comparisons are presented for only a subset of the key variables for brevity. The descriptive statistics for these variables are compared across the actual and synthetic data samples in Table 2. The means and standard deviations of the key variables in the synthetic data are in close agreement with those of the actual data. The synthetic dataset's validity in comparison to the actual data (with complete information) is further supported by the similar correlations between variables in both datasets.

PASTE FIGURE 3 HERE

PASTE TABLE 2 HERE

4.2 Descriptive Statistics

Figure 4 illustrates the distribution of two dependent variables, namely PHT and ISS. Both of these variables are characterized by a corner-solution set-up, which enables them to be modeled using Tobit regression. For further information, please refer to the methodology section.

PASTE FIGURE 4 HERE

The summary statistics of the key variables are displayed in Table 3. The data provides valuable information about the characteristics and trends of RTCs in Karachi, Pakistan. The average ISS for individuals involved in crashes is 6.20, with a standard deviation of 11.80. As per the categorization of the ISS (marked with [a]), 82.35% (N = 245,955), 12.37% (N = 36,935), 2.21% (N = 6,603), and 3.07% (N = 9,161) of the cases had minor, moderate, severe, and very severe ISS. The average PHT is 104.30 minutes, with a significant standard deviation of 205.66 minutes, while the longest reported PHT is 1439 minutes. While the maximum value of PHT (1439 minutes ~ 24 hours) may seem to be an outlier, we included crashes with such large values to highlight the slow response and its consequences. Out of all the crashes, a significant percentage of 35.68% took place on roads that had four lanes in each direction. Moreover, 75% of crashes occurred on straight road segments, while 37% occurred at night. Figure 5 shows the distribution of variables including the type of vehicles, type of crash victims, and mode of evacuation associated with RTCs. Referring to the distribution of crashes based on the vehicle types involved, motorcycles accounted for the largest proportion of crashes (69.41%), followed by other vehicles such as taxis (7.58%), buses (5.27%), passenger vans (2.42%), bicycles (1.32%), trucks (1.76%), private automobiles (0.97%), and rickshaws (three-wheelers) (0.35%). The most susceptible individuals involved in RTCs were riders and passengers of two-wheelers, as well as pedestrians, accounting for 48.12%, 13.78%, and 23.08% of the total crash victims, respectively. In terms of the mode of evacuation, 61.00% of crash victims were taken to medical facilities utilizing private transport, while 34.33% made use of ambulance services. For the distribution of other key variables, please refer to Table 3.

[a]VanDerHeyden, N., & Cox, T. B. (2008). Trauma scoring. In *Current therapy of trauma and surgical critical care* (pp. 26-32). Mosby.

PASTE FIGURE 5 HERE

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4.3 *Modeling Results*

Considering the study objectives and the path analysis framework, the PHT (response variable in Model 1) was used as an explanatory variable in Model 2 (ISS Model). The final models were systematically derived for each outcome type, incorporating the most significant variables (based on research objectives), statistical significance, intuition, theoretical justifications, and specification parsimony. To this end, the likelihood ratio test, and improvement in the AIC and BIC statistics were considered. A 95% confidence criterion was employed to determine the statistical significance of the variables in either model. The subsequent subsections provide details about key findings that were obtained from both models. While the final modeling results (below) are based on the models which were estimated in an independent fashion, we want to mention that we tried to estimate the two models in a joint fashion (as discussed in sub-section 3.6) to account for potential correlation between the unobserved factors associated with PHT and ISS. However, there was no significant evidence found that significant correlation exists between the unobserved factors associated with the two dependent variables (i.e., PHT and ISS). As discussed earlier, the results obtained from the independent models are still consistent and used in recent research studies, therefore after see no significant correlation between the unobserved factors, the path analysis, results, and discussion sections are based on the models estimated in an independent fashion.

4.3.1 Model 1: Factors Affecting Pre-Hospital Time

The results of the final Tobit model related to the factors affecting PHT (Model-1) are presented in Table 4. 10 explanatory variables were found to be statistically significant as per 95% confidence level criteria. Results of the final PHT model show that crashes at intersections are linked to a significant decrease in PHT compared to those on road segments. On the other hand, crashes on roads without a median are associated with a statistically significant increase in PHT. Moreover, crashes on roads with less than four lanes in each direction significantly result in a shorter time required to reach a hospital. Whereas, nighttime crashes, as opposed to daytime ones, lead to a significant increase in PHT. In terms of mode of evacuation, the use of ambulances is linked to a significant increase in the PHT. Furthermore, multi-vehicle crashes and crashes involving large vehicles (such as trucks or buses) are likely to result in longer PHT. However, crashes involving VRUs, like pedestrians and cyclists, result in a significant decrease in the time before reaching a hospital. Furthermore, the results indicate that the PHT increases with each additional injured body part. It should be noted that there was no issue of multicollinearity as mentioned in the footnote of Table 4. For further details related to the results of other key variables that showed significant association with PHT, please refer to the discussion section.

PASTE TABLE 4 HERE

4.3.2 Model 2: Factors Affecting Injury Severity Score

Following testing of several combinations and specifications, a final Tobit model for ISS was established including PHT as an independent variable. In the final ISS model, we found 13 explanatory variables, including PHT, to have statistically significant (as per 95% confidence level criteria) association with ISS (Table 5). The final model clearly underscores a significant association of the PHT with the ISS, indicating that as PHT increases, the ISS also tends to increase significantly. The higher degree polynomial (i.e., squared term) of PHT shows a significant correlation with ISS, indicating sufficient evidence of non-linearity in the association of PHT with ISS. Furthermore, the findings indicate that crashes on undivided roadways are associated with higher ISS, while crashes occurring on roads with less than four lanes are likely to result in a lower ISS. Referring to the association of crash location with ISS, we found that the ISS significantly reduces if the crashes occur at intersections. With regards to the effects of natural light conditions on ISS, the findings reveal that ISS significantly increases for victims of crashes occurring during nighttime suggesting more serious injuries at night. Moreover, crashes occurring outside of morning peak hours generally result in a lower ISS. There are distinct seasonal variations, as crashes occurring outside the summer season lead to a decrease in ISS. As per the results of the final ISS model, we found that the mode of evacuation significantly affects the severity of injuries, where interestingly, the use of ambulances is associated with a higher ISS. This interesting finding is discussed in detail in the discussion section. Referring to the impacts of vehicle type on ISS, the results reveal that the involvement of multiple vehicles and heavy vehicles in crashes also leads to significantly higher ISS. VRUs experience more severe injuries, causing an increase in ISS. Additionally, there is a significant positive correlation between the number of body parts injured in a crash and the ISS, with each additional injured body part resulting in a higher ISS.

PASTE TABLE 5 HERE

4.3.3 Path Analysis

Table 6 presents the results of the path analysis, which uncovers the direct and indirect relationships of the key factors (i.e., related to roadways and environment, response, traffic, and crash) with the ISS for the victims of RTCs. The direct effects of key explanatory variables on the ISS (ME-1) are obtained from Table 5, which is based on Model-2. Whereas, in order to determine the indirect effects of key explanatory variables on ISS, we compute them by multiplying the ME (ME-1) of each individual variable from Model-1 with the ME (ME-1) of PHT on ISS obtained from Model-2. The outcomes of these computations, which emphasize the indirect effects of the key explanatory variables on ISS, are compiled in Table 6, which presents the direct, indirect, and total impacts of each explanatory variable.

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5 Discussion

The distribution of key variables such as ISS and PHT offers useful insights into the nature and outcomes of RTCs. The ISS, with an average of 6.20 and a high standard deviation of 11.80, suggests a wide variation in injury severity, from minor to critical injuries, highlighting the diverse impact of RTCs. The PHT average of 104.30 minutes points to significant delays in emergency responses, which could worsen injury outcomes and indicates a pressing need for improvements in EMS and transportation infrastructure. As discussed earlier, to understand the relationships of key factors related to response, roadway and environment, and traffic with ISS directly and through PHT, we estimated two Tobit models considering the fact that the distribution of the two variables (PHT and ISS) exhibits corner-solution setups. The two models (PHT model and ISS model) revealed some useful results which were then used in the path analysis.

Referring to the results of model-1 (PHT model), the crash location ME-1 demonstrates a 21.53 times decrease in PHT for crashes that happen at intersections as opposed to segments (Table 4). The strong negative correlation indicates that the process of rescuing crash victims and transporting them to the hospital is relatively faster at (or near) intersections, potentially because these locations are easily identifiable and accessible. In contrast, crashes occurring on undivided roadways significantly leads to a 4.03 times rise in the PHT. This positive correlation may arise from the inherent difficulties in negotiating undivided roads, including potentialy higher traffic conflicts and restricted room for emergency vehicles to navigate. The results are consistent with previous research that highlights the significant impact of off or opposing-lane crash location on clearance time and the subsequent total PHT [47]. The findings also indicate that crashes occurring on roads with less than four lanes in each direction significantly reduce the PHT by 10.21 times. This finding was expected as roads with lower traffic volume (less number of lanes) are more conducive to faster response times because they experience less congestion and provide better access for emergency vehicles. Moreover, there is a significant rise (16.17 times) in PHT for nighttime crashes, as opposed to daytime, highlighting the difficulties faced in responding to emergencies during the night. The finding makes sense as the challenges encompass reduced visibility, apparently decreased staffing numbers, and heightened difficulty in locating crash scenes. Moreover, the limited availability of public or private transportation during nighttime could also lead to longer PHT. Similar results can be seen in previous research suggesting that the average emergency response time is greatest during nighttime when visibility may be restricted [48]. With regards to the association of mode of evacuation with PHT, the findings interestingly indicate that the utilization of modes for evacuation other than ambulance is linked with a 4.36 times decrease in PHT, suggesting that ambulance modes in the city tend to be more inefficient. The unexpected outcome may be attributed to the formal procedures and protocols adhered to by ambulance services, which, although guaranteeing comprehensive care, could result in extended response durations in the mega metropolitan city of Pakistan. Dependence on private or public transportation during emergencies may bypass certain procedural delays but could potentially endanger the standard of medical care during transportation. The findings also suggest that crashes involving multiple vehicles and heavy vehicles lead to an increase of 2.73 and 21.24 times in PHT respectively, which may be most likely because of the challenges associated with handling scenes that involve either multiple or heavy vehicles. The complexity of such situations inherently prolongs the time it takes to respond, highlighting the necessity for well-coordinated emergency response techniques. These findings align with past research that has shown the significant impact of the number of vehicles and the involvement of heavy vehicles on clearance time and overall duration of PHT [47]. Crashes involving VRUs, such as pedestrians and cyclists, lead to a 25.75 times reduction in the PHT. The strong negative association indicates that VRU crashes exhibit reduced PHT, which may be attributable to the comparatively effortless accessibility of the victims in contrast to occupants of vehicles. The visibility of these crashes and the possibility of prompt assistance from bystanders may also contribute to quicker response times, resulting in reduced PHT.

To understand the association of PHT and leading factors (i.e., related to response, roadway and environment, traffic etc.) with ISS, the results (ME-1) of the Model 2 (ISS model) are discussed. The findings from the ISS model suggest a significant positive correlation of PHT with ISS. More precisely, with each extra minute increase in PHT, the ISS shows an increase (i.e., by 0.01 unit), highlighting the need for immediate medical intervention to reduce the severity of injuries. Receiving medical care with delays can aggravate injuries, resulting in worse outcomes. This finding is consistent with previous studies, that emphasize the significance of prompt medical intervention in cases of trauma [28, 29, 30, 31, 32, 33]. Nevertheless, the presence of a statistically significant negative coefficient for the higher (i.e., squared) degree polynomial of PHT indicates a significant evidence of variability in the slope of PHT (i.e., effects of PHT on ISS). However, further research is needed to identify and understand the prevalent trends in the nonlinear relationship between these two variables which is not the focus of the present study. Our findings suggest that cashes on undivided roadways significantly increase the ISS by a 0.37 times. Undivided roadways without median barriers frequently witness more severe head-on crashes, leading to increased injury severity which is aligned with the past research [25, 49, 50, 51]. In contrast, crashes that happen at intersections are linked to a 0.36 times reduction in ISS compared to those on straight-road segments. Although intersections are areas of potential conflict, they tend to have reduced impact speeds as a result of traffic management systems, leading to less serious injuries. Crashes that occur at night are linked to a 0.32 times rise in ISS, indicating greater severity of injuries during nighttime hours. Reduced visibility, driver exhaustion, and an increased probability of impaired driving, combined with decreased law enforcement during nighttime, contribute to more serious injuries. To avoid these hazards, it would be beneficial to increase nighttime enforcement, visibility/conspicuity, and infrastructure [52]. The research findings support previous studies showing that driving at night can lead to impaired hazard perception and reaction time due to factors such as empty roads, speeding, reduced driver awareness, substance abuse, fatigue, and inadequate street lighting. This increases the risk of crashes that result in serious injuries and fatalities. Therefore, it is crucial to have emergency response services available around the clock [25, 53, 54, 55, 56, 57]. Furthermore, we found crashes that happen outside the morning peak hours are linked to a reduction in the ISS, which suggests that crashes during morning peak hours are more severe. Previous research also suggests that drivers tend to drive faster in the early morning to make sure they get to work on time, and this increased speed is associated with more serious injuries. Additionally, many commercial vehicle drivers operate their vehicles alone throughout the night without taking any breaks. As a result, they experience slower reflexes in the morning due to fatigue, leading to a higher incidence of crashes and injuries [25, 58]. The utilization of non-ambulance (private vehicles) modes for evacuation significantly reduces the ISS by 3.91 times. This finding is not consistent with the findings reported from studies conducted in other regions [59, 60, 61, 62], emphasizing the significance of implementing an advanced EMS system in order to enhance the outcomes for those involved in tragic crashes. VRUs, which include pedestrians, motorcyclists, and bikers, experience higher injury severity, leading to a 0.41 times increase in ISS. The lack of protections for VRUs makes them exceptionally vulnerable, underscoring the requirement for enhanced safety protocols, such as the implementation of exclusive lanes and the promotion of public awareness initiatives. The severity of injuries is directly related to the number of body parts injured, as seen by a significant increase in ISS for each additional wounded body part. Providing thorough medical care to more badly injured victims leads to longer pre-hospital delays and higher overall injury severity. The present findings are consistent with other research that has reported similar outcomes [63, 64, 65].

5.1 Path Analysis

Referring to the results of path analysis, most factors with a significant direct association with ISS also have shown a significant association with PHT. PHT, in turn, is associated with ISS, creating an indirect association of these factors with ISS as well (see Figure 6). Consequently, the overall effects of some of the key variables on ISS are different from their direct effects (as shown in Table 6) – something that could not be explored without the path analysis. The results indicate that certain factors have both direct and indirect effects on increasing the ISS, with the overall effects being higher than their direct effects. For example, if a crash occurs at night, it would increase the ISS by 0.32 times. However, when considering the indirect effects (0.16) on ISS via PHT, the overall effects are found to be 0.48, which is much higher than the direct effects of 0.32. Similarly, factors that tend to reduce the ISS, both directly and indirectly (e.g., crash location), also result in overall effects that are higher than their direct effects. Interestingly, some factors directly increase the ISS but reduce it through their indirect effects. For example, the involvement of VRUs in a crash would increase the ISS by 0.41 times; however, when its indirect effects (-0.26) are also considered, the overall effects are found to be 0.15, which is much lower than the direct effects. This information cannot be obtained using conventional modeling techniques.

6 Practical Implications

The findings have significant practical implications for improving road safety and emergency response that could potentially lead to substantial reductions in the severity of injuries and fatalities. The significant and prolonged delays in PHT, which average over 104 minutes, emphasize the urgent need to improve EMS, especially in the city from where the data was analyzed. The implementation of more effective ambulance services, possibly using advanced technology like GPS tracking, has the potential to significantly reduce preventable hospitalizations and thus alleviate the severity of injuries. Moreover, it is crucial to enhance the skills and resources available to first responders to ensure expedited and more efficient medical interventions. Furthermore, there is a need for stricter enforcement of traffic regulations, especially regarding large vehicles and violations leading to RTCs. Targeted enforcement campaigns and stringent penalties could effectively discourage dangerous driving habits, particularly during night and morning peak traffic hours, due to the increased severity of injuries associated with such incidents. Enhancing visibility and deploying law enforcement personnel at night could mitigate the heightened risks of severe injuries associated with reduced visibility and impaired driving. The increased vulnerability of VRUs, including pedestrians and cyclists, underscores an urgent need for public awareness initiatives specifically targeting road safety. By promoting the use of helmets, reflective clothing, and marked crossing locations, as well as providing education to drivers on responsible road sharing, it is possible to mitigate the extent of injuries sustained by these specific groups.

PASTE FIGURE 6 HERE

7 Research Limitations and Scope for Future Research

This study analyzed data obtained from the RTIRPC, which is one of the most extensive national initiatives conducted thus far. Despite being an extensive and detailed collection effort in developing countries like Pakistan which can have several benefits, we acknowledge several potential limitations. The results are specifically applicable to crashes that resulted in injuries (where crash victims were shifted to hospitals) and cannot be generalized to instances that involve property damage only. Furthermore, the data was acquired upon the arrival of crash victims at the hospitals. As a result, information regarding the conditions of the road, the circumstances of the crash, and parts of the response were not collected at the crash scene. Similarly, the medical condition of the victims was also documented upon their arrival at the hospital without information about pre-, on-scene, and post-hospital times. One of the potential research avenues can be to explore the approaches that can include information about the aforementioned variables (roadway, pre- and on-scene medical conditions, etc.). Furthermore, as discussed earlier, each of the injury scales including KABCO, AIS, ISS, and NISS has its own advantages and limitations considering which the selection of a specific injury measures depends on the situation and scope of the study. For instance, it is important to highlight that ISS may not always lead to accurate prediction of injury outcomes as we consider that the same ISS score can have different clinical outcomes due to differences in types of injuries, responses of the patients, patient age, and cure. While the present research does not look at the prediction of injury outcomes based on ISS and/or other injury measures including AIS or NISS, we consider it important to account for the potential endogeneity issues within the ISS in future research. For instance, it would be interesting to see the role of interaction of ISS and patient age/injury types (based on body parts) in predicting the final clinical outcome (i.e., morbibity versus survival). Furthermore, as discussed in the data section, our findings are based on the hospital-based detailed data which was collected as a part of a funded project in Karachi, Pakistan where the later can have its unique chracteristics including socio-economics, traffic, behaviors, emergency response, and trauma protocols. To assess the transferability or differences across cities or locations in the country (or abroad), similar study can be extended to other cities or localities in the country and/or abroad. Future research also necessitates the collaboration of transportation and medical professionals. This interdisciplinary approach has the potential to yield useful insights that can improve overall road safety and enhance the medical care of crash victims. Moreover, it is necessary to broaden the scope of national-level projects, such as the RTIRPC, by incorporating a wider variety of geographic and socio-economic circumstances. Researchers can enhance the development of more efficient techniques to reduce injury severity and improve the outcomes for individuals involved in road crashes.

8 Conclusion

The research investigates the effects of various factors, such as road conditions, environmental variables, crash-specific elements, and response measures, on ISS directly as well as through the PHT, analyzing a unique and fine crash data obtained from hospital records in Karachi, Pakistan. To address issues related to missing values and ensure accuracy in analysis, synthetic data generation was employed. Considering the corner-solution distribution of PHT and ISS, two tobit models were applied using path analysis. The analysis revealed a significant association between PHT and ISS. It found that a one-unit increase in PHT corresponds to a 0.01-unit increase in ISS, highlighting the importance of swift evacuation and immediate medical care for crash victims. The study identified the mode of evacuation as a crucial factor, with ambulance transportation resulting in longer PHT and higher ISS compared to private or public transport modes. The research also showed that crashes occurring at night not only increased ISS directly, but also led to longer PHT which itself showed a positive correlation with ISS. Crashes at intersections were found to result in reduced PHT and ISS, whereas, crashes on undivided roads and those involving multiple or large (heavy) vehicles were associated with increased PHT and ISS, signifying more complex and severe collision scenarios. The path analysis showed that the overall effects of several significant explanatory variables on ISS were higher than their individual direct or indirect effects, demonstrating the efficacy of this analytical approach in capturing the multifaceted impacts on the finer injury measures. For instance, the direct effect of crash location on ISS is -0.36, whereas the actual total effect (including its -0.22 indirect effect on ISS via PHT) for this variable is -0.58. Based on the findings, the study provides useful knowledge that can be helpful in improving the EMS infrastructure by enhancing the availability and effectiveness of ambulances, as well as improving emergency response times, especially during the night, in populous and congested cities. We also consider that implementing specific road safety measures, such as enhanced traffic enforcement on non-divided roadways and improved visibility can be beneficial. Public awareness efforts focused on educating individuals about proper emergency response and first aid have the potential to reduce the seriousness of injuries in RTCs as unlike the developed world majority of the RTC victims are shifted to hospitals or emergency units by the public in private vehicles. Overall, the findings of this study bring about significant practical implications that may help shape national policies aimed at preventing unnecessary deaths and serious injuries in RTCs by improving road safety and emergency responses.

References

[1] L. Norman, "Road traffic accidents: Epidemiology, Control and Prevention," World Health Organization (WHO), Geneva, 1962.

[2] D. Odatuwa-Omagbemi, A. Oruma, E. Roy, C. Otene, C. G. Iwegbu, M. Okeke and E. Akpojevwe, "Epidemiology of Road Traffic Crash Injuries as Seen in the Emergency Room of a Tertiary Hospital in Delta State, Nigeria," *British Journal of Medicine and Medical Research,* vol. 21, pp. 1-8, 2017.

[3] World Health Organization (WHO), 13 December 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. [Accessed 21 February 2024].

[4] J. Antony, V. Jayaseelan, J. J. Olickal, J. Alexis and M. Sakthivel, "Time to Reach Health-Care Facility and Hospital Exit Outcome Among Road Traffic Accident Victims Attending a Tertiary Care Hospital, Puducherry," *Journal of Education and Health Promotion,* 2021.

[5] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi , "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* 2010.

[6] J. Brown, M. Rosengart, R. Forsythe, B. Reynolds, M. Gestring, W. Hallinan, A. Peitzman, T. Billiar and J. Sperry, "Not All Prehospital Time is Equal: Influence of Scene Time on Mortality," *Journal of Trauma and Acute Care Surgery,* pp. 93-100, 2016.

[7] "Pakistan Reports Most Road Accident Deaths in Asia," The News International, 2022.

[8] "Karachi Ranks Fourth in Road Accident Deaths in World, Moot Told," DAWN News, 2019.

[9] "Karachi's population rises to over 17.6 million: PBS data," The Nation, Karachi, 2023.

[10] P. L. Chen and C. W. Pai, "Evaluation of Injuries Sustained by Motorcyclists in Approach-Turn Crashes in Taiwan," *Accident Analysis & Prevention,* vol. 38, no. 5, pp. 1019-1027, 2019.

[11] S. Palmer, M. Bader, A. Qureshi, J. Palmer, T. Shaver, M. Borzatta and C. Stalcup, "The Impact on Outcomes in a Community Hospital Setting of Using the AANS Traumatic Brain Injury Guidelines," *Journal of Trauma and Acute Care Surgery* , vol. 50, no. 4, pp. 657-664, 2001.

[12] B. Wali , A. J. Khattak and N. Ahmad, "Examining Correlations Between Motorcyclist's Conspicuity, Apparel Related Factors and Injury Severity Score: Evidence from New Motorcycle Crash Causation Study," *Accident Analysis & Prevention,* vol. 131, pp. 45-62, 2019.

[13] A. J. Khattak , N. Ahmad, B. Wali and E. Dumbaugh, "A Taxonomy of Driving Errors and Violations: Evidence from the Naturalistic Driving Study," *Accident Analysis & Prevention,* vol. 151, 2021.

[14] B. Wali, A. J. Khattak and N. Ahmad, "Towards Better Measurement of Traffic Injuries – Comparison of Anatomical Injury Measures in Predicting Clinical Outcomes in Motorcycle Crashes," *Journal of Safety Research,* 2022.

[15] F. Mannering and C. Bhat, "Analytic Methods in Accident Research: Methodological Frontier and Future Directions," in *Analytic Methods in Accident Research*, 2014, pp. 1-22.

[16] J. Short and B. Caulfield, "Record Linkage for Road Traffic Injuries in Ireland Using Police Hospital and Injury Claims Data," *Journal of Safety Research* , vol. 58, pp. 1-14, 2016.

[17] N. Ahmad, B. Wali, A. J. Khattak and E. Dumbaugh, "Built Environment, Driving Errors and Violations, and Crashes in Naturalistic Driving Environment," *Accident Analysis & Prevention,* vol. 157, 2021.

[18] K. L. Loftis, J. Price and P. J. Gillich, "Evolution of the Abbreviated Injury Scale: 1990–2015," *Traffic Injury Prevention,* vol. 19, no. Sup2, pp. 109-113, 2018.

[19] S. Baker, B. o'Neill, H. Jr. and W. W. Long, "The Injury Severity Score: A Method for Describing Patients with Multiple Injuries and Evaluating Emergency Care," *The Journal of Trauma and Acute Care Surgery,* vol. 14, no. 3, pp. 187-196, 1974.

[20] A. G. Rapsang and D. C. Shyam, "Scoring Systems of Severity in Patients with Multiple Trauma," *Cirugía Española (English Edition),* vol. 93, no. 4, pp. 213-221, 2013.

[21] M. Stevenson, M. Segui-Gomez, I. Lescohier, C. Di Scala and G. Mcdonald-Smith, "An Overview of the Injury Severity Score and the New Injury Severity Ccore," *Injury Prevention,* vol. 7, no. 7, pp. 10-13, 2001.

[22] S. Ankarath, P. Giannoudis, I. Barlow, M. Bellamy, S. Matthews and R. Smith, "Injury Patterns Associated with Mortality Following Motorcycle Crashes," *Injury* , vol. 33, no. 6, pp. 473-477, 2002.

[23] L. Camilloni, P. Rossi, S. Farchi, F. Chini, P. Borgia and G. Guasticchi, "Triage and Injury Severity Scores as Predictors of Mortality and Hospital Admission for Injuries: A Validation Study," *Accident Analysis & Prevention,* vol. 42, no. 6, pp. 1958-1965, 2010.

[24] O. Bolorunduro, C. Villegas, T. Oyetunji, E. Haut, K. Stevens, D. Chang, E. Cornwell III, D. Efron and A. Haider, "Validating the Injury Severity Score (ISS) in Different Populations: ISS Predicts Mortality Better Among Hispanics and Females," *Journal of Surgical Research,* vol. 166, no. 1, pp. 40-44, 2011.

[25] U. Hanif, F. Asim and A. S. Akhtar, "An Empirical Assessment of Factors Influencing Injury Severities of Motor Vehicle Crashes on National Highways of Pakistan," *Journal of Advanced Transportation,* 2021.

[26] H. Li, "Impacts of Traffic Interventions on Road Safety: An Application of Causal Models," 2013.

[27] G. Zhang, K. K. Yau and G. Chen, "Risk Factors Associated with Traffic Violations and Accident Severity in China," *Accident Analysis & Prevention,* vol. 59, pp. 18-25, 2013.

[28] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi, "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* vol. 10, 2010.

[29] Z. Mengstu, A. Ali and T. Abegaz, "Prehospital Care and 24-hour Crash Injury Mortality Among Road Traffic Crash Victims in Addis Ababa," *Science Journal of Public Health,* vol. 9, pp. 23-29, 2021.

[30] A. Thamer, M. A. Yousef, H. A. I. Mahmudul, A. A. Monerah, A. Adil, A. Ibrahim and M. Ilias, "Emergency Medical Service Response Time for Road Traffic Accidents in the Kingdom of Saudi Arabia: Analysis of National Data (2016–2020)," *International Journal of Environmental Research and Public Health,* 2023.

[31] M. K. Doaa, E. Elmorsy, A. Ahmed, A. N. Hesham and S. Lamiaa, "Factors Affecting Prehospital Time Delay of the Injured Patients Arriving at the Emergency Department of Beni-Suef University Hospital in Egypt: A Cross-Sectional Study," *PLOS ONE,* 2021.

[32] R. Pankaja, P. NB and D. M, "A study of Road Traffic Accidents and Road Safety Behavior in Pune: A Mixed-Method Approach," *Indian Journal of Community & Family Medicine,* pp. 75-78, 2015.

[33] K.-Z. Davoud, M. Reza and B. Katarina, "Factors Influencing Pre-Hospital Care Time Intervals in Iran: a Qualitative Study," *Journal of Injury and Violence Research,* pp. 83-90, 2018.

[34] T. Suzuki, O. Phonesavanh and S. Thongsna, "Relationship Between Prehospital Time and 24-h Mortality in Road Traffic-Injured Patients in Laos," *World Journal of Surgery,* vol. 46, pp. 800-806, 2022.

[35] J. Rashid and A. S. Masood, "Road Traffic Crash Related Injured and Fatal Victims in Karachi from 2007 to 2014: A Time-Series Analysis," *Journal of the Pakistan Medical Association,* pp. 622-626, 2017.

[36] S. A. Mir and A. Afzal, "Development and Analysis of GIS-Based Road Traffic Injury Database for Karachi, Pakistan," in *The 14th HKSTS International Conference*, Hong Kong, 2009.

[37] N. Ahmad, R. Arvin and A. J. Khattak, "How is the Duration of Distraction Related to Safety–Critical Events? Harnessing Naturalistic Driving Data to Explore the Role of Driving Instability," *Journal of Safety Research,* vol. 85, no. 5, 2023.

[38] P. Anastasopoulos, A. Tarko and F. Mannering, "Tobit Analysis of Vehicle Accident Rates on Interstate Highways," *Accident Analysis & Prevention,* vol. 40, no. 2, pp. 768-775, 2008.

[39] S. Washington, M. Karlaftis and F. Mannering, "Statistical and Econometric Methods for Transportation Data Analysis," 2010.

[40] X. Ma, F. Chen and S. Chen, "Modeling Crash Rates for a Mountainous Highway by Using Refined-Scale Panel Data," *Transportation Research Record,* vol. 2515, no. 1, pp. 10-16, 2015.

[41] L. Sigelman and L. Zeng, "Analyzing Censored and Sample-Selected Data with Tobit and Heckit Models," *Political Analysis* , vol. 8, no. 2, pp. 167-182, 1999.

[42] A. Numan, A. Ramin and K. Asad J., "Exploring Pathways from Driving Errors and Violations to Crashes: The Role of Instability in Driving," *Accident Analysis & Prevention,* 2023.

[43] J. Liu, A. Khattak, S. Richards and S. Nambisan, "What are the Differences in Driver Injury Outcomes at Highway-Rail Grade Crossings? Untangling the Role of Pre-Crash Behaviors," *Accident Analysis & Prevention,* vol. 85, pp. 157-169, 2015.

[44] M. Zhang, A. Khattak, J. Liu and D. Clarke, "A Comparative Study of Rail-Pedestrian Trespassing Crash Injury Severity Between Highway-Rail Grade Crossings and Non-Crossings," *Accident Analysis & Prevention,* vol. 117, pp. 427-438, 2018.

[45] J. Liu and A. Khattak, "Are Gates at Rail Grade Crossings Always Safe? Examining Motorist Gate-Violation Behaviors Using Path Analysis," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 55, pp. 314-324, 2018.

[46] R. Arvin, M. Kamrani and A. Khattak, "The Role of Pre-Crash Driving Instability in Contributing to Crash Intensity Using Naturalistic Driving Data," *Accident Analysis & Prevention* , vol. 132, 2019.

[47] J.-T. Lee and J. Fazio, "Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods," *Traffic Injury Prevention,* vol. 6, no. 4, pp. 331-339, 2005.

[48] S. R. Vanga, P. M. Ligrani, M. Doustmohammadi and M. Anderson, "Effects of Different Crash Data Variables on EMS Response Time for a Rural County in Alabama," *Journal of Family Medicine and Primary Care,* vol. 11, no. 4, p. 1462–1467, 2022.

[49] N. Eluru, C. R. Bhat and D. Hensher, "A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Level in Traffic Crashes," *Accident Analysis & Prevention,* vol. 40, no. 3, p. 1033–1054, 2008.

[50] M. Kamruzzaman, "Analysis of Traffic Injury Severity in a Mega City of a Developing Country," in *4th Road Safety International Conference*, Sydney, Australia., 2013.

[51] C. O'donnell and D. Connor, "Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice," *Accident Analysis & Prevention,* vol. 28, no. 6, p. 739–753, 1996.

[52] D. Daddah, Y. Glèlè Ahanhanzo, A. Kpozehouen, B. Santos, E. Bonnet, A. Levêque and Y. Coppieters, "Understanding the Factors of Road Crash Severity in Benin: A Matched Case-Control Study," *Journal of Public Health in Africa,* vol. 14, 2023.

[53] C. Chan, B. Huang, X. Yan and S. Richards, "Investigating Effects of Asphalt Pavement Conditions on Traffic Accidents in Tennessee Based on the Pavement Management System (PMS)," *Journal of Advanced Transportation,* vol. 44, no. 3, p. 150–161, 2010.

[54] Fylan F., "Why Do People Drive When They Can't See Clearly?," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 56, pp. 123-133, 2018.

[55] E. de Bellis, "Blind Haste: As Light Decreases, Speeding Increases," *PLoS One,* vol. 13, 2018.

[56] F. Malin, I. Norros and S. Innamaa, "Accident Risk of Road and Weather Conditions on Different Road Types," *Accident Analysis & Prevention,* vol. 122, p. 181–188, 2019.

[57] A. Chandrasekharan, A. J. Nanavati, S. Prabhakar and S. Prabhakar, "Factors Impacting Mortality in the Pre-Hospital Period After Road Traffic Accidents in Urban India," *Trauma Monthly,* vol. 21, no. 3, 2016.

[58] W. Hao, C. Kamga and D. Wan, "The Effect of Time of Day on Driver's Injury Severity at Highway-Rail Grade Crossings in the United States," *Journal of Traffic and Transportation Engineering (English Edition),* vol. 3, no. 1, p. 37–50, 2016.

[59] K. Khan, M. Jamil, I. Memon and Z. Idrees, "Pattern of Injuries in Motorbike Accidents," *Journal of Pakistan Orthopaedic Association,* vol. 30, no. 2, pp. 123-127, 2018.

[60] V. Akinpelu, A. Oladele, Y. Amusa, O. Ogundipe, A. Adeolu and E. Komolafe, "Review of Road Traffic Accident Admissions in a Nigerian Tertiary Hospital," *East and Central African Journal of Surgery,* vol. 12, no. 1, 2007.

[61] E. Naddumba, "A Cross-Sectional Retrospective Study of Boda Boda Injuries At Mulago Hospital IN Kampala-Uganda," *East and Central African Journal of Surgery,* vol. 9, no. 1, 2004.

[62] G. Tulu, S. Washington and M. King, "Characteristics of Police-Reported Road Traffic Crashes in Ethiopia Over a Six Year Period," in *Australasian Road Safety Research, Policing & Education Conference*, Brisbane, Queensland, 2013.

[63] R. Gebresenbet and A. Aliyu, "Injury Severity Level and Associated Factors Among Road Traffic Accident Victims Attending Emergency Department of Tirunesh Beijing Hospital, Addis Ababa, Ethiopia: A Cross Sectional Hospital-Based Study," *PLoS ONE,* vol. 14, no. 9, 2019.

[64] A. Baru, A. Azazh and L. Beza, "njury Severity Levels and Associated Factors Among Road Traffic Collision Victims Referred to Emergency Departments of Selected Public Hospitals in Addis Ababa, Ethiopia: The Study Based on the Haddon Matrix," *BMC Emergency Medicine,* vol. 19, no. 2, 2019.

[65] S. Mutooro, E. Mutakooha and P. Kyamanywa, "A Comparison of Kampala Trauma Score II with the New Injury Severity Score in Mbarara University Teaching Hospital in Uganda," *East and Central African Journal of Surgery,* vol. 15, 2010.

How Mode of Evacuation, Roadway Environment, and Traffic Conditions Relate to Injury Severity Score? Untangling the Role of Pre-hospital Time in Road Crashes

Abstract

This study explores the effects of some of the key factors, including emergency response measures, roadway and environment, traffic-related attributes, and crash-specific factors, on the Injury Severity Score (ISS) of Road Traffic Crashes' (RTCs) victims, both directly and through pre-hospital time (PHT) using rigorous path analysis. Data for 298,654 crashes, compiled by the Road Traffic Injury Research and Prevention Center (RTIRPC) in Karachi (Pakistan), were used for analyses. Owing to the corner-solution distribution of the response variables (PHT and ISS), two Tobit regression models are estimated after accounting for missing values through synthetic data generation. Marginal effects from these models are used in the path analysis. The findings suggest that ISS increases by 0.01 units with a unit increase in PHT, highlighting the critical need for rapid evacuation of crash victims to medical facilities. The mode of evacuation emerged as a crucial factor, with ambulances resulting in increased PHT and ISS compared to private or public transport, underscoring the improvement needed in the dedicated ambulance-based emergency response. PHT and ISS were found to be higher in nighttime crashes, necessitating better emergency medical services (EMS) response during the night. Intersection crashes were associated with lower PHT and ISS; whereas, crashes on undivided roads and those involving multiple or large vehicles increased PHT and ISS. The path analysis revealed that the overall effects of some of the key variables on ISS were higher than their direct effects – something that could not be explored without the path analysis. These insights can help policymakers develop strategies to improve emergency response and road safety, ultimately reducing the number of RTC-related injuries and fatalities.

Keywords: Pre-hospital time, Injury severity score, Road traffic crashes, Synthetic data, Tobit regression, Path analysis, Emergency medical services

1. Introduction

With 20 to 50 million road traffic injuries (RTIs) and 1.19 million road traffic fatalities (RTFs) annually worldwide, road traffic crashes (RTCs) have become a serious public health concern [1]. The situation is severe, especially in low- and middle-income countries, defined as those with a gross national income (GNI) per capita of $13,845 or less in 2022 [2]. The fatality rate from RTCs in low- and middle-income countries is approximately twice that of their high-income counterparts [2]. The outcome for victims of RTCs largely depends on receiving timely and efficient medical care. One critical aspect of medical treatment is the time between the occurrence of a crash and the provision of proper medical care, either on the spot or at hospitals/emergency units. The total pre-hospital time (PHT), which encompasses the time between the occurrence of an RTC and the crash victim's arrival at the hospital, can be divided into multiple phases: response time, scene time, and transport time. The time between the emergency medical services (EMS) notification and their arrival at the RTC scene is usually termed the "response time". "Scene time" refers to the duration between EMS arrival at the crash scene and their departure for the hospital. "Transport time" is the time it takes to travel from the crash scene to the hospital if additional medical treatment is needed [3]. Contrary to the developed countries, in low- and middle-income countries, crash victims are frequently transported to hospitals by family members, taxi drivers, truck drivers, police officers, or other road users, many of whom lack formal training. The dedicated (but limited) ambulance service is generally accessible only in urban areas. Many neurological injuries appear to be the consequence of inadequate immobilization or improper extraction procedures during the carriage of crash victims, which is frequently performed by individuals who lack adequate training. Past research suggests that the severe consequences of RTIs are predominantly attributable to inadequate public health infrastructure and limited access to (or poor) healthcare services [4]. The time to provide medical care to the victims of RTCs becomes more important in cases where the first medical aid is either unavailable or the victims need to be shifted to hospitals for extensive or additional treatment due to severe injuries. These situations are more critical as the PHT may significantly determine the final injuries and survival of the victims in RTCs who are to be shifted to the hospital(s) for extensive treatment.

Understanding the effects of the leading factors (i.e., roadway and environmental factors, traffic-related attributes, and response as well as evacuation-related factors) on injury outcome(s) of RTCs is significant, and several past studies have analyzed these relationships via traditional modeling approaches, usually capturing only the direct associations. However, we consider that in addition to the direct effects, the abovementioned factors can have a significant association with the injury outcomes through some of the mediating variables (i.e., PHT in the present case), which, if not captured, the overall relationships may be overlooked. To the best of the authors' knowledge, none of the studies investigated how the above-mentioned factors relate to ISS (being a fine injury measure), both directly and via PHT. Furthermore, recognizing the critical role of PHT in determining the injury outcome(s) of RTCs, it is vital to understand how various roadway and environmental factors, traffic-related attributes, response as well as evacuation-related factors relate to the PHT. For instance, the PHT for the victims in an RTC occurring on a roadway segment may significantly differ from that at intersections, as the chance of being timely noticed and assisted can be higher in the latter case. Similarly, different roadway types, weather, light conditions, crash locations, time of the crash, etc., may have diverse effects on the PHT. While studies mostly investigated how various roadway and environmental factors relate to response time, the factors affecting the "pre-hospital" time (which mostly relate to more critical injuries to be treated at hospitals) are lightly researched. In particular, the association of some of the important factors e.g., roadway types (divided versus undivided, and number of lanes, etc.), visibility-related factors (weather and light conditions), crash locations (segments versus intersections), and time of the crash considering traffic flow (peak versus off-peak hours), etc. with the PHT needs an in-depth investigation. As discussed earlier, the above-mentioned factors may also significantly relate to the injury severity directly. To understand the overall effects of the aforementioned factors on injury severity, it is important to unveil the effects of these factors on injury severity (especially using hospital-based fine injury data and measures like Injury Severity Score “ISS”), both directly and indirectly (via PHT) which are not well investigated to date.

This research aims to bridge the aforementioned gaps by investigating how the above-mentioned factors relate to ISS both directly and indirectly (via PHT) using rigorous path analysis while analyzing nine years (2007 to 2015) of hospital-based RTCs data collected by the Road Traffic Injuries Research and Prevention Center (RTIRPC) for Karachi, Pakistan. In particular, complex pathways leading from diverse roadways and environments, and crash- as well as response-related factors to ISS are aimed to be explored in this study, which can provide a more comprehensive and in-depth picture of the system.

2. Literature review

Several injury classification systems are employed to categorize the injuries experienced by roadway users involved in RTCs [5, 6]. The often-employed injury severity scales in transportation engineering include the KABCO Scale, Abbreviated Injury Scale (AIS), and Injury Severity Score etc. The KABCO injury scale serves as the basis for injury data recorded in police crash reports. It involves a five-point scale (Fatal (K), Serious (A), Moderate (B), Minor (C), and None (O)) to assess the severity of an RTC. In general, the KABCO scale offers a simple and easy-to-understand system for categorizing injuries. However, it also has obvious limitations [7, 8, 9, 10, 11, 12]. In contrast to the KABCO scale, the AIS is a global severity scoring system that is anatomically based, consensus-derived, and considers the relative significance of each injury in classifying it by body region on a six-point ordinal scale: 1 = Minor injury, 2 = Moderate injury, 3 = Serious injury, 4 = Severe injury, 5 = Critical injury, and 6 = Un-survivable (fatal) injury. The AIS assigns a numerical value to each injury based on its level of severity. Based on the anatomical structure, the human body can be categorized into nine body parts as shown in Figure 1 [13, 14]. Although the AIS describes anatomical injuries, it lacks internal consistency. Nevertheless, the anatomically based AIS has served as the foundation for various anatomical assessments of injury severity, such as the ISS [9, 15, 16]. The ISS is a well-established medical scoring system and is considered the leading and most reliable system for assessing injuries [14, 16]. The ISS is highly pertinent to evaluating the severity of injuries in RTCs as it enables the assessment of multiple injuries in several body regions. Specifically, the ISS is determined by considering the AIS scores of the three most serious injuries in three distinct anatomical locations.

Past research shows that ISS has a high level of proficiency in forecasting mortality, morbidity, and the duration of hospitalization [9, 17, 18, 19]. Previous research has found a wide range of factors that are associated with RTCs of different levels of injury severity. The investigation largely considered the impact of driver demographics and behavior, crash characteristics, roadway features, and environmental variables. Research also indicated that there are three main elements that have an impact on RTCs: traffic characteristics, road network and infrastructure, and demographic and environmental features [20]. It is also highlighted that several factors significantly influence road traffic casualties, including gender, vehicle condition, safety status, overloading, street lighting, weekends, type of vehicle, driver experience, morning rush hours, and severe weather conditions [21].

The idea of the "Golden Hour" emphasizes the significance of the period before arrival at the hospital in providing care for trauma patients. Most trauma experts believe that the initial 60 minutes following a crash, commonly known as the "golden hour," are crucial for maximizing the chances of preserving lives. Following this period, there is a substantial increase in the likelihood of fatality or the severity of injuries [22]. Unfortunately, the quality of pre-hospital care in many low- and middle-income countries is inadequate, resulting in a significant number of deaths during the pre-hospital stage [22]. Due to the absence of established EMS systems in most of these countries, most crash victims are rescued by bystanders at the crash scene. Moreover, many of these bystanders rely on commercial vehicles to transport the crash victims to a healthcare facility [23]. Consequently, a considerable number of neurological injuries appear to occur due to the procedure of extrication or shifting the crash victims without appropriate immobilization, which is frequently carried out by inexperienced persons [22].

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Studies show that several socio-demographic characteristics are strongly linked to various aspects of response time, such as geographical regions, types of crash, age, gender, and nationality. Gaining a comprehensive understanding of these elements is crucial for maximizing efficiency during the period spent before reaching the hospital [24]. Furthermore, places exhibit pre-hospital delays that are correlated with criteria such as older age, living in rural areas, and the level of consciousness of crash victims [25]. Environmental and infrastructural variables, such as the day of the week, whether the site is urban or rural, the exact details of the crash, and the time it takes for emergency response, have a considerable impact on the time it takes to clear the scene and the total duration during peak traffic hours. The delays in transferring crash victims to hospitals are sometimes caused by the unavailability of specialized transportation, communication difficulties, and a lack of awareness regarding nearby medical services [2, 26]. The EMS plays a vital role in minimizing the duration of care provided before a patient reaches the hospital.

The association between prehospital time and injury severity has primarily been studied in developed countries. However, it is still uncertain whether these findings can be applied to developing countries, particularly in low-resource settings, due to the existing status of pre-hospital and in-hospital care [27]. Moreover, the available literature clearly shows that both the direct effects of PHT and factors (i.e., environmental, highway, and crash-related elements) affecting it can have a significant influence on injury outcomes. Hence, in order to comprehend the comprehensive impact of the aforementioned elements on ISS, it is crucial to uncover their direct and indirect effects on ISS, particularly via PHT. Although the literature has documented the direct impact of the aforementioned factors (including PHT) on ISS, gaining an understanding of the indirect effects of these factors on ISS (via PHT) can offer valuable insights for developing or improving a comprehensive strategy to enhance road safety and decrease injury severity for victims of RTCs. For a summary of the relevant past literature, please refer to Table 1.

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3. Methodology

3.1. Data Source

This study analyzes the RTCs data acquired from the Road Traffic Injuries Research and Prevention Center (RTIRPC) for a period of nine years (2007 to 2015), focused on Karachi, Pakistan. The dataset contains details about 298,654 crashes and includes extensive information such as demographic, socioeconomic, roadway and environmental, and crash-related aspects. During the data cleaning process, we noticed that 160,365 entries (which accounted for approximately 54% of the total) had missing or improper values for one or more variables. For instance, there were ~7% (N=20,465) cases in which no AIS score was assigned to any of the nine body parts despite being taken to hospitals for treatment. This resulted in 138,289 entries (approximately 46%) having complete and accurate information for all the variables of interest. To address this problem, synthetic data generation techniques were used to account for the missing or incorrect values by generating 160,365 entries, using the distribution of the key variables of interest (along with their correlation with each other), from the cleaned data (N = 138,289). Subsequently, the final dataset with a sample size of 298,654 observations was used for analyses.

3.2. Synthetic Data Generation

The employment of synthetic data in this context is relevant, as it guarantees the optimal utilization of vital information that could otherwise be lost owing to improper or missing inputs arising from data entry errors. The "synthpop" program in R software was utilized to generate a synthetic dataset for the key variables based on the complete observed data. The "synthpop" technique involves the selection of an initial variable (by the user) to be synthesized, followed by the generation of values randomly using a method that samples with replacement from the observed data with complete information [28, 29]. Then, a parametric or non-parametric approach can be selected in the synthpop technique to predict the values of subsequent variables, utilizing the previously synthesized variables as predictors [30, 31]. This study used a non-parametric classification and regression tree (CART) approach for synthetic data generation. The selection of the CART method, whether it is regression or classification, was determined by the nature of the variable, such as whether it is continuous, binary, or categorical. This method generated a synthetic data clone, which was similar to the original data in terms of the distribution of variables and correlation among them, therefore maintaining the accuracy and usefulness of the dataset [28, 31]. For an in-depth understanding of the methodology, please refer to the studies in parentheses [28, 30, 29, 32, 33, 34].

3.3. Injury Severity Score

To calculate the ISS for a particular crash victim, the nine body parts (head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and external) are classified into six ISS body regions as shown in Figure-1. The injury is evaluated at each specific anatomical location, and a severity score based on the AIS is assigned to each individual injury. Then the highest severity code (AIS) for each of the three most severely injured body regions is squared and then summed to obtain the ISS score for a crash victim, which can be shown below:

$$\text{ISS} = X^2 + Y^2 + Z^2 \quad (1)$$

Where X, Y, and Z represent the AIS scores of the three body regions with the most serious injuries according to the ISS scale. The ISS scores span a range of 1 to 75.

3.4. Conceptual Framework

This research aims to examine the relationships of various factors, including roadway and environmental factors, and crash- and response-related aspects with the ISS of the victims in RTCs both directly and through PHT. The motivation for this research is based on our hypotheses that various factors, including the characteristics of the road (such as the presence of a median, number of lanes in each direction, etc.), the location of the crash (at an intersection or on a straight portion), the time of day (day or night), and the volume of traffic (during peak or off-peak hours), can have statistically significant effects on the PHT where the latter may significantly relate to the ISS. For example, during peak hours, congested, undivided roadway portions may have prolonged PHT for RTCs due to the complex road network and dense traffic, which may hinder the prompt arrival of emergency personnel. In contrast, RTCs occurring on uncongested divided roadway segments during non-peak hours may encounter faster response times, resulting in shorter pre-hospital durations. Furthermore, we consider that there can be a potential direct association of roadway and environmental conditions, and crash- and response-related factors with ISS. In order to systematically approach the research objectives, this study uses a two-stage path analysis (as depicted in Figure 2) to understand the overall effects of the key variables on the ISS while accounting for indirect pathways from these factors to the ISS via PHT.

PASTE FIGURE 2 HERE

3.5. Modelling Framework

This study used the Tobit model due to the continuous nature and distribution of the response variables (PHT for Model 1 and ISS for Model 2) in our data. The Tobit model is appropriate for addressing the corner-solution problem, which occurs when the dependent variable shows clustering or a spike at its lowest and/or highest extreme value [35, 7]. This characteristic was observed in both ISS and PHT in this study where the two variables exhibit spikes at the lower end. A brief description of the Tobit model can be found below:-

3.5.1. Tobit Regression

In the statistical literature, truncation and censoring are regarded as distinct phenomena; however, they both pertain to data observability concerns [36, 37, 38]. Censoring refers to a situation when a significant proportion of observations exceed the censoring threshold or events are not recorded for a considerable number of observations. Alternatively, truncation happens when a substantial number of observations surpasses the maximum observable range. Even without any censoring or truncation, the dependent variable can exhibit a cluster at the lowest extreme value (spike at 0 or 1), which is referred to as a corner-solution problem. In our case, we observed that both the distribution of ISS and the PHT exhibit a left spike, indicating corner-solution problems. It is important to highlight that there is no issue with data observability in our case. To fully incorporate and take into account all observations, research indicates that Tobit regression can be employed for all three phenomena [35, 36, 37, 38]. Thus, in this study, Tobit regression is used to estimate the ISS and PHT because of the corner-solution setup seen in the ISS and PHT:-

$$Yi^* = \beta 1Xi + \varepsilon 1, (i = 1, 2, 3, \ldots, N) \tag{2}$$

$$Yi = Yi^* \; (if \; Yi^* > \tau) \tag{3}$$

$$Yi = \tau_Y \; (if \; Yi^* \leq \tau) \tag{4}$$

In equation (2), the latent variable (stochastic index) is denoted as $Yi*$, the observed dependent variable is Yi, $\boldsymbol{\beta 1}$ represents a set of estimable parameters associated with independent variables ($\mathbf{X}\boldsymbol{i}$), N represents the number of observations, and $\varepsilon 1$ represents residuals that are assumed to follow a normal distribution with $\mathbf{N}(\mathbf{0}, \boldsymbol{\sigma 1}^2)$. The log-likelihood function for Tobit regression can be derived as follows:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset (\frac{Y-\mu}{\sigma})]^{di}[1 - \emptyset (\frac{\mu-\tau}{\sigma})]^{1-di} \quad (5)$$

In equation (5), τ represents the threshold in the data where a corner-solution (left-spikes) is observed, $\emptyset$ denotes the standard cumulative normal distribution function, and $\emptyset$ represents the standard normal density function. By setting $\tau = 0$ and expressing μ as a function of observed variables and their estimated parameters ($\beta 1 \mathrm{X} i$), the log-likelihood function for the Tobit model can be obtained:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset (\frac{Yi-\beta 1Xi}{\sigma})]^{di}[1 - \emptyset (\frac{\beta 1Xi}{\sigma})]^{1-di} \quad (6)$$

By further expanding equation (6), the log-likelihood functions can be expressed as:

$$lnL = \sum_i^N \{di\,(-ln\sigma + ln\emptyset\,(\frac{Yi-\beta 1Xi}{\sigma})) + (1 - di)ln\,(1 - \emptyset\,(\frac{\beta 1Xi}{\sigma}))\} \quad (7)$$

The equation (7) comprises two components: 1) the standard regression for uncensored observations and 2) the probability of censoring for specific observations. Marginal effects (MEs) can be calculated to see the impact of a unit increase in a specific continuous variable (or a transition from 0 to 1 in an indicator) on the response variable while holding all other variables in the model at their average values. Three distinct forms of MEs can be determined in Tobit regression, based on different predicted values of the dependent variable [39]. It should be noted that, depending on the extent, one or more of these MEs can be utilized. With that being stated, we calculate and furnish all three MEs for this research. However, we eventually utilize and interpret ME-1. It should be noted that ME-1 is calculated using both uncensored and censored observations. In our scenario, the ISS and PHT suggest a situation where the lowest limits are reached, known as a corner solution with left spikes [35, 39]. However, there is no actual censorship, as previously mentioned. Therefore, we employ ME-1, taking into account both censored and uncensored data, as shown below:-

$$\frac{\partial E[Yi]}{\partial Xi} = \varphi\,(\frac{\beta 1Xi}{\sigma})\,\beta 1 \quad (8)$$

To calculate the chance of an observation being uncensored, ME-2 can be determined using the following method:-

$$\frac{\partial Pr[Yi>1|Xi]}{\partial Xi} = \varphi\,(\frac{\beta 1Xi}{\sigma})\,\frac{\beta 1}{\sigma} \quad (9)$$

The equation (10) provided below can be utilized for MEs (ME-3) that rely solely on unfiltered observations of response variables:-

$$\frac{\partial E[Yi|Yi>0]}{\partial Xi} = \beta i\,\{1 - \lambda(\alpha)\,[\frac{\beta 1Xi}{\sigma} + \lambda(\alpha)]\} \quad (10)$$

Where, $$\lambda(\alpha) = \frac{\emptyset\,(\frac{\beta 1Xi}{\sigma})}{\varphi\,(\frac{\beta 1Xi}{\sigma})} \quad (11)$$

It is important to mention that the ME-3 is more applicable in situations of "true censoring," which is not the case in this study.

In summary, we employed the ME-1 method, which incorporates both censored and uncensored observations, from the Tobit model in our final path analysis. This allowed us to assess the indirect and total effects of PHT and other important factors on ISS [35, 40].

3.6. Path Analysis

Within the path analysis framework, the MEs obtained from the individual models are utilized to ascertain the direct, indirect, and overall effects of relevant factors on the ultimate response variable (ISS), as depicted in Figure 1 [41, 42]. The impact of a specific independent variable on the ISS is determined by multiplying the estimated effects (MEs) obtained from the PHT model (Model 1) with the ME of PHT obtained from the ISS model (Model 2). It should be noted that the "ISS model" quantifies the direct impact of the leading independent factors, and PHT on ISS sustained by a crash victim. When combined with the indirect effect, these factors provide the overall impact of a specific explanatory variable on ISS. The equations for calculating the indirect and total impacts of certain explanatory variables are provided below [12, 43, 44]:-

$$\text{Indirect MEs} = (\text{MEs from PHT model}) * (\text{MEs of PHT from ISS model}) \quad (12)$$

$$\text{Total MEs} = \text{Direct MEs} + \text{Indirect MEs} \quad (13)$$

While consistent estimates can be obtained via standard path analysis (i.e., independent estimation of models), studies suggest that achieving more efficient results if potential correlation between the unobserved factors exists and is taken into account via joint estimation [35, 45]. To account for potential correlation between the unobserved factors which can be associated with both PHT and ISS, we used the limited information maximum likelihood procedure for the estimation of the two models jointly via Conditional Mixed Process (CMPT), where the latter is a user-written STATA routine [46]. The joint estimation considers the two error terms ($\varepsilon 1$ and $\varepsilon 2$), associated with PHT and ISS, to have multivariate normal distribution [46].

4. Results

4.1. Actual Versus Synthetic Data

The cleaned RTIRPC data, which consisted of 138,289 observations, were employed to produce a synthetic dataset with 160,365 observations, as previously mentioned. Subsequently, these datasets were merged to produce a combined sample size that was equivalent to the original RTIRPC data (N=298,654). The distribution of key variables in both the actual and synthetic datasets is compared in Figure 3. The synthetic data's distribution of all variables appears to be reasonable when compared with the actual (observed) data. Comparisons are presented for only a subset of the key variables for brevity. The descriptive statistics for these variables are compared across the actual and synthetic data samples in Table 2. The means and standard deviations of the key variables in the synthetic data are in close agreement with those of the actual data.

PASTE FIGURE 3 HERE

PASTE TABLE 2 HERE

4.2. Descriptive Statistics

Figure 4 illustrates the distribution of two dependent variables, namely PHT and ISS. Both of these variables are characterized by a corner-solution set-up, which enables them to be modeled using Tobit regression. For further information, please refer to the methodology section.

PASTE FIGURE 4 HERE

The summary statistics of the key variables are displayed in Table 3. The mean ISS for individuals involved in crashes is 6.20, with a standard deviation of 11.80. The mean PHT is 104.30 minutes, with a significant standard deviation of 205.66 minutes, while the longest reported PHT is 1439 minutes. While the maximum value of PHT (1439 minutes ~ 24 hours) may seem to be an outlier, we included crashes with such large values to highlight the slow response and its consequences. Out of all the crashes, a significant percentage of 35.68% took place on roads that had four lanes in each direction. Moreover, 75% of crashes occurred on straight road segments, while 37% occurred at night. Figure 5 shows the distribution of variables, including the type of vehicles, type of crash victims, and mode of evacuation associated with RTCs. Referring to the distribution of crashes based on the vehicle types involved, motorcycles accounted for the largest proportion of crashes (69.41%), followed by other vehicles such as taxis (7.58%), buses (5.27%), passenger vans (2.42%), bicycles (1.32%), trucks (1.76%), private automobiles (0.97%), and rickshaws (three-wheelers) (0.35%). The most susceptible individuals involved in RTCs were riders and passengers of two-wheelers, as well as pedestrians, accounting for 48.12%, 13.78%, and 23.08% of the total crash victims, respectively. In terms of the mode of evacuation, 61.00% of crash victims were taken to medical facilities utilizing private transport, while 34.33% made use of ambulance services. For the distribution of other key variables, please refer to Table 3.

PASTE FIGURE 5 HERE

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4.3. Modeling Results

The final models (Model 1 and Model 2 for PHT and ISS, respectively) were systematically derived for each outcome type, incorporating the most significant variables (based on the research objectives), statistical significance, intuition, theoretical justifications, and specification parsimony. To this end, the likelihood ratio test and improvement in the AIC and BIC statistics were considered. A 95% confidence criterion was employed to determine the statistical significance of the variables in either model. The subsequent subsections provide details about key findings that were obtained from both models. While the final modeling results (below) are based on the models which were estimated in an independent fashion, we want to mention that we tried to estimate the two models in a joint fashion (as discussed in sub-section 3.6) to account for potential correlation between the unobserved factors associated with PHT and ISS. However, there was no significant evidence found that a significant correlation exists between the unobserved factors associated with the two dependent variables (i.e., PHT and ISS). As discussed earlier, the results obtained from the independent models are still consistent and used in recent research studies based on the independently estimated models.

4.3.1. Model 1: Factors Affecting Pre-Hospital Time

The results of the final PHT Model suggest a significant reduction in PHT for RTCs which occur at intersections (compared to mid-block locations), on roadway segments with fewer than four lanes per direction, involve VRUs (especially pedestrians and cyclists), and if the post-crash evacuation is carried out by modes other than a dedicated ambulance service. On the other hand, PHT is significantly higher for RTCs occurring on undivided roadways, in seasons other than summer, during nighttime, and in RTCs with multiple or heavy vehicles involved. As stated in the footnote of Table 4, there was no statistical evidence of multicollinearity among the variables included in the final model. For detailed results and relevant discussion of the model results, please refer to Table 4 and the discussion section, respectively.

PASTE TABLE 4 HERE

4.3.2. Model 2: Factors Affecting Injury Severity Score

In the final ISS model, we found 13 explanatory variables, including PHT, to have statistically significant (as per 95% confidence level criteria) association with ISS (Table 5). The final model underscores a significant association of the PHT with the ISS, indicating that as PHT increases, the ISS also tends to increase significantly. The higher degree polynomial (i.e., squared term) of PHT shows a significant correlation with ISS, indicating sufficient evidence of non-linearity in the association of PHT with ISS. Furthermore, RTCs, which occur on undivided roadway segments at nighttime, on Fridays, and involve VRUs, lead to significantly higher ISS for the crash victims. Similarly, the involvement of multiple or heavy vehicles in RTCs tends to result in higher ISS. On the other hand, ISS significantly reduces for the victims in RTCs which occur at intersections (as opposed to mid-block locations), on roadways with fewer than 4 lanes in each direction, during time other than morning peak hours, during seasons other than summer, and if post-crash evacuation is carried out via modes other than ambulance. Furthermore, a significant positive correlation between the number of body parts injured in a crash and the ISS was found. For inclusive results and discussion, please refer to Table 5 and the discussion section, respectively. Furthermore, there is a significant positive correlation between the number of body parts injured in a crash and the ISS, with each additional injured body part resulting in a higher ISS.

PASTE TABLE 5 HERE

4.3.3. Path Analysis

Table 6 presents the results of the path analysis, which uncovers the direct and indirect relationships of the key factors (i.e., related to roadways and environment, response, traffic, and crash) with the ISS for the victims of RTCs. The direct effects of key explanatory variables on the ISS (ME-1) are obtained from Table 5, which is based on Model 2. Whereas, in order to determine the indirect effects of key explanatory variables on ISS, we compute them by multiplying the ME (ME-1) of each individual variable from Model-1 with the ME (ME-1) of PHT on ISS obtained from Model-2. The outcomes of these computations, which emphasize the indirect effects of the key explanatory variables on ISS, are compiled in Table 6, which presents the direct, indirect, and total impacts of each explanatory variable.

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5. Discussion

The distribution of key variables such as ISS and PHT offers useful insights into the nature and outcomes of RTCs. The ISS, with a mean of 6.20 and a high standard deviation of 11.80, suggests a wide variation in injury severity, highlighting the diverse impact of RTCs. The mean PHT of 104.30 minutes points to significant delays in emergency responses, which could worsen injury outcomes and indicate a pressing need for improvements in EMS and transportation infrastructure.

Referring to the results of Model 1 (PHT model), the crash location ME-1 demonstrates a 21.53 times decrease in PHT for crashes that happen at intersections as opposed to segments (Table 4). The strong negative correlation indicates that the process of rescuing crash victims and transporting them to the hospital is relatively faster at (or near) intersections, potentially because these locations are easily identifiable and accessible. In contrast, crashes occurring on undivided roadways significantly lead to a 4.03 times rise in the PHT. The results are consistent with previous research that highlights the significant impact of off or opposing-lane crash location on clearance time and the subsequent total PHT [47]. The findings also indicate that crashes occurring on roads with less than four lanes in each direction significantly reduce the PHT by 10.21 times. This finding was expected as roads with lower traffic volume (less number of lanes) are more conducive to faster response times because they experience less congestion and provide better access for emergency vehicles. Moreover, there is a significant rise (16.17 times) in PHT for nighttime crashes, as opposed to daytime, highlighting the difficulties faced in responding to emergencies during the night. Moreover, the limited availability of public or private transportation during nighttime could also lead to longer PHT. Similar results can be seen in previous research [48]. With regards to the association of mode of evacuation with PHT, the findings interestingly indicate that the utilization of modes for evacuation, compared to an ambulance, is linked with a 4.36 times decrease in PHT, suggesting that ambulance modes in the city tend to be more inefficient. The unexpected outcome may be attributed to the formal procedures and protocols adhered to by ambulance services, which, although guaranteeing comprehensive care, could result in extended response durations in the megacapital city of Pakistan. Dependence on private or public transportation during emergencies may bypass certain procedural delays, but could potentially endanger the standard of medical care during transportation. The findings also suggest that crashes involving multiple vehicles and heavy vehicles lead to an increase of 2.73 and 21.24 times in PHT, respectively, which may be most likely because of the challenges associated with handling scenes that involve either multiple or heavy vehicles. These findings align with past research that has shown the significant impact of the number of vehicles and the involvement of heavy vehicles on clearance time and overall duration of PHT [47]. Crashes involving VRUs, such as pedestrians and cyclists, lead to a 25.75 times reduction in the PHT. The strong negative association indicates that VRU crashes exhibit reduced PHT, which may be attributable to the comparatively effortless accessibility of the victims in contrast to occupants of vehicles. The visibility of these crashes and the possibility of prompt assistance from bystanders may also contribute to quicker response times, resulting in reduced PHT.

Referring to Model 2 (ISS Model), the findings suggest a significant positive correlation of PHT with ISS. More precisely, with each extra minute increase in PHT, the ISS shows an increase (i.e., by 0.01 unit), highlighting the need for immediate medical intervention to reduce the severity of injuries. Receiving medical care with delays can aggravate injuries, resulting in worse outcomes, which is consistent with the past studies [22, 23, 24, 25, 26, 49]. Nevertheless, the presence of a statistically significant negative coefficient for the higher (i.e., squared) degree polynomial of PHT indicates significant evidence of variability in the slope of PHT (i.e., effects of PHT on ISS). However, further research is needed to identify and understand the prevalent trends in the nonlinear relationship between these two variables, which is not the focus of the present study. Referring to the roadway types, our findings suggest that crashes on undivided roadways significantly increase the ISS by 0.37 times. Undivided roadways without median barriers frequently witness more severe head-on crashes, leading to increased injury severity, which is aligned with the past research [50, 51, 52, 53]. In contrast, crashes that happen at intersections are linked to a 0.36 times reduction in ISS compared to those on straight-road segments. Although intersections are areas of potential conflict, they tend to have reduced impact speeds as a result of traffic management systems, leading to less serious injuries. Crashes that occur at night are linked to a 0.32 times rise in ISS, indicating greater severity of injuries during nighttime hours. Reduced visibility, driver exhaustion, and an increased probability of impaired driving, combined with decreased law enforcement during nighttime, contribute to more serious injuries. To avoid these hazards, it would be beneficial to increase nighttime enforcement, visibility/conspicuity, and infrastructure [54]. Furthermore, it is crucial to have emergency response services available around the clock [50, 55, 56, 57, 58, 59]. Referring to the surrounding traffic conditions, we found that crashes that happen outside the morning peak hours are linked to a reduction in the ISS, which suggests that crashes during morning peak hours are more severe. Previous research also suggests that drivers/riders tend to drive/ride faster in the early morning to make sure they get to work on time, especially when 69.41% of the crashes involved motorcyclists who are prone to injuries even at lower speeds when involved in an RTC. The utilization of non-ambulance (private vehicles) modes for evacuation significantly reduces the ISS by 3.91 times. This finding is not consistent with the findings reported from studies conducted in other regions [60, 61, 62, 63], emphasizing the significance of implementing an advanced EMS system in order to enhance the outcomes for those involved in tragic crashes. VRUs, which include pedestrians, motorcyclists, and bikers, experience higher injury severity, leading to a 0.41 times increase in ISS. The lack of protections for VRUs makes them exceptionally vulnerable, underscoring the requirement for enhanced safety protocols, such as the implementation of exclusive lanes and the promotion of public awareness initiatives. The severity of injuries is directly related to the number of body parts injured, as seen by a significant increase in ISS for each additional wounded body part. Providing thorough medical care to more badly injured victims leads to longer pre-hospital delays and higher overall injury severity. The present findings are consistent with other research that has reported similar outcomes [64, 65, 66].

Referring to the results of path analysis, most factors with a significant direct association with ISS also have shown a significant association with PHT. PHT, in turn, is associated with ISS, creating an indirect association of these factors with ISS as well (see Figure 6). Consequently, the overall effects of some of the key variables on ISS are different from their direct effects (as shown in Table 6). The results indicate that certain factors have both direct and indirect effects on increasing the ISS, with the overall effects being higher than their direct effects. For example, if a crash occurs at night, it would increase the ISS by 0.32 times. However, when considering the indirect effects (0.16) on ISS via PHT, the overall effects are found to be 0.48, which is much higher than the direct effects of 0.32. Similarly, factors that tend to reduce the ISS, both directly and indirectly (e.g., crash location), also result in overall effects that are higher than their direct effects. Interestingly, some factors directly increase the ISS but reduce it through their indirect effects. For example, the involvement of VRUs in a crash would increase the ISS by 0.41 times; however, when its indirect effects (-0.26) are also considered, the overall effects are found to be 0.15, which is much lower than the direct effects. This information cannot be obtained using conventional modeling techniques.

6. Practical Implications

The findings have significant practical implications for improving road safety and emergency response that could potentially lead to substantial reductions in the severity of injuries and fatalities. The significant and prolonged delays in PHT, which average over 104 minutes, emphasize the urgent need to improve EMS, especially in the city from which the data was analyzed. The implementation of more effective ambulance services, possibly using advanced technology like GPS tracking, has the potential to significantly reduce preventable hospitalizations and thus alleviate the severity of injuries. Moreover, it is crucial to enhance the skills and resources available to first responders to ensure expedited and more efficient medical interventions. Furthermore, there is a need for stricter enforcement of traffic regulations, especially regarding large vehicles and violations leading to RTCs. Targeted enforcement campaigns and stringent penalties could effectively discourage dangerous driving habits, particularly during night and morning peak traffic hours, due to the increased severity of injuries associated with such incidents. Enhancing visibility and deploying law enforcement personnel at night could mitigate the heightened risks of severe injuries associated with reduced visibility and impaired driving. The increased vulnerability of VRUs, including pedestrians and cyclists, underscores an urgent need for public awareness initiatives specifically targeting road safety. By promoting the use of helmets, reflective clothing, and marked crossing locations, as well as providing education to drivers on responsible road sharing, it is possible to mitigate the extent of injuries sustained by these specific groups.

PASTE FIGURE 6 HERE

7. Research Limitations and Scope for Future Research

This study analyzed data obtained from the RTIRPC, which is one of the most extensive national initiatives conducted thus far. Despite being an extensive and detailed collection effort in developing countries like Pakistan, which can have several benefits, we acknowledge several potential limitations. The results are specifically applicable to crashes that resulted in injuries (where crash victims were shifted to hospitals) and cannot be generalized to instances that involve property damage only. Furthermore, the data was acquired upon the arrival of crash victims at the hospitals. As a result, information regarding the conditions of the road, the circumstances of the crash, and parts of the response were not collected at the crash scene. Similarly, the medical condition of the victims was also documented upon their arrival at the hospital without information about pre-, on-scene, and post-hospital times. One of the potential research avenues can be to explore the approaches that can include information about the aforementioned variables (roadway, pre- and on-scene medical conditions, etc.). Furthermore, as discussed earlier, each of the injury scales, including KABCO, AIS, ISS, and NISS, has its own advantages and limitations, considering which the selection of a specific injury measure depends on the situation and scope of the study. For instance, it is important to highlight that ISS may not always lead to an accurate prediction of injury outcomes, as we consider that the same ISS score can have different clinical outcomes due to differences in types of injuries, responses of the patients, patient age, and cure. While the present research does not look at the prediction of injury outcomes based on ISS and/or other injury measures, including AIS or NISS, we consider it important to account for the potential endogeneity issues within the ISS in future research. For instance, it would be interesting to see the role of interaction of ISS and patient age/injury types (based on body parts) in predicting the final clinical outcome (i.e., morbidity versus survival). Furthermore, as discussed in the data section, our findings are based on the hospital-based detailed data, which was collected as a part of a funded project in Karachi, Pakistan, where the latter can have its unique characteristics, including socio-economics, traffic, behaviors, emergency response, and trauma protocols. To assess the transferability or differences across cities or locations in the country (or abroad), a similar study can be extended to other cities or localities in the country and/or abroad. Future research also necessitates the collaboration of transportation and medical professionals. This interdisciplinary approach has the potential to yield useful insights that can improve overall road safety and enhance the medical care of crash victims. Moreover, it is necessary to broaden the scope of national-level projects, such as the RTIRPC, by incorporating a wider variety of geographic and socio-economic circumstances. Researchers can enhance the development of more efficient techniques to reduce injury severity and improve the outcomes for individuals involved in road crashes.

8. Conclusion

The research investigates how roadway environment, crash-specific features, and evacuation/response measures relate to ISS directly and via PHT – something that is lightly researched. To achieve the research objectives, a unique and fine crash data obtained from hospital records in Karachi (Pakistan) was analyzed. To address issues related to missing values and ensure accuracy in analysis, a synthetic data generation procedure was employed. Considering the corner-solution distribution of PHT and ISS, two Tobit models were applied using rigorous path analysis. The analysis revealed a significant association between PHT and ISS, suggesting that a one-unit increase in PHT corresponds to a 0.01-unit increase in ISS, highlighting the importance of swift evacuation and immediate medical care for the crash victims. The study identified the mode of evacuation as a crucial factor, with ambulance transportation resulting in longer PHT and higher ISS compared to private or public transport modes. The findings also showed that crashes occurring at night not only increased ISS directly, but also led to longer PHT, where the latter itself showed a positive correlation with ISS. Furthermore, our findings reveal that undivided roadways and involvement of multiple or heavy vehicles are critical, as these significantly increase both PHT and ISS, signifying more complex and severe collision scenarios. The path analysis showed that the overall effects of several explanatory variables on ISS were higher than their individual direct or indirect effects, demonstrating the efficacy of this analytical approach in capturing the multifaceted impacts on the finer injury measures in RTCs. Based on the findings, the study provides useful knowledge that can help in improving the EMS infrastructure by enhancing the deployment and effectiveness of ambulances (e.g., by implementing and using GPS tracking systems for the dedicated emergency response service), as well as improving emergency response times, especially during the night, in populous and congested cities. We also consider that implementing specific road safety measures, such as enhanced traffic enforcement on undivided roadways and improved visibility, can be beneficial. Public awareness efforts focused on educating individuals about proper emergency response and first aid have the potential to reduce the seriousness of injuries in RTCs, as, unlike the developed world majority of the RTC victims are shifted to hospitals or emergency units by the public in private vehicles.

References

[1] World Health Organization (WHO), 13 December 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. [Accessed 21 February 2024].

[2] J. Antony, V. Jayaseelan, J. J. Olickal, J. Alexis and M. Sakthivel, "Time to Reach Health-Care Facility and Hospital Exit Outcome Among Road Traffic Accident Victims Attending a Tertiary Care Hospital, Puducherry," *Journal of Education and Health Promotion,* 2021.

[3] J. Brown, M. Rosengart, R. Forsythe, B. Reynolds, M. Gestring, W. Hallinan, A. Peitzman, T. Billiar and J. Sperry, "Not All Prehospital Time is Equal: Influence of Scene Time on Mortality," *Journal of Trauma and Acute Care Surgery,* pp. 93-100, 2016.

[4] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi , "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* 2010.

[5] P. L. Chen and C. W. Pai, "Evaluation of Injuries Sustained by Motorcyclists in Approach-Turn Crashes in Taiwan," *Accident Analysis & Prevention,* vol. 38, no. 5, pp. 1019-1027, 2019.

[6] S. Palmer, M. Bader, A. Qureshi, J. Palmer, T. Shaver, M. Borzatta and C. Stalcup, "The Impact on Outcomes in a Community Hospital Setting of Using the AANS Traumatic Brain Injury Guidelines," *Journal of Trauma and Acute Care Surgery ,* vol. 50, no. 4, pp. 657-664, 2001.

[7] B. Wali , A. J. Khattak and N. Ahmad, "Examining Correlations Between Motorcyclist's Conspicuity, Apparel Related Factors and Injury Severity Score: Evidence from New Motorcycle Crash Causation Study," *Accident Analysis & Prevention,* vol. 131, pp. 45-62, 2019.

[8] A. J. Khattak , N. Ahmad, B. Wali and E. Dumbaugh, "A Taxonomy of Driving Errors and Violations: Evidence from the Naturalistic Driving Study," *Accident Analysis & Prevention,* vol. 151, 2021.

[9] B. Wali, A. J. Khattak and N. Ahmad, "Towards Better Measurement of Traffic Injuries – Comparison of Anatomical Injury Measures in Predicting Clinical Outcomes in Motorcycle Crashes," *Journal of Safety Research,* 2022.

[10] F. Mannering and C. Bhat, "Analytic Methods in Accident Research: Methodological Frontier and Future Directions," in *Analytic Methods in Accident Research*, 2014, pp. 1-22.

[11] J. Short and B. Caulfield, "Record Linkage for Road Traffic Injuries in Ireland Using Police Hospital and Injury Claims Data," *Journal of Safety Research ,* vol. 58, pp. 1-14, 2016.

[12] N. Ahmad, B. Wali, A. J. Khattak and E. Dumbaugh, "Built Environment, Driving Errors and Violations, and Crashes in Naturalistic Driving Environment," *Accident Analysis & Prevention,* vol. 157, 2021.

[13] K. L. Loftis, J. Price and P. J. Gillich, "Evolution of the Abbreviated Injury Scale: 1990–2015," *Traffic Injury Prevention,* vol. 19, no. Sup2, pp. 109-113, 2018.

[14] S. Baker, B. o'Neill, H. Jr. and W. W. Long, "The Injury Severity Score: A Method for Describing Patients with Multiple Injuries and Evaluating Emergency Care," *The Journal of Trauma and Acute Care Surgery,* vol. 14, no. 3, pp. 187-196, 1974.

[15] A. G. Rapsang and D. C. Shyam, "Scoring Systems of Severity in Patients with Multiple Trauma," *Cirugía Española (English Edition),* vol. 93, no. 4, pp. 213-221, 2013.

[16] M. Stevenson, M. Segui-Gomez, I. Lescohier, C. Di Scala and G. Mcdonald-Smith, "An Overview of the Injury Severity Score and the New Injury Severity Ccore," *Injury Prevention,* vol. 7, no. 7, pp. 10-13, 2001.

[17] S. Ankarath, P. Giannoudis, I. Barlow, M. Bellamy, S. Matthews and R. Smith, "Injury Patterns Associated with Mortality Following Motorcycle Crashes," *Injury* , vol. 33, no. 6, pp. 473-477, 2002.

[18] L. Camilloni, P. Rossi, S. Farchi, F. Chini, P. Borgia and G. Guasticchi, "Triage and Injury Severity Scores as Predictors of Mortality and Hospital Admission for Injuries: A Validation Study," *Accident Analysis & Prevention,* vol. 42, no. 6, pp. 1958-1965, 2010.

[19] O. Bolorunduro, C. Villegas, T. Oyetunji, E. Haut, K. Stevens, D. Chang, E. Cornwell III, D. Efron and A. Haider, "Validating the Injury Severity Score (ISS) in Different Populations: ISS Predicts Mortality Better Among Hispanics and Females," *Journal of Surgical Research,* vol. 166, no. 1, pp. 40-44, 2011.

[20] H. Li, "Impacts of Traffic Interventions on Road Safety: An Application of Causal Models," 2013.

[21] G. Zhang, K. K. Yau and G. Chen, "Risk Factors Associated with Traffic Violations and Accident Severity in China," *Accident Analysis & Prevention,* vol. 59, pp. 18-25, 2013.

[22] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi, "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* vol. 10, 2010.

[23] Z. Mengstu, A. Ali and T. Abegaz, "Prehospital Care and 24-hour Crash Injury Mortality Among Road Traffic Crash Victims in Addis Ababa," *Science Journal of Public Health,* vol. 9, pp. 23-29, 2021.

[24] A. Thamer, M. A. Yousef, H. A. I. Mahmudul, A. A. Monerah, A. Adil, A. Ibrahim and M. Ilias, "Emergency Medical Service Response Time for Road Traffic Accidents in the Kingdom of Saudi Arabia: Analysis of National Data (2016–2020)," *International Journal of Environmental Research and Public Health,* 2023.

[25] M. K. Doaa, E. Elmorsy, A. Ahmed, A. N. Hesham and S. Lamiaa, "Factors Affecting Prehospital Time Delay of the Injured Patients Arriving at the Emergency Department of Beni-Suef University Hospital in Egypt: A Cross-Sectional Study," *PLOS ONE,* 2021.

[26] R. Pankaja, P. NB and D. M, "A study of Road Traffic Accidents and Road Safety Behavior in Pune: A Mixed-Method Approach," *Indian Journal of Community & Family Medicine,* pp. 75-78, 2015.

[27] T. Suzuki, O. Phonesavanh and S. Thongsna, "Relationship Between Prehospital Time and 24-h Mortality in Road Traffic-Injured Patients in Laos," *World Journal of Surgery,* vol. 46, pp. 800-806, 2022.

[28] N. Ahmad, T. Bhowmik, V. V. Gayah and N. Eluru, "On the Need to Address Fixed-Parameter Issues Before Applying Random Parameters: A Simulation-Based Study," *Analytic Methods in Accident Research,* vol. 41, 2024.

[29] J. Abowd and J. Lane, "New Approaches to Confidentiality Protection: Synthetic Data, Remote Access and Research Data Centers," in *Proceedings of the International Workshop on Privacy in Statistical Databases*, 2004.

[30] J. Abowd and S. Woodcock, "Multiply-Imputing Confidential Characteristics and File Links in Longitudinal Linked Data," in *Proceedings of the International Workshop on Privacy in Statistical Databases*, 2004.

[31] Z. U. Rehman, N. Ahmad, A. Ahmed and W. I. Kayani, "Investigating the Association of Post-Crash Medical Conditions and Human Factors with Motorcyclists Injuries: Insights from Fine Injury Data From Hospital Records," in *Transportation Research Board Annual Meeting by National Academies of Sciences, Engineering, and Medicine*, Washington, D.C., 2025.

[32] J. Reiter, "Releasing Multiply Imputed, Synthetic Public Use Microdata: An Illustration and Empirical Study," *Journal of the Royal Statistical Society: Series A (Statistics in Society),* vol. 168, no. 1, pp. 185-205, 2005.

[33] J. Drechsler and J. Reiter, "Sampling with Synthesis: A New Approach for Releasing Public Use Census Micro Data," *Journal of the American Statistical Association,* vol. 105, no. 492, pp. 1347-1357, 2010.

[34] S. Kinney, J. Reiter and J. Berger, "Model Selection when Multiple Imputation is Used to Protect Confidentiality in Public Use Data," *Journal of Privacy and Confidentiality,* vol. 2, no. 2, 2011.

[35] N. Ahmad, R. Arvin and A. J. Khattak, "How is the Duration of Distraction Related to Safety–Critical Events? Harnessing Naturalistic Driving Data to Explore the Role of Driving Instability," *Journal of Safety Research,* vol. 85, no. 5, 2023.

[36] P. Anastasopoulos, A. Tarko and F. Mannering, "Tobit Analysis of Vehicle Accident Rates on Interstate Highways," *Accident Analysis & Prevention,* vol. 40, no. 2, pp. 768-775, 2008.

[37] S. Washington, M. Karlaftis and F. Mannering, "Statistical and Econometric Methods for Transportation Data Analysis," 2010.

[38] X. Ma, F. Chen and S. Chen, "Modeling Crash Rates for a Mountainous Highway by Using Refined-Scale Panel Data," *Transportation Research Record,* vol. 2515, no. 1, pp. 10-16, 2015.

[39] L. Sigelman and L. Zeng, "Analyzing Censored and Sample-Selected Data with Tobit and Heckit Models," *Political Analysis* , vol. 8, no. 2, pp. 167-182, 1999.

[40] A. Numan, A. Ramin and K. Asad J., "Exploring Pathways from Driving Errors and Violations to Crashes: The Role of Instability in Driving," *Accident Analysis & Prevention,* 2023.

[41] J. Liu, A. Khattak, S. Richards and S. Nambisan, "What are the Differences in Driver Injury Outcomes at Highway-Rail Grade Crossings? Untangling the Role of Pre-Crash Behaviors," *Accident Analysis & Prevention,* vol. 85, pp. 157-169, 2015.

[42] M. Zhang, A. Khattak, J. Liu and D. Clarke, "A Comparative Study of Rail-Pedestrian Trespassing Crash Injury Severity Between Highway-Rail Grade Crossings and Non-Crossings," *Accident Analysis & Prevention,* vol. 117, pp. 427-438, 2018.

[43] J. Liu and A. Khattak, "Are Gates at Rail Grade Crossings Always Safe? Examining Motorist Gate-Violation Behaviors Using Path Analysis," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 55, pp. 314-324, 2018.

[44] R. Arvin, M. Kamrani and A. Khattak, "The Role of Pre-Crash Driving Instability in Contributing to Crash Intensity Using Naturalistic Driving Data," *Accident Analysis & Prevention* , vol. 132, 2019.

[45] N. Ahmad, R. Arvin and A. Khattak, "Exploring pathways from driving errors and violations to crashes: The role of instability in driving," *Accident Analysis & Prevention,* vol. 2023, no. 179, p. 106876, 2023.

[46] D. Roodman, "Mixed-process models with CMP," in *Proceedings of the DC09 Stata Conference*, 2009.

[47] J.-T. Lee and J. Fazio, "Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods," *Traffic Injury Prevention,* vol. 6, no. 4, pp. 331-339, 2005.

[48] S. R. Vanga, P. M. Ligrani, M. Doustmohammadi and M. Anderson, "Effects of Different Crash Data Variables on EMS Response Time for a Rural County in Alabama," *Journal of Family Medicine and Primary Care,* vol. 11, no. 4, p. 1462–1467, 2022.

[49] K.-Z. Davoud, M. Reza and B. Katarina, "Factors Influencing Pre-Hospital Care Time Intervals in Iran: a Qualitative Study," *Journal of Injury and Violence Research,* pp. 83-90, 2018.

[50] U. Hanif, F. Asim and A. S. Akhtar, "An Empirical Assessment of Factors Influencing Injury Severities of Motor Vehicle Crashes on National Highways of Pakistan," *Journal of Advanced Transportation*, 2021.

[51] N. Eluru, C. R. Bhat and D. Hensher, "A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Level in Traffic Crashes," *Accident Analysis & Prevention,* vol. 40, no. 3, p. 1033–1054, 2008.

[52] M. Kamruzzaman, "Analysis of Traffic Injury Severity in a Mega City of a Developing Country," in *4th Road Safety International Conference*, Sydney, Australia., 2013.

[53] C. O'donnell and D. Connor, "Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice," *Accident Analysis & Prevention,* vol. 28, no. 6, p. 739–753, 1996.

[54] D. Daddah, Y. Glèlè Ahanhanzo, A. Kpozehouen, B. Santos, E. Bonnet, A. Levêque and Y. Coppieters, "Understanding the Factors of Road Crash Severity in Benin: A Matched Case-Control Study," *Journal of Public Health in Africa,* vol. 14, 2023.

[55] C. Chan, B. Huang, X. Yan and S. Richards, "Investigating Effects of Asphalt Pavement Conditions on Traffic Accidents in Tennessee Based on the Pavement Management System (PMS)," *Journal of Advanced Transportation,* vol. 44, no. 3, p. 150–161, 2010.

[56] Fylan F., "Why Do People Drive When They Can't See Clearly?," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 56, pp. 123-133, 2018.

[57] E. de Bellis, "Blind Haste: As Light Decreases, Speeding Increases," *PLoS One,* vol. 13, 2018.

[58] F. Malin, I. Norros and S. Innamaa, "Accident Risk of Road and Weather Conditions on Different Road Types," *Accident Analysis & Prevention,* vol. 122, p. 181–188, 2019.

[59] A. Chandrasekharan, A. J. Nanavati, S. Prabhakar and S. Prabhakar, "Factors Impacting Mortality in the Pre-Hospital Period After Road Traffic Accidents in Urban India," *Trauma Monthly,* vol. 21, no. 3, 2016.

[60] K. Khan, M. Jamil, I. Memon and Z. Idrees, "Pattern of Injuries in Motorbike Accidents," *Journal of Pakistan Orthopaedic Association,* vol. 30, no. 2, pp. 123-127, 2018.

[61] V. Akinpelu, A. Oladele, Y. Amusa, O. Ogundipe, A. Adeolu and E. Komolafe, "Review of Road Traffic Accident Admissions in a Nigerian Tertiary Hospital," *East and Central African Journal of Surgery,* vol. 12, no. 1, 2007.

[62] E. Naddumba, "A Cross-Sectional Retrospective Study of Boda Boda Injuries At Mulago Hospital IN Kampala-Uganda," *East and Central African Journal of Surgery,* vol. 9, no. 1, 2004.

[63] G. Tulu, S. Washington and M. King, "Characteristics of Police-Reported Road Traffic Crashes in Ethiopia Over a Six Year Period," in *Australasian Road Safety Research, Policing & Education Conference*, Brisbane, Queensland, 2013.

[64] R. Gebresenbet and A. Aliyu, "Injury Severity Level and Associated Factors Among Road Traffic Accident Victims Attending Emergency Department of Tirunesh Beijing Hospital, Addis Ababa, Ethiopia: A Cross Sectional Hospital-Based Study," *PLoS ONE,* vol. 14, no. 9, 2019.

[65] A. Baru, A. Azazh and L. Beza, "njury Severity Levels and Associated Factors Among Road Traffic Collision Victims Referred to Emergency Departments of Selected Public Hospitals in Addis Ababa, Ethiopia: The Study Based on the Haddon Matrix," *BMC Emergency Medicine,* vol. 19, no. 2, 2019.

[66] S. Mutooro, E. Mutakooha and P. Kyamanywa, "A Comparison of Kampala Trauma Score II with the New Injury Severity Score in Mbarara University Teaching Hospital in Uganda," *East and Central African Journal of Surgery,* vol. 15, 2010.

How Mode of Evacuation, Roadway Environment, and Traffic Conditions Relate to Injury Severity Score? Untangling the Role of Pre-hospital Time in Road Crashes

Abstract

This study explores the effects of some of the key factors, including emergency response measures, roadway and environment, traffic-related attributes, and crash-specific factors, on the Injury Severity Score (ISS) of Road Traffic Crashes' (RTCs) victims, both directly and through pre-hospital time (PHT) using rigorous path analysis. Data for 298,654 crashes, compiled by the Road Traffic Injury Research and Prevention Center (RTIRPC) in Karachi (Pakistan), were used for analyses. Owing to the corner-solution distribution of the response variables (PHT and ISS), two Tobit regression models are estimated after accounting for missing values through synthetic data generation. Marginal effects from these models are used in the path analysis. The findings suggest that ISS increases by 0.01 units with a unit increase in PHT, highlighting the critical need for rapid evacuation of crash victims to medical facilities. The mode of evacuation emerged as a crucial factor, with ambulances resulting in increased PHT and ISS compared to private or public transport, underscoring the improvement needed in the dedicated ambulance-based emergency response. PHT and ISS were found to be higher in nighttime crashes, necessitating better emergency medical services (EMS) response during the night. Intersection crashes were associated with lower PHT and ISS; whereas, crashes on undivided roads and those involving multiple or large vehicles increased PHT and ISS. The path analysis revealed that the overall effects of some of the key variables on ISS were higher than their direct effects – something that could not be explored without the path analysis. These insights can help policymakers develop strategies to improve emergency response and road safety, ultimately reducing the number of RTC-related injuries and fatalities.

Keywords: Pre-hospital time, Injury severity score, Road traffic crashes, Synthetic data, Tobit regression, Path analysis, Emergency medical services

1. Introduction

With 20 to 50 million road traffic injuries (RTIs) and 1.19 million road traffic fatalities (RTFs) annually worldwide, road traffic crashes (RTCs) have become a serious public health concern [1]. The situation is severe, especially in low- and middle-income countries, defined as those with a gross national income (GNI) per capita of $13,845 or less in 2022 [2]. The fatality rate from RTCs in low- and middle-income countries is approximately twice that of their high-income counterparts [2]. The outcome for victims of RTCs largely depends on receiving timely and efficient medical care. One critical aspect of medical treatment is the time between the occurrence of a crash and the provision of proper medical care, either on the spot or at hospitals/emergency units. The total pre-hospital time (PHT), which encompasses the time between the occurrence of an RTC and the crash victim's arrival at the hospital, can be divided into multiple phases: response time, scene time, and transport time. The time between the emergency medical services (EMS) notification and their arrival at the RTC scene is usually termed the "response time". "Scene time" refers to the duration between EMS arrival at the crash scene and their departure for the hospital. "Transport time" is the time it takes to travel from the crash scene to the hospital if additional medical treatment is needed [3]. Contrary to the developed countries, in low- and middle-income countries, crash victims are frequently transported to hospitals by family members, taxi drivers, truck drivers, police officers, or other road users, many of whom lack formal training. The dedicated (but limited) ambulance service is generally accessible only in urban areas. Many neurological injuries appear to be the consequence of inadequate immobilization or improper extraction procedures during the carriage of crash victims, which is frequently performed by individuals who lack adequate training. Past research suggests that the severe consequences of RTIs are predominantly attributable to inadequate public health infrastructure and limited access to (or poor) healthcare services [4]. The time to provide medical care to the victims of RTCs becomes more important in cases where the first medical aid is either unavailable or the victims need to be shifted to hospitals for extensive or additional treatment due to severe injuries. These situations are more critical as the PHT may significantly determine the final injuries and survival of the victims in RTCs who are to be shifted to the hospital(s) for extensive treatment.

Understanding the effects of the leading factors (i.e., roadway and environmental factors, traffic-related attributes, and response as well as evacuation-related factors) on injury outcome(s) of RTCs is significant, and several past studies have analyzed these relationships via traditional modeling approaches, usually capturing only the direct associations. However, we consider that in addition to the direct effects, the abovementioned factors can have a significant association with the injury outcomes through some of the mediating variables (i.e., PHT in the present case), which, if not captured, the overall relationships may be overlooked. To the best of the authors' knowledge, none of the studies investigated how the above-mentioned factors relate to ISS (being a fine injury measure), both directly and via PHT. Furthermore, recognizing the critical role of PHT in determining the injury outcome(s) of RTCs, it is vital to understand how various roadway and environmental factors, traffic-related attributes, response as well as evacuation-related factors relate to the PHT. For instance, the PHT for the victims in an RTC occurring on a roadway segment may significantly differ from that at intersections, as the chance of being timely noticed and assisted can be higher in the latter case. Similarly, different roadway types, weather, light conditions, crash locations, time of the crash, etc., may have diverse effects on the PHT. While studies mostly investigated how various roadway and environmental factors relate to response time, the factors affecting the "pre-hospital" time (<u>which mostly relate to more critical injuries to be treated at hospitals</u>) are lightly researched. In particular, the association of some of the important factors e.g., roadway types (divided versus undivided, and number of lanes, etc.), visibility-related factors (weather and light conditions), crash locations (segments versus intersections), and time of the crash considering traffic flow (peak versus off-peak hours), etc. with the PHT needs an in-depth investigation. As discussed earlier, the above-mentioned factors may also significantly relate to the injury severity directly. To understand the overall effects of the aforementioned factors on injury severity, it is important to unveil the effects of these factors on injury severity (<u>especially using hospital-based fine injury</u>

data and measures like Injury Severity Score “ISS”), both directly and indirectly (via PHT) which are not well investigated to date.

This research aims to bridge the aforementioned gaps by investigating how the above-mentioned factors relate to ISS both directly and indirectly (via PHT) using rigorous path analysis while analyzing nine years (2007 to 2015) of hospital-based RTCs data collected by the Road Traffic Injuries Research and Prevention Center (RTIRPC) for Karachi, Pakistan. In particular, complex pathways leading from diverse roadways and environments, and crash- as well as response-related factors to ISS are aimed to be explored in this study, which can provide a more comprehensive and in-depth picture of the system.

2. Literature review

Several injury classification systems are employed to categorize the injuries experienced by roadway users involved in RTCs [5, 6]. The often-employed injury severity scales in transportation engineering include the KABCO Scale, Abbreviated Injury Scale (AIS), and Injury Severity Score etc. The KABCO injury scale serves as the basis for injury data recorded in police crash reports. It involves a five-point scale (Fatal (K), Serious (A), Moderate (B), Minor (C), and None (O)) to assess the severity of an RTC. In general, the KABCO scale offers a simple and easy-to-understand system for categorizing injuries. However, it also has obvious limitations [7, 8, 9, 10, 11, 12]. In contrast to the KABCO scale, the AIS is a global severity scoring system that is anatomically based, consensus-derived, and considers the relative significance of each injury in classifying it by body region on a six-point ordinal scale: 1 = Minor injury, 2 = Moderate injury, 3 = Serious injury, 4 = Severe injury, 5 = Critical injury, and 6 = Un-survivable (fatal) injury. The AIS assigns a numerical value to each injury based on its level of severity. Based on the anatomical structure, the human body can be categorized into nine body parts as shown in Figure 1 [13, 14]. Although the AIS describes anatomical injuries, it lacks internal consistency. Nevertheless, the anatomically based AIS has served as the foundation for various anatomical assessments of injury severity, such as the ISS [9, 15, 16]. The ISS is a well-established medical scoring system and is considered the leading and most reliable system for assessing injuries [14, 16]. The ISS is highly pertinent to evaluating the severity of injuries in RTCs as it enables the assessment of multiple injuries in several body regions. Specifically, the ISS is determined by considering the AIS scores of the three most serious injuries in three distinct anatomical locations.

Past research shows that ISS has a high level of proficiency in forecasting mortality, morbidity, and the duration of hospitalization [9, 17, 18, 19]. Previous research has found a wide range of factors that are associated with RTCs of different levels of injury severity. The investigation largely considered the impact of driver demographics and behavior, crash characteristics, roadway features, and environmental variables. Research also indicated that there are three main elements that have an impact on RTCs: traffic characteristics, road network and infrastructure, and demographic and environmental features [20]. It is also highlighted that several factors significantly influence road traffic casualties, including gender, vehicle condition, safety status, overloading, street lighting, weekends, type of vehicle, driver experience, morning rush hours, and severe weather conditions [21].

The idea of the "Golden Hour" emphasizes the significance of the period before arrival at the hospital in providing care for trauma patients. Most trauma experts believe that the initial 60 minutes following a crash, commonly known as the "golden hour," are crucial for maximizing the chances of preserving lives. Following this period, there is a substantial increase in the likelihood of fatality or the severity of injuries [22]. Unfortunately, the quality of pre-hospital care in many low- and middle-income countries is inadequate, resulting in a significant number of deaths during the pre-hospital stage [22]. Due to the absence of established EMS systems in most of these countries, most crash victims are rescued by bystanders at the crash scene. Moreover, many of these bystanders rely on commercial vehicles to transport the crash victims to a healthcare facility [23]. Consequently, a considerable number of neurological injuries appear to occur due to the procedure of extrication or shifting the crash victims without appropriate immobilization, which is frequently carried out by inexperienced persons [22].

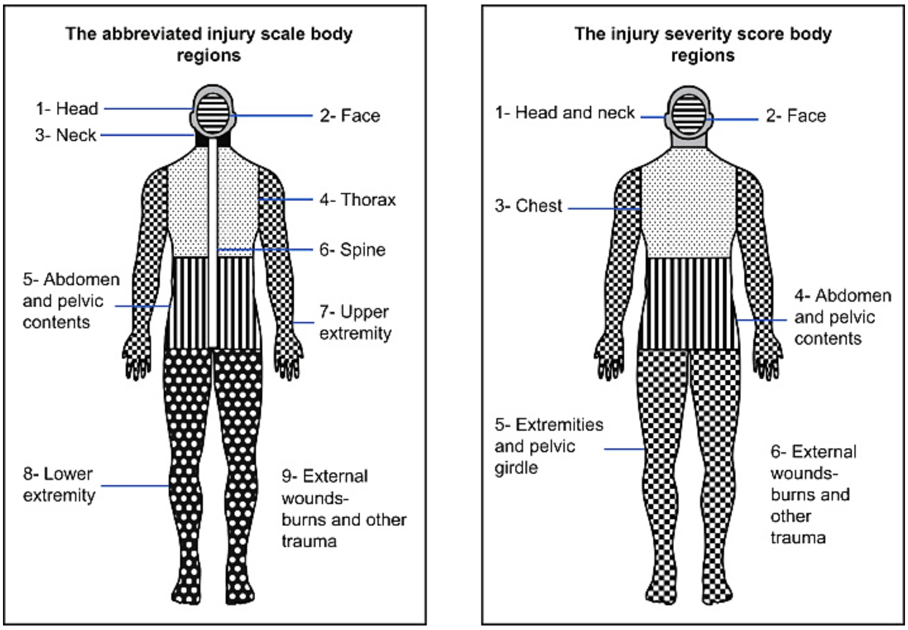


Figure 1: The Abbreviated Injury Scale and Injury Severity Score Body Regions

(Source: https://www.sciencedirect.comsciencearticlepiiS0007091221006528)

Studies show that several socio-demographic characteristics are strongly linked to various aspects of response time, such as geographical regions, types of crash, age, gender, and nationality. Gaining a comprehensive understanding of these elements is crucial for maximizing efficiency during the period spent before reaching the hospital [24]. Furthermore, places exhibit pre-hospital delays that are correlated with criteria such as older age, living in rural areas, and the level of consciousness of crash victims [25]. Environmental and infrastructural variables, such as the day of the week, whether the site is urban or rural, the exact details of the crash, and the time it takes for emergency response, have a considerable impact on the time it takes to clear the scene and the total duration during peak traffic hours. The delays in transferring crash victims to hospitals are sometimes caused by the unavailability of specialized transportation, communication difficulties, and a lack of awareness regarding nearby medical services [2, 26]. The EMS plays a vital role in minimizing the duration of care provided before a patient reaches the hospital.

The association between prehospital time and injury severity has primarily been studied in developed countries. However, it is still uncertain whether these findings can be applied to developing countries, particularly in low-resource settings, due to the existing status of pre-hospital and in-hospital care [27]. Moreover, the available literature clearly shows that both the direct effects of PHT and factors (i.e., environmental, highway, and crash-related elements) affecting it can have a significant influence on injury outcomes. Hence, in order to comprehend the comprehensive impact of the aforementioned elements on ISS, it is crucial to uncover their direct and indirect effects on ISS, particularly via PHT. Although the literature has documented the direct impact of the aforementioned factors (including PHT) on ISS, gaining an understanding of the indirect effects of these factors on ISS (via PHT) can offer valuable insights for developing or improving a comprehensive strategy to enhance road safety and decrease injury severity for victims of RTCs. For a summary of the relevant past literature, please refer to Table 1.

Table 1: Summary of the Relevant Past Literature

Title	Reference	Key Findings
Validating the Injury Severity Score (ISS) in Different Populations: ISS Predicts Mortality Better among Hispanics and Females	Bolorunduro, et al., 2011	• The ISS is widely used as a measure of injury severity • It effectively predicts trauma mortality based on multiple data sets • The ISS demonstrates strong discriminative ability across all groups, based on race and gender
Towards Better Measurement of Traffic Injuries – Comparison of Anatomical Injury Measures in Predicting Clinical Outcomes in Motorcycle Crashes	Wali, et al., 2022	• Despite its simplicity and clarity, the KABCO scale has significant limitations • The ISS is a more sophisticated scoring system than the KABCO scale, capable of accurately assessing overall injury severity and facilitating a more comprehensive evaluation
An Empirical Assessment of Factors Influencing Injury Severities of Motor Vehicle Crashes on National Highways of Pakistan	Hanif, et al., 2021	• Factors such as overspeeding, driver fatigue, driver negligence, driver age, type of vehicle (truck, rickshaw, single vehicle), road conditions (horizontal curve, potholes, night driving without road lights), time/day/month of crash occurrence, weather conditions (e.g., cloudy, clear) contribute to the injury severity in a crash
Prehospital Care and 24-hour Crash Injury Mortality Among Road Traffic Crash Victims in Addis Ababa	Mengstu, et al, 2021	• Without pre-hospital care, the chance of early death in RTCs is significantly higher • Key areas to focus on include reducing the time spent in the pre-hospital environment, using ambulance services, and increasing public awareness of pre-hospital care, particularly within the platinum 10-minute scene time and golden one-hour PHT
The Prehospital Time Impact on Traffic Injury from Hospital Fatality and Inpatient Recovery Perspectives	Sara et al, 2019	• The impact of PHT differs among observations and is positively associated with duration of hospital stay and Healthcare costs • Factors such as age and gender of the victim, crash type, hospital, and injury severity (i.e., AIS) significantly influence both the likelihood of mortality and the recovery rate of crash victims
Emergency Medical Service Response Time for Road Traffic Accidents in the Kingdom of Saudi Arabia: Analysis of National Data (2016–2020)	Thamer, et al., 2023	• Response time is significantly affected by various socio-demographic factors, such as geographical regions, causes of crash, age, gender, and nationality • Acquiring a thorough knowledge of these aspects is essential for optimizing efficiency during the PHT

Factors Affecting Prehospital Time Delay of the Injured Patients Arriving at the Emergency Department of Beni-Suef University Hospital in Egypt: A Cross-Sectional Study	Khalil, et al., 2021	• The delay in receiving medical care before reaching the hospital is associated with old age, living in rural areas, and the level of consciousness of crash victims • Implementing health education programs aimed at educating elderly individuals and those living in rural areas about the importance of minimizing PHT is necessary
Time to Reach Healthcare Facility and Hospital Exit Outcome among Road Traffic Accident Victims Attending a Tertiary Care Hospital, Puducherry	Antony, et al., 2021	• Various environmental and infrastructural factors, such as the day of the week, urban or rural location, specific crash details, and emergency response duration, significantly impact PHT
Factors Influencing Pre-Hospital Care Time Intervals in Iran: A Qualitative Study	Davoud, et al., 2018	• The EMS play a crucial role in reducing the PHT • Challenges associated with prompt response include the collaboration of the public, the allocation of EMS facilities, the accessibility of ambulances, and the availability of personnel
Pre-Hospital Trauma Care in Road Traffic Accidents in Kashan, Iran	Paravar, et al., 2013	• Trauma patients involved in RTCs on intercity roads have longer PHT and more serious injuries compared to those involved in RTCs on city streets • Consequently, this group requires more PHT-related measures
Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods	Lee et al, 2006	• EMS response times are most significantly influenced by the severity of RTCs • RTCs resulting in injuries or fatalities have EMS response times up to 20% less than crashes exclusively involving property damage • Total PHT during peak periods is greatly influenced by the day of the week, urban or rural location, off or opposing-lane crash location, number of vehicles involved, heavy vehicle involvement, and reaction time

3. Methodology

3.1. Data Source

This study analyzes the RTCs data acquired from the Road Traffic Injuries Research and Prevention Center (RTIRPC) for a period of nine years (2007 to 2015), focused on Karachi, Pakistan. The dataset contains details about 298,654 crashes and includes extensive information such as demographic, socioeconomic, roadway and environmental, and crash-related aspects. During the data cleaning process, we noticed that 160,365 entries (which accounted for approximately 54% of the total) had missing or improper values for one or more variables. For instance, there were ~7% (N=20,465) cases in which no AIS score was assigned to any of the nine body parts despite being taken to hospitals for treatment. This resulted in 138,289 entries (approximately 46%) having complete and accurate information for all the variables of interest. To address this problem, synthetic data generation techniques were used to account for the missing or incorrect values by generating 160,365 entries, using the distribution of the key variables of interest (along with their correlation with each other), from the cleaned data (N = 138,289). Subsequently, the final dataset with a sample size of 298,654 observations was used for analyses.

3.2. Synthetic Data Generation

The employment of synthetic data in this context is relevant, as it guarantees the optimal utilization of vital information that could otherwise be lost owing to improper or missing inputs arising from data entry errors. The "synthpop" program in R software was utilized to generate a synthetic dataset for the key variables based on the complete observed data. The "synthpop" technique involves the selection of an initial variable (by the user) to be synthesized, followed by the generation of values randomly using a method that samples with replacement from the observed data with complete information [28, 29]. Then, a parametric or non-parametric approach can be selected in the synthpop technique to predict the values of subsequent variables, utilizing the previously synthesized variables as predictors [30, 31]. This study used a non-parametric classification and regression tree (CART) approach for synthetic data generation. The selection of the CART method, whether it is regression or classification, was determined by the nature of the variable, such as whether it is continuous, binary, or categorical. This method generated a synthetic data clone, which was similar to the original data in terms of the distribution of variables and correlation among them, therefore maintaining the accuracy and usefulness of the dataset [28, 31]. For an in-depth understanding of the methodology, please refer to the studies in parentheses [28, 30, 29, 32, 33, 34].

3.3. Injury Severity Score

To calculate the ISS for a particular crash victim, the nine body parts (head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and external) are classified into six ISS body regions as shown in Figure-1. The injury is evaluated at each specific anatomical location, and a severity score based on the AIS is assigned to each individual injury. Then the highest severity code (AIS) for each of the three most severely injured body regions is squared and then summed to obtain the ISS score for a crash victim, which can be shown below:

$$\text{ISS} = X^2 + Y^2 + Z^2 \tag{1}$$

Where X, Y, and Z represent the AIS scores of the three body regions with the most serious injuries according to the ISS scale. The ISS scores span a range of 1 to 75.

3.4. Conceptual Framework

This research aims to examine the relationships of various factors, including roadway and environmental factors, and crash- and response-related aspects with the ISS of the victims in RTCs both directly and through PHT. The motivation for this research is based on our hypotheses that various factors, including the characteristics of the road (such as the presence of a median, number of lanes in each direction, etc.), the location of the crash (at an intersection or on a straight portion), the time of day (day or night), and the volume of traffic (during peak or off-peak hours), can have statistically significant effects on the PHT where the latter may significantly relate to the ISS. For example, during peak hours, congested, undivided roadway portions may have prolonged PHT for RTCs due to the complex road network and dense traffic, which may hinder the prompt arrival of emergency personnel. In contrast, RTCs occurring on uncongested divided roadway segments during non-peak hours may encounter faster response times, resulting in shorter pre-hospital durations. Furthermore, we consider that there can be a potential direct association of roadway and environmental conditions, and crash- and response-related factors with ISS. In order to systematically approach the research objectives, this study uses a two-stage path analysis (as depicted in Figure 2) to understand the overall effects of the key variables on the ISS while accounting for indirect pathways from these factors to the ISS via PHT.

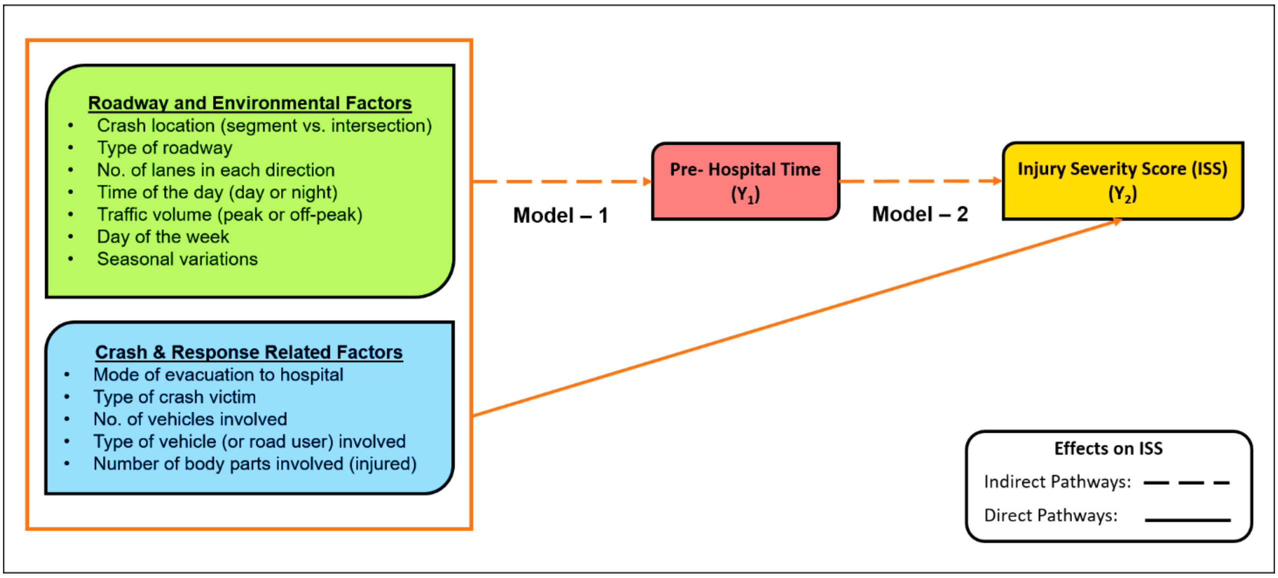


Figure 2: Conceptual Framework

3.5. Modelling Framework

This study used the Tobit model due to the continuous nature and distribution of the response variables (PHT for Model 1 and ISS for Model 2) in our data. The Tobit model is appropriate for addressing the corner-solution problem, which occurs when the dependent variable shows clustering or a spike at its lowest and/or highest extreme value [35, 7]. This characteristic was observed in both ISS and PHT in this study where the two variables exhibit spikes at the lower end. A brief description of the Tobit model can be found below:-

3.5.1. Tobit Regression

In the statistical literature, truncation and censoring are regarded as distinct phenomena; however, they both pertain to data observability concerns [36, 37, 38]. Censoring refers to a situation when a significant proportion of observations exceed the censoring threshold or events are not recorded for a considerable number of observations. Alternatively, truncation happens when a substantial number of observations surpasses the maximum observable range. Even without any censoring or truncation, the dependent variable can exhibit a cluster at the lowest extreme value (spike at 0 or 1), which is referred to as a corner-solution problem. In our case, we observed that both the distribution of ISS and the PHT exhibit a left spike, indicating corner-solution problems. It is important to highlight that there is no issue with data observability in our case. To fully incorporate and take into account all observations, research indicates that Tobit regression can be employed for all three phenomena [35, 36, 37, 38]. Thus, in this study, Tobit regression is used to estimate the ISS and PHT because of the corner-solution setup seen in the ISS and PHT:-

$$Yi^* = \beta 1Xi + \varepsilon 1, (i = 1, 2, 3, \dots, N) \tag{2}$$

$$Yi = Yi^* \; (if\; Yi^* > \tau) \tag{3}$$

$$Yi = \tau_Y \; (if\; Yi^* \leq \tau) \tag{4}$$

In equation (2), the latent variable (stochastic index) is denoted as $Yi*$, the observed dependent variable is Yi, $\boldsymbol{\beta 1}$ represents a set of estimable parameters associated with independent variables ($\mathbf{X}\boldsymbol{i}$), N represents the number of observations, and $\varepsilon 1$ represents residuals that are assumed to follow a normal distribution with $\mathbf{N}(\mathbf{0}, \boldsymbol{\sigma}\mathbf{1}^2)$. The log-likelihood function for Tobit regression can be derived as follows:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset\, (\frac{Y-\mu}{\sigma})]^{di}[1 - \emptyset\, (\frac{\mu-\tau}{\sigma})]^{1-di} \tag{5}$$

In equation (5), τ represents the threshold in the data where a corner-solution (left-spikes) is observed, $\emptyset$ denotes the standard cumulative normal distribution function, and $\emptyset$ represents the standard normal density function. By setting $\tau = 0$ and expressing μ as a function of observed variables and their estimated parameters ($\beta 1\mathrm{X}i$), the log-likelihood function for the Tobit model can be obtained:-

$$L = \prod_i^N [\frac{1}{\sigma} \emptyset\, (\frac{Yi-\beta 1Xi}{\sigma})]^{di}[1 - \emptyset\, (\frac{\beta 1Xi}{\sigma})]^{1-di} \tag{6}$$

By further expanding equation (6), the log-likelihood functions can be expressed as:

$$lnL = \sum_i^N \{di\,(-ln\sigma + ln\emptyset\,(\frac{Yi-\beta 1Xi}{\sigma})) + (1 - di)ln\,(1 - \emptyset\,(\frac{\beta 1Xi}{\sigma}))\} \tag{7}$$

The equation (7) comprises two components: 1) the standard regression for uncensored observations and 2) the probability of censoring for specific observations. Marginal effects (MEs) can be calculated to see the impact of a unit increase in a specific continuous variable (or a transition from 0 to 1 in an indicator) on the response variable while holding all other variables in the model at their average values. Three distinct forms of MEs can be determined in Tobit regression, based on different predicted values of the dependent variable [39]. It should be noted that, depending on the extent, one or more of these MEs can be utilized. With that being stated, we calculate and furnish all three MEs for this research. However, we eventually utilize and interpret ME-1. It should be noted that ME-1 is calculated using both uncensored and censored observations. In our scenario, the ISS and PHT suggest a situation where the lowest limits are reached, known as a corner solution with left spikes [35, 39]. However, there is no actual censorship, as previously mentioned. Therefore, we employ ME-1, taking into account both censored and uncensored data, as shown below:-

$$\frac{\partial E[Yi]}{\partial Xi} = \varphi\,(\frac{\beta 1Xi}{\sigma})\,\beta 1 \tag{8}$$

To calculate the chance of an observation being uncensored, ME-2 can be determined using the following method:-

$$\frac{\partial Pr[Yi>1|Xi]}{\partial Xi} = \varphi\left(\frac{\beta 1Xi}{\sigma}\right)\frac{\beta 1}{\sigma} \tag{9}$$

The equation (10) provided below can be utilized for MEs (ME-3) that rely solely on unfiltered observations of response variables:-

$$\frac{\partial E[Yi|Yi>0]}{\partial Xi} = \beta i\left\{1 - \lambda(\alpha)\left[\frac{\beta 1Xi}{\sigma} + \lambda(\alpha)\right]\right\} \tag{10}$$

Where, $$\lambda(\alpha) = \frac{\phi\left(\frac{\beta 1Xi}{\sigma}\right)}{\varphi\left(\frac{\beta 1Xi}{\sigma}\right)} \tag{11}$$

It is important to mention that the ME-3 is more applicable in situations of "true censoring," which is not the case in this study.

In summary, we employed the ME-1 method, which incorporates both censored and uncensored observations, from the Tobit model in our final path analysis. This allowed us to assess the indirect and total effects of PHT and other important factors on ISS [35, 40].

3.6. Path Analysis

Within the path analysis framework, the MEs obtained from the individual models are utilized to ascertain the direct, indirect, and overall effects of relevant factors on the ultimate response variable (ISS), as depicted in Figure 1 [41, 42]. The impact of a specific independent variable on the ISS is determined by multiplying the estimated effects (MEs) obtained from the PHT model (Model 1) with the ME of PHT obtained from the ISS model (Model 2). It should be noted that the "ISS model" quantifies the direct impact of the leading independent factors, and PHT on ISS sustained by a crash victim. When combined with the indirect effect, these factors provide the overall impact of a specific explanatory variable on ISS. The equations for calculating the indirect and total impacts of certain explanatory variables are provided below [12, 43, 44]:-

Indirect MEs = (MEs from PHT model) *(MEs of PHT from ISS model) (12)

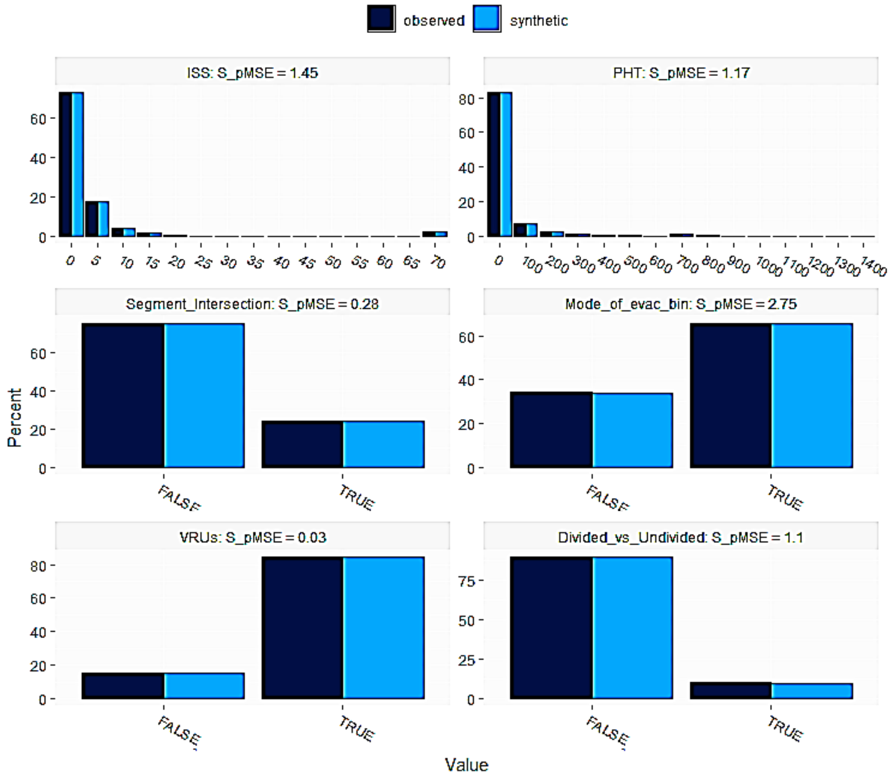
Total MEs = Direct MEs + Indirect MEs (13)

While consistent estimates can be obtained via standard path analysis (i.e., independent estimation of models), studies suggest that achieving more efficient results if potential correlation between the unobserved factors exists and is taken into account via joint estimation [35, 45]. To account for potential correlation between the unobserved factors which can be associated with both PHT and ISS, we used the limited information maximum likelihood procedure for the estimation of the two models jointly via Conditional Mixed Process (CMPT), where the latter is a user-written STATA routine [46]. The joint estimation considers the two error terms ($\varepsilon 1$ and $\varepsilon 2$), associated with PHT and ISS, to have multivariate normal distribution [46].

4. Results

4.1. Actual Versus Synthetic Data

The cleaned RTIRPC data, which consisted of 138,289 observations, were employed to produce a synthetic dataset with 160,365 observations, as previously mentioned. Subsequently, these datasets were merged to produce a combined sample size that was equivalent to the original RTIRPC data (N=298,654). The distribution of key variables in both the actual and synthetic datasets is compared in Figure 3. The synthetic data's distribution of all variables appears to be reasonable when compared with the actual (observed) data. Comparisons are presented for only a subset of the key variables for brevity. The descriptive statistics for these variables are compared across the actual and synthetic data samples in Table 2. The means and standard deviations of the key variables in the synthetic data are in close agreement with those of the actual data.



Note: *False and true refer to 0 and 1 for the indicator variables*

Figure 3: Percentage-Wise Distribution of Variables - Observed (Actual) Versus Synthetic Data

Table 2: Descriptive Statistics - Actual Data versus Synthetic Data

Observed Data					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
ISS	138,289	6.17	11.69	1	75
PHT (in minutes)	138,289	104.81	206.73	1	1439
Crash Location (0 if segment, 1 if intersection)	138,289	0.25	0.43	0	1
Mode of Evacuation (1 if ambulance, 0 otherwise)	138,289	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	138,289	0.86	0.34	0	1
Type of Roadway (0 if divided, 1 otherwise)	138,289	0.10	0.30	0	1
Synthetic Data					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**

ISS	160,365	6.22	11.89	1	75
PHT (in minutes)	160,365	103.86	204.74	1	1439
Crash Location (0 if segment, 1 if intersection)	160,365	0.25	0.43	0	1
Mode of Evacuation (1 if ambulance, 0 otherwise)	160,365	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	160,365	0.87	0.33	0	1
Type of Roadway (0 if divided, 1 otherwise)	160,365	0.10	0.30	0	1

4.2. Descriptive Statistics

Figure 4 illustrates the distribution of two dependent variables, namely PHT and ISS. Both of these variables are characterized by a corner-solution set-up, which enables them to be modeled using Tobit regression. For further information, please refer to the methodology section.

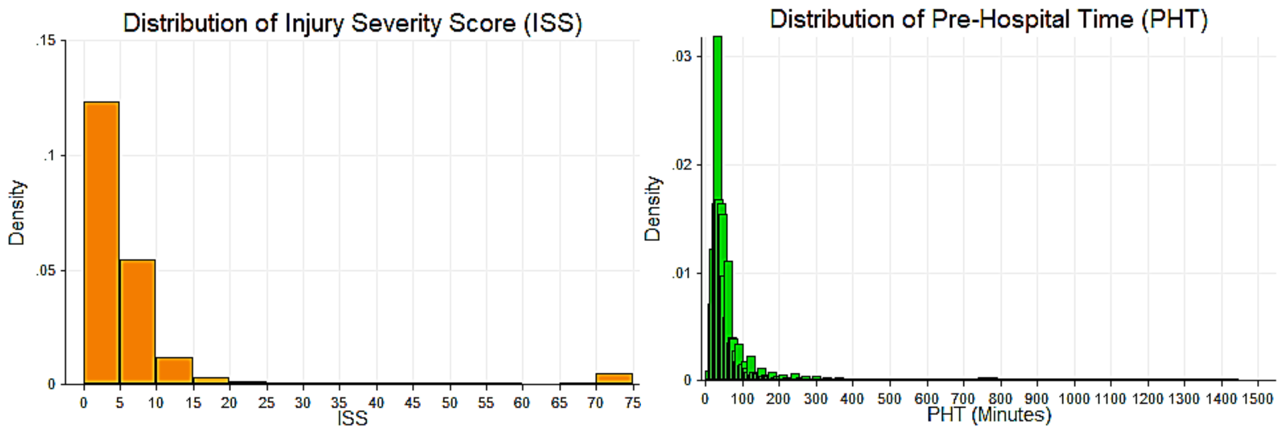


Figure 4: Distribution of ISS and Pre-hospital Time

The summary statistics of the key variables are displayed in Table 3. The mean ISS for individuals involved in crashes is 6.20, with a standard deviation of 11.80. The mean PHT is 104.30 minutes, with a significant standard deviation of 205.66 minutes, while the longest reported PHT is 1439 minutes. While the maximum value of PHT (1439 minutes ~ 24 hours) may seem to be an outlier, we included crashes with such large values to highlight the slow response and its consequences. Out of all the crashes, a significant percentage of 35.68% took place on roads that had four lanes in each direction. Moreover, 75% of crashes occurred on straight road segments, while 37% occurred at night. Figure 5 shows the distribution of variables, including the type of vehicles, type of crash victims, and mode of evacuation associated with RTCs. Referring to the distribution of crashes based on the vehicle types involved, motorcycles accounted for the largest proportion of crashes (69.41%), followed by other vehicles such as taxis (7.58%), buses (5.27%), passenger vans (2.42%), bicycles (1.32%), trucks (1.76%), private automobiles (0.97%), and rickshaws (three-wheelers) (0.35%). The most susceptible individuals involved in RTCs were riders and passengers of two-wheelers, as well as pedestrians, accounting for 48.12%, 13.78%, and 23.08% of the total crash victims, respectively. In terms of the mode of evacuation, 61.00% of crash victims were taken to medical facilities utilizing private transport, while 34.33% made use of ambulance services. For the distribution of other key variables, please refer to Table 3.

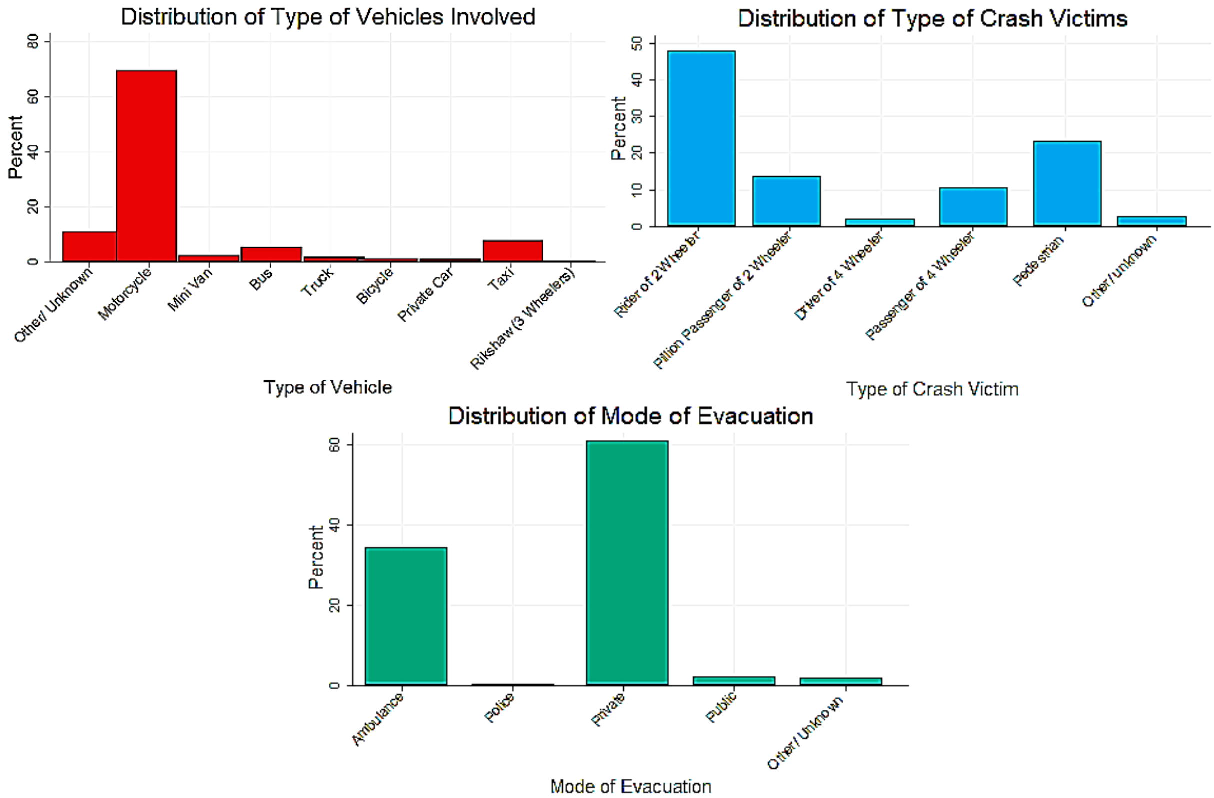


Figure 5: Distribution of Type of Vehicles Involved, Type of Crash victims, and Mode of Evacuation

Table 3: Descriptive Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
ISS	298,654	6.20	11.80	1	75
PHT (in minutes)	298,654	104.30	205.66	1	1439
Independent Variables					
Roadway Environment and Traffic-Related Factors					
Crash Location (0 if segment, 1 if intersection)	298,654	0.25	0.43	0	1
Type of Roadway (0 if divided, 1 otherwise)	298,654	0.10	0.30	0	1
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	298,654	0.35	0.48	0	1
Time of the Day (0 if day, 1 otherwise)	298,654	0.37	0.48	0	1
Traffic Volume (0 if morning peak, 1 otherwise)	298,654	0.95	0.23	0	1
Day of the Week (1 if Friday, 0 otherwise)	298,654	0.13	0.34	0	1
Seasonal Variations (0 if summer,1 otherwise)	298,654	0.68	0.47	0	1
Crash and Response-Related Factors					
Mode of Evacuation (0 if ambulance, 1 otherwise)	298,654	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	298,654	0.87	0.34	0	1
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	298,654	0.35	0.48	0	1
Heavy Vehicles vs Other (1 if heavy vehicle i.e., truck or bus, 0 otherwise)	298,654	0.08	0.27	0	1
Number of Body Parts Injured	298,654	1.90	0.91	1	8

4.3. Modeling Results

The final models (Model 1 and Model 2 for PHT and ISS, respectively) were systematically derived for each outcome type, incorporating the most significant variables (based on the research objectives), statistical significance, intuition, theoretical justifications, and specification parsimony. To this end, the likelihood ratio test and improvement in the AIC and BIC statistics were considered. A 95% confidence criterion was employed to determine the statistical significance of the variables in either model. The subsequent subsections provide details about key findings that were obtained from both models. While the final modeling results (below) are based on the models which were estimated in an independent fashion, we want to mention that we tried to estimate the two models in a joint fashion (as discussed in sub-section 3.6) to account for potential correlation between the unobserved factors associated with PHT and ISS. However, there was no significant evidence found that a significant correlation exists between the unobserved factors associated with the two dependent variables (i.e., PHT and ISS). As discussed earlier, the results obtained from the independent models are still consistent and used in recent research studies based on the independently estimated models.

4.3.1. Model 1: Factors Affecting Pre-Hospital Time

The results of the final PHT Model suggest a significant reduction in PHT for RTCs which occur at intersections (compared to mid-block locations), on roadway segments with fewer than four lanes per direction, involve VRUs (especially pedestrians and cyclists), and if the post-crash evacuation is carried out by modes other than a dedicated ambulance service. On the other hand, PHT is significantly higher for RTCs occurring on undivided roadways, in seasons other than summer, during nighttime, and in RTCs with multiple or heavy vehicles involved. As stated in the footnote of Table 4, there was no statistical evidence of multicollinearity among the variables included in the final model. For detailed results and relevant discussion of the model results, please refer to Table 4 and the discussion section, respectively.

Table 4: Results of Model-1 (PHT Model)

PHT	Coef.	Std. Err.	t-stat	ME-1	ME-2	ME-3
Roadway Environment and Traffic-Related Factors						
Crash Location (0 if segment, 1 if intersection)	-31.3014	0.8740	-35.82	-21.53	-0.05	-15.20
Type of Roadway (0 if divided, 1 otherwise)	5.8517	1.4132	4.14	4.03	0.01	2.84
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-14.8500	0.8847	-16.79	-10.21	-0.03	-7.21
Time of the Day (0 if day, 1 otherwise)	23.5048	0.7820	30.06	16.17	0.04	11.41
Seasonal Variations (0 if summer,1 otherwise)	2.4386	0.8067	3.02	1.68	0.00	1.18
Crash and Response-Related Factors						
Mode of Evacuation (0 if ambulance, 1 otherwise)	-6.3341	0.8170	-7.75	-4.36	-0.01	-3.08
Type of Crash Victim (1 if VRUs, 0 otherwise)	-37.4407	1.2485	-29.99	-25.75	-0.06	-18.18
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	3.9627	0.7991	4.96	2.73	0.01	1.92
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	30.8792	1.5850	19.48	21.24	0.05	14.99
Number of Body Parts Injured	9.7848	0.4170	23.46	6.73	0.02	4.75
Constant	119.0316	1.7351	68.60	-	-	-
Sigma	205.4065	0.2678	-	-	-	-
Model Summary						
Log Likelihood	-1992007					
AIC	3984038					
BIC	3984165					

***Note:** The Variance Inflation Factors (VIF) were calculated to assess multicollinearity among variables, and the values for all the key regressors were less than 1.27 (well below the threshold of 10), indicating the absence of problematic collinearity.*

4.3.2. Model 2: Factors Affecting Injury Severity Score

In the final ISS model, we found 13 explanatory variables, including PHT, to have statistically significant (as per 95% confidence level criteria) association with ISS (Table 5). The final model underscores a significant association of the PHT with the ISS, indicating that as PHT increases, the ISS also tends to increase significantly. The higher degree polynomial (i.e., squared term) of PHT shows a significant correlation with ISS, indicating sufficient evidence of non-linearity in the association of PHT with ISS. Furthermore, RTCs, which occur on undivided roadway segments at nighttime, on Fridays, and involve VRUs, lead to significantly higher ISS for the crash victims. Similarly, the involvement of multiple or heavy vehicles in RTCs tends to result in higher ISS. On the other hand, ISS significantly reduces for the victims in RTCs which occur at intersections (as opposed to mid-block locations), on roadways with fewer than 4 lanes in each direction, during time other than morning peak hours, during seasons other than summer, and if post-crash evacuation is carried out via modes other than ambulance. Furthermore, a significant positive correlation between the number of body parts injured in a crash and the ISS was found. For inclusive results and discussion, please refer to Table 5 and the discussion section, respectively. Furthermore, there is a significant positive correlation between the number of body parts injured in a crash and the ISS, with each additional injured body part resulting in a higher ISS.

Table 5: Results of Model-2 (ISS Model)

ISS	Coef.	Std. Err.	t-stat	ME-1	ME-2	ME-3
PHT	0.0111	0.0004	27.32	0.01	0.0003	0.004
c.PHT#c.PHT	-0.00001	0.0000004	-23.25			
Roadway Environment and Traffic-Related Factors						
Crash Location (0 if segment, 1 if intersection)	-0.6464	0.0612	-10.56	-0.36	-0.02	-0.27
Type of Roadway (0 if divided, 1 otherwise)	0.6556	0.0990	6.62	0.37	0.02	0.27
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-0.4880	0.0620	-7.87	-0.28	-0.01	-0.20
Time of the Day (0 if day, 1 otherwise)	0.5749	0.0555	10.36	0.32	0.02	0.24
Traffic Volume (0 if morning peak, 1 otherwise)	-1.4299	0.1159	-12.34	-0.81	-0.04	-0.59
Day of the Week (1 if Friday, 0 otherwise)	0.2037	0.0778	2.62	0.11	0.01	0.08
Seasonal Variations (0 if summer,1 otherwise)	-0.1559	0.0562	-2.77	-0.09	-0.01	-0.06
Crash and Response-Related Factors						
Mode of Evacuation (0 if ambulance, 1 otherwise)	-6.9258	0.0560	-123.58	-3.91	-0.19	-2.85
Type of Crash Victim (1 if VRUs, 0 otherwise)	0.7227	0.0865	8.35	0.41	0.02	0.30
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	1.0494	0.0556	18.87	0.59	0.03	0.43
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	2.2932	0.1087	21.09	1.29	0.06	0.94
Number of Body Parts Injured	3.6425	0.0295	123.28	2.05	0.10	1.50
Constant	0.6223	0.1647	3.78	-	-	-
Sigma	13.5519	0.0206	-	-	-	-
Model Summary						
Log Likelihood	-947745					
AIC	1895522					
BIC	1895691					

***Note:** While values for the t-stat and MEs are reported up to two decimal places, values for the coefficients and standard error are reported up to four. However, to account for the first non-zero value after the decimal points, there are minor differences in how PHT and its squared term are reported. Moreover, the VIF values* *for all the key regressors are also less than 1.27 (well below the threshold of 10), indicating the absence of problematic collinearity.*

4.3.3. Path Analysis

Table 6 presents the results of the path analysis, which uncovers the direct and indirect relationships of the key factors (i.e., related to roadways and environment, response, traffic, and crash) with the ISS for the victims of RTCs. The direct effects of key explanatory variables on the ISS (ME-1) are obtained from Table 5, which is based on Model 2. Whereas, in order to determine the indirect effects of key explanatory variables on ISS, we compute them by multiplying the ME (ME-1) of each individual variable from Model-1 with the ME (ME-1) of PHT on ISS obtained from Model-2. The outcomes of these computations, which emphasize the indirect effects of the key explanatory variables on ISS, are compiled in Table 6, which presents the direct, indirect, and total impacts of each explanatory variable.

Table 6: Path Analysis Results: Direct, Indirect, and Total Effects of Key Variables

Independent Variables	Direct Effects	Indirect Effects	Total Effects
PHT	0.01	-	0.01
Roadway Environment and Traffic-Related Factors			
Crash Location (0 if segment, 1 if intersection)	-0.36	-0.22	-0.58
Type of Roadway (0 if divided, 1 otherwise)	0.37	0.04	0.41
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-0.28	-0.10	-0.38
Time of the Day (0 if day, 1 otherwise)	0.32	0.16	0.48
Traffic Volume (0 if morning peak, 1 otherwise)	-0.81	-	-0.81
Day of the Week (1 if Friday, 0 otherwise)	0.11	-	0.11
Seasonal Variations (0 if summer,1 otherwise)	-0.09	0.02	-0.07
Crash and Response-Related Factors			
Mode of Evacuation (0 if ambulance, 1 otherwise)	-3.91	-0.04	-3.95
Type of Crash Victim (1 if VRUs, 0 otherwise)	0.41	-0.26	0.15
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	0.59	0.03	0.62
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	1.29	0.21	1.50
Number of Body Parts Injured	2.05	0.07	2.12

5. Discussion

The distribution of key variables such as ISS and PHT offers useful insights into the nature and outcomes of RTCs. The ISS, with a mean of 6.20 and a high standard deviation of 11.80, suggests a wide variation in injury severity, highlighting the diverse impact of RTCs. The mean PHT of 104.30 minutes points to significant delays in emergency responses, which could worsen injury outcomes and indicate a pressing need for improvements in EMS and transportation infrastructure.

Referring to the results of Model 1 (PHT model), the crash location ME-1 demonstrates a 21.53 times decrease in PHT for crashes that happen at intersections as opposed to segments (Table 4). The strong negative correlation indicates that the process of rescuing crash victims and transporting them to the hospital is relatively faster at (or near) intersections, potentially because these locations are easily identifiable and accessible. In contrast, crashes occurring on undivided roadways significantly lead to a 4.03 times rise in the PHT. The results are consistent with previous research that highlights the significant impact of off or opposing-lane crash location on clearance time and the subsequent total PHT [47]. The findings also indicate that crashes occurring on roads with less than four lanes in each direction significantly reduce the PHT by 10.21 times. This finding was expected as roads with lower traffic volume (less number of lanes) are more conducive to faster response times because they experience less congestion and provide better access for emergency vehicles. Moreover, there is a significant rise (16.17 times) in PHT for nighttime crashes, as opposed to daytime, highlighting the difficulties faced in responding to emergencies during the night. Moreover, the limited availability of public or private transportation during nighttime could also lead to longer PHT. Similar results can be seen in previous research [48]. With regards to the association of mode of evacuation with PHT, the findings interestingly indicate that the utilization of modes for evacuation, compared to an ambulance, is linked with a 4.36 times decrease in PHT, suggesting that ambulance modes in the city tend to be more inefficient. The unexpected outcome may be attributed to the formal procedures and protocols adhered to by ambulance services, which, although guaranteeing comprehensive care, could result in extended response durations in the megacapital city of Pakistan. Dependence on private or public transportation during emergencies may bypass certain procedural delays, but could potentially endanger the standard of medical care during transportation. The findings also suggest that crashes involving multiple vehicles and heavy vehicles lead to an increase of 2.73 and 21.24 times in PHT, respectively, which may be most likely because of the challenges associated with handling scenes that involve either multiple or heavy vehicles. These findings align with past research that has shown the significant impact of the number of vehicles and the involvement of heavy vehicles on clearance time and overall duration of PHT [47]. Crashes involving VRUs, such as pedestrians and cyclists, lead to a 25.75 times reduction in the PHT. The strong negative association indicates that VRU crashes exhibit reduced PHT, which may be attributable to the comparatively effortless accessibility of the victims in contrast to occupants of vehicles. The visibility of these crashes and the possibility of prompt assistance from bystanders may also contribute to quicker response times, resulting in reduced PHT.

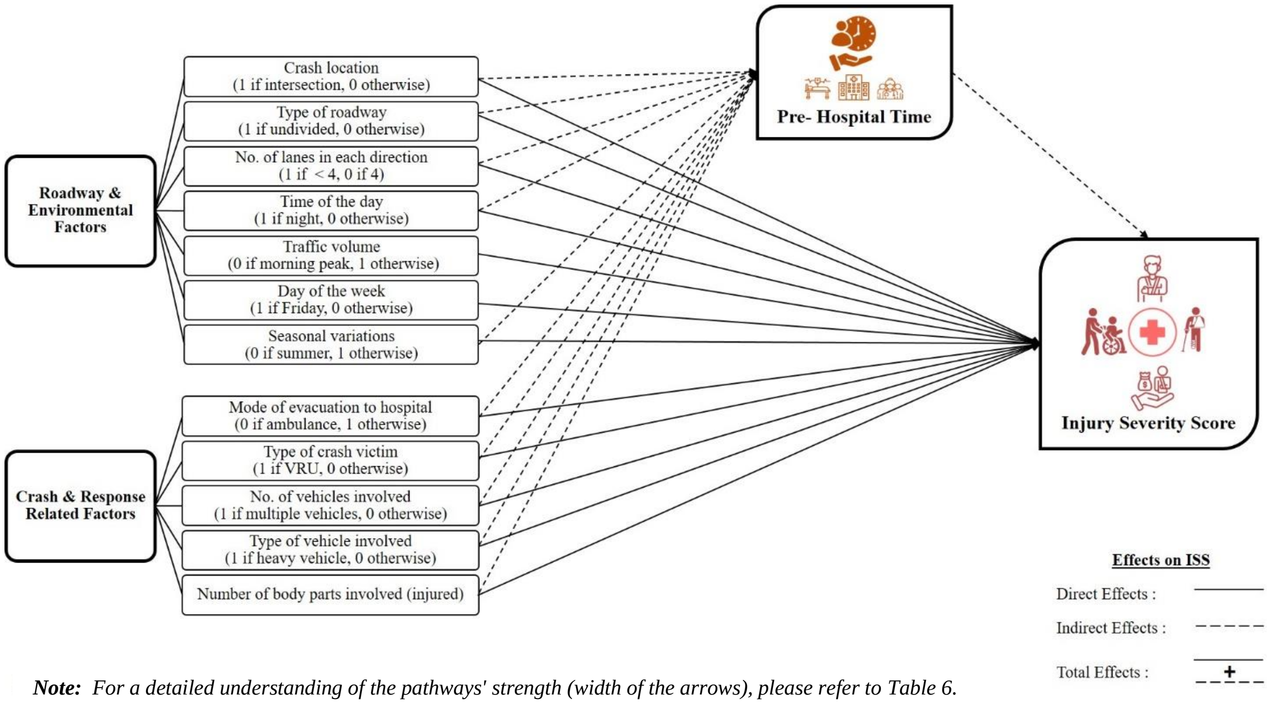
Referring to Model 2 (ISS Model), the findings suggest a significant positive correlation of PHT with ISS. More precisely, with each extra minute increase in PHT, the ISS shows an increase (i.e., by 0.01 unit), highlighting the need for immediate medical intervention to reduce the severity of injuries. Receiving medical care with delays can aggravate injuries, resulting in worse outcomes, which is consistent with the past studies [22, 23, 24, 25, 26, 49]. Nevertheless, the presence of a statistically significant negative coefficient for the higher (i.e., squared) degree polynomial of PHT indicates significant evidence of variability in the slope of PHT (i.e., effects of PHT on ISS). However, further research is needed to identify and understand the prevalent trends in the nonlinear relationship between these two variables, which is not the focus of the present study. Referring to the roadway types, our findings suggest that crashes on undivided roadways significantly increase the ISS by 0.37 times. Undivided roadways without median barriers frequently witness more severe head-on crashes, leading to increased injury severity, which is aligned with the past research [50, 51, 52, 53].

In contrast, crashes that happen at intersections are linked to a 0.36 times reduction in ISS compared to those on straight-road segments. Although intersections are areas of potential conflict, they tend to have reduced impact speeds as a result of traffic management systems, leading to less serious injuries. Crashes that occur at night are linked to a 0.32 times rise in ISS, indicating greater severity of injuries during nighttime hours. Reduced visibility, driver exhaustion, and an increased probability of impaired driving, combined with decreased law enforcement during nighttime, contribute to more serious injuries. To avoid these hazards, it would be beneficial to increase nighttime enforcement, visibility/conspicuity, and infrastructure [54]. Furthermore, it is crucial to have emergency response services available around the clock [50, 55, 56, 57, 58, 59]. Referring to the surrounding traffic conditions, we found that crashes that happen outside the morning peak hours are linked to a reduction in the ISS, which suggests that crashes during morning peak hours are more severe. Previous research also suggests that drivers/riders tend to drive/ride faster in the early morning to make sure they get to work on time, especially when 69.41% of the crashes involved motorcyclists who are prone to injuries even at lower speeds when involved in an RTC. The utilization of non-ambulance (private vehicles) modes for evacuation significantly reduces the ISS by 3.91 times. This finding is not consistent with the findings reported from studies conducted in other regions [60, 61, 62, 63], emphasizing the significance of implementing an advanced EMS system in order to enhance the outcomes for those involved in tragic crashes. VRUs, which include pedestrians, motorcyclists, and bikers, experience higher injury severity, leading to a 0.41 times increase in ISS. The lack of protections for VRUs makes them exceptionally vulnerable, underscoring the requirement for enhanced safety protocols, such as the implementation of exclusive lanes and the promotion of public awareness initiatives. The severity of injuries is directly related to the number of body parts injured, as seen by a significant increase in ISS for each additional wounded body part. Providing thorough medical care to more badly injured victims leads to longer pre-hospital delays and higher overall injury severity. The present findings are consistent with other research that has reported similar outcomes [64, 65, 66].

Referring to the results of path analysis, most factors with a significant direct association with ISS also have shown a significant association with PHT. PHT, in turn, is associated with ISS, creating an indirect association of these factors with ISS as well (see Figure 6). Consequently, the overall effects of some of the key variables on ISS are different from their direct effects (as shown in Table 6). The results indicate that certain factors have both direct and indirect effects on increasing the ISS, with the overall effects being higher than their direct effects. For example, if a crash occurs at night, it would increase the ISS by 0.32 times. However, when considering the indirect effects (0.16) on ISS via PHT, the overall effects are found to be 0.48, which is much higher than the direct effects of 0.32. Similarly, factors that tend to reduce the ISS, both directly and indirectly (e.g., crash location), also result in overall effects that are higher than their direct effects. Interestingly, some factors directly increase the ISS but reduce it through their indirect effects. For example, the involvement of VRUs in a crash would increase the ISS by 0.41 times; however, when its indirect effects (-0.26) are also considered, the overall effects are found to be 0.15, which is much lower than the direct effects. This information cannot be obtained using conventional modeling techniques.

6. Practical Implications

The findings have significant practical implications for improving road safety and emergency response that could potentially lead to substantial reductions in the severity of injuries and fatalities. The significant and prolonged delays in PHT, which average over 104 minutes, emphasize the urgent need to improve EMS, especially in the city from which the data was analyzed. The implementation of more effective ambulance services, possibly using advanced technology like GPS tracking, has the potential to significantly reduce preventable hospitalizations and thus alleviate the severity of injuries. Moreover, it is crucial to enhance the skills and resources available to first responders to ensure expedited and more efficient medical interventions. Furthermore, there is a need for stricter enforcement of traffic regulations, especially regarding large vehicles and violations leading to RTCs. Targeted enforcement campaigns and stringent penalties could effectively discourage dangerous driving habits, particularly during night and morning peak traffic hours, due to the increased severity of injuries associated with such incidents. Enhancing visibility and deploying law enforcement personnel at night could mitigate the heightened risks of severe injuries associated with reduced visibility and impaired driving. The increased vulnerability of VRUs, including pedestrians and cyclists, underscores an urgent need for public awareness initiatives specifically targeting road safety. By promoting the use of helmets, reflective clothing, and marked crossing locations, as well as providing education to drivers on responsible road sharing, it is possible to mitigate the extent of injuries sustained by these specific groups.



Note: *For a detailed understanding of the pathways' strength (width of the arrows), please refer to Table 6.*

Figure 6: Path Analysis: Direct and Indirect Effects of Key Variables on Injury Severity Score

7. Research Limitations and Scope for Future Research

This study analyzed data obtained from the RTIRPC, which is one of the most extensive national initiatives conducted thus far. Despite being an extensive and detailed collection effort in developing countries like Pakistan, which can have several benefits, we acknowledge several potential limitations. The results are specifically applicable to crashes that resulted in injuries (where crash victims were shifted to hospitals) and cannot be generalized to instances that involve property damage only. Furthermore, the data was acquired upon the arrival of crash victims at the hospitals. As a result, information regarding the conditions of the road, the circumstances of the crash, and parts of the response were not collected at the crash scene. Similarly, the medical condition of the victims was also documented upon their arrival at the hospital without information about pre-, on-scene, and post-hospital times. One of the potential research avenues can be to explore the approaches that can include information about the aforementioned variables (roadway, pre- and on-scene medical conditions, etc.). Furthermore, as discussed earlier, each of the injury scales, including KABCO, AIS, ISS, and NISS, has its own advantages and limitations, considering which the selection of a specific injury measure depends on the situation and scope of the study. For instance, it is important to highlight that ISS may not always lead to an accurate prediction of injury outcomes, as we consider that the same ISS score can have different clinical outcomes due to differences in types of injuries, responses of the patients, patient age, and cure. While the present research does not look at the prediction of injury outcomes based on ISS and/or other injury measures, including AIS or NISS, we consider it important to account for the potential endogeneity issues within the ISS in future research. For instance, it would be interesting to see the role of interaction of ISS and patient age/injury types (based on body parts) in predicting the final clinical outcome (i.e., morbidity versus survival). Furthermore, as discussed in the data section, our findings are based on the hospital-based detailed data, which was collected as a part of a funded project in Karachi, Pakistan, where the latter can have its unique characteristics, including socio-economics, traffic, behaviors, emergency response, and trauma protocols. To assess the transferability or differences across cities or locations in the country (or abroad), a similar study can be extended to other cities or localities in the country and/or abroad. Future research also necessitates the collaboration of transportation and medical professionals. This interdisciplinary approach has the potential to yield useful insights that can improve overall road safety and enhance the medical care of crash victims. Moreover, it is necessary to broaden the scope of national-level projects, such as the RTIRPC, by incorporating a wider variety of geographic and socio-economic circumstances. Researchers can enhance the development of more efficient techniques to reduce injury severity and improve the outcomes for individuals involved in road crashes.

8. Conclusion

The research investigates how roadway environment, crash-specific features, and evacuation/response measures relate to ISS directly and via PHT – something that is lightly researched. To achieve the research objectives, a unique and fine crash data obtained from hospital records in Karachi (Pakistan) was analyzed. To address issues related to missing values and ensure accuracy in analysis, a synthetic data generation procedure was employed. Considering the corner-solution distribution of PHT and ISS, two Tobit models were applied using rigorous path analysis. The analysis revealed a significant association between PHT and ISS, suggesting that a one-unit increase in PHT corresponds to a 0.01-unit increase in ISS, highlighting the importance of swift evacuation and immediate medical care for the crash victims. The study identified the mode of evacuation as a crucial factor, with ambulance transportation resulting in longer PHT and higher ISS compared to private or public transport modes. The findings also showed that crashes occurring at night not only increased ISS directly, but also led to longer PHT, where the latter itself showed a positive correlation with ISS. Furthermore, our findings reveal that undivided roadways and involvement of multiple or heavy vehicles are critical, as these significantly increase both PHT and ISS, signifying more complex and severe collision scenarios. The path analysis showed that the overall effects of several explanatory variables on ISS were higher than their individual direct or indirect effects, demonstrating the efficacy of this analytical approach in capturing the multifaceted impacts on the finer injury measures in RTCs. Based on the findings, the study provides useful knowledge that can help in improving the EMS infrastructure by enhancing the deployment and effectiveness of ambulances (e.g., by implementing and using GPS tracking systems for the dedicated emergency response service), as well as improving emergency response times, especially during the night, in populous and congested cities. We also consider that implementing specific road safety measures, such as enhanced traffic enforcement on undivided roadways and improved visibility, can be beneficial. Public awareness efforts focused on educating individuals about proper emergency response and first aid have the potential to reduce the seriousness of injuries in RTCs, as, unlike the developed world majority of the RTC victims are shifted to hospitals or emergency units by the public in private vehicles.

References

[1] World Health Organization (WHO), 13 December 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries. [Accessed 21 February 2024].

[2] J. Antony, V. Jayaseelan, J. J. Olickal, J. Alexis and M. Sakthivel, "Time to Reach Health-Care Facility and Hospital Exit Outcome Among Road Traffic Accident Victims Attending a Tertiary Care Hospital, Puducherry," *Journal of Education and Health Promotion,* 2021.

[3] J. Brown, M. Rosengart, R. Forsythe, B. Reynolds, M. Gestring, W. Hallinan, A. Peitzman, T. Billiar and J. Sperry, "Not All Prehospital Time is Equal: Influence of Scene Time on Mortality," *Journal of Trauma and Acute Care Surgery,* pp. 93-100, 2016.

[4] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi , "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* 2010.

[5] P. L. Chen and C. W. Pai, "Evaluation of Injuries Sustained by Motorcyclists in Approach-Turn Crashes in Taiwan," *Accident Analysis & Prevention,* vol. 38, no. 5, pp. 1019-1027, 2019.

[6] S. Palmer, M. Bader, A. Qureshi, J. Palmer, T. Shaver, M. Borzatta and C. Stalcup, "The Impact on Outcomes in a Community Hospital Setting of Using the AANS Traumatic Brain Injury Guidelines," *Journal of Trauma and Acute Care Surgery ,* vol. 50, no. 4, pp. 657-664, 2001.

[7] B. Wali , A. J. Khattak and N. Ahmad, "Examining Correlations Between Motorcyclist's Conspicuity, Apparel Related Factors and Injury Severity Score: Evidence from New Motorcycle Crash Causation Study," *Accident Analysis & Prevention,* vol. 131, pp. 45-62, 2019.

[8] A. J. Khattak , N. Ahmad, B. Wali and E. Dumbaugh, "A Taxonomy of Driving Errors and Violations: Evidence from the Naturalistic Driving Study," *Accident Analysis & Prevention,* vol. 151, 2021.

[9] B. Wali, A. J. Khattak and N. Ahmad, "Towards Better Measurement of Traffic Injuries – Comparison of Anatomical Injury Measures in Predicting Clinical Outcomes in Motorcycle Crashes," *Journal of Safety Research,* 2022.

[10] F. Mannering and C. Bhat, "Analytic Methods in Accident Research: Methodological Frontier and Future Directions," in *Analytic Methods in Accident Research*, 2014, pp. 1-22.

[11] J. Short and B. Caulfield, "Record Linkage for Road Traffic Injuries in Ireland Using Police Hospital and Injury Claims Data," *Journal of Safety Research ,* vol. 58, pp. 1-14, 2016.

[12] N. Ahmad, B. Wali, A. J. Khattak and E. Dumbaugh, "Built Environment, Driving Errors and Violations, and Crashes in Naturalistic Driving Environment," *Accident Analysis & Prevention,* vol. 157, 2021.

[13] K. L. Loftis, J. Price and P. J. Gillich, "Evolution of the Abbreviated Injury Scale: 1990–2015," *Traffic Injury Prevention,* vol. 19, no. Sup2, pp. 109-113, 2018.

[14] S. Baker, B. o'Neill, H. Jr. and W. W. Long, "The Injury Severity Score: A Method for Describing Patients with Multiple Injuries and Evaluating Emergency Care," *The Journal of Trauma and Acute Care Surgery,* vol. 14, no. 3, pp. 187-196, 1974.

[15] A. G. Rapsang and D. C. Shyam, "Scoring Systems of Severity in Patients with Multiple Trauma," *Cirugía Española (English Edition),* vol. 93, no. 4, pp. 213-221, 2013.

[16] M. Stevenson, M. Segui-Gomez, I. Lescohier, C. Di Scala and G. Mcdonald-Smith, "An Overview of the Injury Severity Score and the New Injury Severity Ccore," *Injury Prevention,* vol. 7, no. 7, pp. 10-13, 2001.

[17] S. Ankarath, P. Giannoudis, I. Barlow, M. Bellamy, S. Matthews and R. Smith, "Injury Patterns Associated with Mortality Following Motorcycle Crashes," *Injury* , vol. 33, no. 6, pp. 473-477, 2002.

[18] L. Camilloni, P. Rossi, S. Farchi, F. Chini, P. Borgia and G. Guasticchi, "Triage and Injury Severity Scores as Predictors of Mortality and Hospital Admission for Injuries: A Validation Study," *Accident Analysis & Prevention,* vol. 42, no. 6, pp. 1958-1965, 2010.

[19] O. Bolorunduro, C. Villegas, T. Oyetunji, E. Haut, K. Stevens, D. Chang, E. Cornwell III, D. Efron and A. Haider, "Validating the Injury Severity Score (ISS) in Different Populations: ISS Predicts Mortality Better Among Hispanics and Females," *Journal of Surgical Research,* vol. 166, no. 1, pp. 40-44, 2011.

[20] H. Li, "Impacts of Traffic Interventions on Road Safety: An Application of Causal Models," 2013.

[21] G. Zhang, K. K. Yau and G. Chen, "Risk Factors Associated with Traffic Violations and Accident Severity in China," *Accident Analysis & Prevention,* vol. 59, pp. 18-25, 2013.

[22] M. Bigdeli, D. Khorasani-Zavareh and R. Mohammadi, "Pre-Hospital Care Time Intervals Among Victims of Road Traffic Injuries in Iran. A Cross-Sectional Study," *BMC Public Health,* vol. 10, 2010.

[23] Z. Mengstu, A. Ali and T. Abegaz, "Prehospital Care and 24-hour Crash Injury Mortality Among Road Traffic Crash Victims in Addis Ababa," *Science Journal of Public Health,* vol. 9, pp. 23-29, 2021.

[24] A. Thamer, M. A. Yousef, H. A. I. Mahmudul, A. A. Monerah, A. Adil, A. Ibrahim and M. Ilias, "Emergency Medical Service Response Time for Road Traffic Accidents in the Kingdom of Saudi Arabia: Analysis of National Data (2016–2020)," *International Journal of Environmental Research and Public Health,* 2023.

[25] M. K. Doaa, E. Elmorsy, A. Ahmed, A. N. Hesham and S. Lamiaa, "Factors Affecting Prehospital Time Delay of the Injured Patients Arriving at the Emergency Department of Beni-Suef University Hospital in Egypt: A Cross-Sectional Study," *PLOS ONE,* 2021.

[26] R. Pankaja, P. NB and D. M, "A study of Road Traffic Accidents and Road Safety Behavior in Pune: A Mixed-Method Approach," *Indian Journal of Community & Family Medicine,* pp. 75-78, 2015.

[27] T. Suzuki, O. Phonesavanh and S. Thongsna, "Relationship Between Prehospital Time and 24-h Mortality in Road Traffic-Injured Patients in Laos," *World Journal of Surgery,* vol. 46, pp. 800-806, 2022.

[28] N. Ahmad, T. Bhowmik, V. V. Gayah and N. Eluru, "On the Need to Address Fixed-Parameter Issues Before Applying Random Parameters: A Simulation-Based Study," *Analytic Methods in Accident Research,* vol. 41, 2024.

[29] J. Abowd and J. Lane, "New Approaches to Confidentiality Protection: Synthetic Data, Remote Access and Research Data Centers," in *Proceedings of the International Workshop on Privacy in Statistical Databases*, 2004.

[30] J. Abowd and S. Woodcock, "Multiply-Imputing Confidential Characteristics and File Links in Longitudinal Linked Data," in *Proceedings of the International Workshop on Privacy in Statistical Databases*, 2004.

[31] Z. U. Rehman, N. Ahmad, A. Ahmed and W. I. Kayani, "Investigating the Association of Post-Crash Medical Conditions and Human Factors with Motorcyclists Injuries: Insights from Fine Injury Data From Hospital Records," in *Transportation Research Board Annual Meeting by National Academies of Sciences, Engineering, and Medicine*, Washington, D.C., 2025.

[32] J. Reiter, "Releasing Multiply Imputed, Synthetic Public Use Microdata: An Illustration and Empirical Study," *Journal of the Royal Statistical Society: Series A (Statistics in Society),* vol. 168, no. 1, pp. 185-205, 2005.

[33] J. Drechsler and J. Reiter, "Sampling with Synthesis: A New Approach for Releasing Public Use Census Micro Data," *Journal of the American Statistical Association,* vol. 105, no. 492, pp. 1347-1357, 2010.

[34] S. Kinney, J. Reiter and J. Berger, "Model Selection when Multiple Imputation is Used to Protect Confidentiality in Public Use Data," *Journal of Privacy and Confidentiality,* vol. 2, no. 2, 2011.

[35] N. Ahmad, R. Arvin and A. J. Khattak, "How is the Duration of Distraction Related to Safety–Critical Events? Harnessing Naturalistic Driving Data to Explore the Role of Driving Instability," *Journal of Safety Research,* vol. 85, no. 5, 2023.

[36] P. Anastasopoulos, A. Tarko and F. Mannering, "Tobit Analysis of Vehicle Accident Rates on Interstate Highways," *Accident Analysis & Prevention,* vol. 40, no. 2, pp. 768-775, 2008.

[37] S. Washington, M. Karlaftis and F. Mannering, "Statistical and Econometric Methods for Transportation Data Analysis," 2010.

[38] X. Ma, F. Chen and S. Chen, "Modeling Crash Rates for a Mountainous Highway by Using Refined-Scale Panel Data," *Transportation Research Record,* vol. 2515, no. 1, pp. 10-16, 2015.

[39] L. Sigelman and L. Zeng, "Analyzing Censored and Sample-Selected Data with Tobit and Heckit Models," *Political Analysis* , vol. 8, no. 2, pp. 167-182, 1999.

[40] A. Numan, A. Ramin and K. Asad J., "Exploring Pathways from Driving Errors and Violations to Crashes: The Role of Instability in Driving," *Accident Analysis & Prevention,* 2023.

[41] J. Liu, A. Khattak, S. Richards and S. Nambisan, "What are the Differences in Driver Injury Outcomes at Highway-Rail Grade Crossings? Untangling the Role of Pre-Crash Behaviors," *Accident Analysis & Prevention,* vol. 85, pp. 157-169, 2015.

[42] M. Zhang, A. Khattak, J. Liu and D. Clarke, "A Comparative Study of Rail-Pedestrian Trespassing Crash Injury Severity Between Highway-Rail Grade Crossings and Non-Crossings," *Accident Analysis & Prevention,* vol. 117, pp. 427-438, 2018.

[43] J. Liu and A. Khattak, "Are Gates at Rail Grade Crossings Always Safe? Examining Motorist Gate-Violation Behaviors Using Path Analysis," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 55, pp. 314-324, 2018.

[44] R. Arvin, M. Kamrani and A. Khattak, "The Role of Pre-Crash Driving Instability in Contributing to Crash Intensity Using Naturalistic Driving Data," *Accident Analysis & Prevention* , vol. 132, 2019.

[45] N. Ahmad, R. Arvin and A. Khattak, "Exploring pathways from driving errors and violations to crashes: The role of instability in driving," *Accident Analysis & Prevention,* vol. 2023, no. 179, p. 106876, 2023.

[46] D. Roodman, "Mixed-process models with CMP," in *Proceedings of the DC09 Stata Conference*, 2009.

[47] J.-T. Lee and J. Fazio, "Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods," *Traffic Injury Prevention,* vol. 6, no. 4, pp. 331-339, 2005.

[48] S. R. Vanga, P. M. Ligrani, M. Doustmohammadi and M. Anderson, "Effects of Different Crash Data Variables on EMS Response Time for a Rural County in Alabama," *Journal of Family Medicine and Primary Care,* vol. 11, no. 4, p. 1462–1467, 2022.

[49] K.-Z. Davoud, M. Reza and B. Katarina, "Factors Influencing Pre-Hospital Care Time Intervals in Iran: a Qualitative Study," *Journal of Injury and Violence Research,* pp. 83-90, 2018.

[50] U. Hanif, F. Asim and A. S. Akhtar, "An Empirical Assessment of Factors Influencing Injury Severities of Motor Vehicle Crashes on National Highways of Pakistan," *Journal of Advanced Transportation,* 2021.

[51] N. Eluru, C. R. Bhat and D. Hensher, "A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Level in Traffic Crashes," *Accident Analysis & Prevention,* vol. 40, no. 3, p. 1033–1054, 2008.

[52] M. Kamruzzaman, "Analysis of Traffic Injury Severity in a Mega City of a Developing Country," in *4th Road Safety International Conference*, Sydney, Australia., 2013.

[53] C. O'donnell and D. Connor, "Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice," *Accident Analysis & Prevention,* vol. 28, no. 6, p. 739–753, 1996.

[54] D. Daddah, Y. Glèlè Ahanhanzo, A. Kpozehouen, B. Santos, E. Bonnet, A. Levêque and Y. Coppieters, "Understanding the Factors of Road Crash Severity in Benin: A Matched Case-Control Study," *Journal of Public Health in Africa,* vol. 14, 2023.

[55] C. Chan, B. Huang, X. Yan and S. Richards, "Investigating Effects of Asphalt Pavement Conditions on Traffic Accidents in Tennessee Based on the Pavement Management System (PMS)," *Journal of Advanced Transportation,* vol. 44, no. 3, p. 150–161, 2010.

[56] Fylan F., "Why Do People Drive When They Can't See Clearly?," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 56, pp. 123-133, 2018.

[57] E. de Bellis, "Blind Haste: As Light Decreases, Speeding Increases," *PLoS One,* vol. 13, 2018.

[58] F. Malin, I. Norros and S. Innamaa, "Accident Risk of Road and Weather Conditions on Different Road Types," *Accident Analysis & Prevention,* vol. 122, p. 181–188, 2019.

[59] A. Chandrasekharan, A. J. Nanavati, S. Prabhakar and S. Prabhakar, "Factors Impacting Mortality in the Pre-Hospital Period After Road Traffic Accidents in Urban India," *Trauma Monthly,* vol. 21, no. 3, 2016.

[60] K. Khan, M. Jamil, I. Memon and Z. Idrees, "Pattern of Injuries in Motorbike Accidents," *Journal of Pakistan Orthopaedic Association,* vol. 30, no. 2, pp. 123-127, 2018.

[61] V. Akinpelu, A. Oladele, Y. Amusa, O. Ogundipe, A. Adeolu and E. Komolafe, "Review of Road Traffic Accident Admissions in a Nigerian Tertiary Hospital," *East and Central African Journal of Surgery,* vol. 12, no. 1, 2007.

[62] E. Naddumba, "A Cross-Sectional Retrospective Study of Boda Boda Injuries At Mulago Hospital IN Kampala-Uganda," *East and Central African Journal of Surgery,* vol. 9, no. 1, 2004.

[63] G. Tulu, S. Washington and M. King, "Characteristics of Police-Reported Road Traffic Crashes in Ethiopia Over a Six Year Period," in *Australasian Road Safety Research, Policing & Education Conference*, Brisbane, Queensland, 2013.

[64] R. Gebresenbet and A. Aliyu, "Injury Severity Level and Associated Factors Among Road Traffic Accident Victims Attending Emergency Department of Tirunesh Beijing Hospital, Addis Ababa, Ethiopia: A Cross Sectional Hospital-Based Study," *PLoS ONE,* vol. 14, no. 9, 2019.

[65] A. Baru, A. Azazh and L. Beza, "njury Severity Levels and Associated Factors Among Road Traffic Collision Victims Referred to Emergency Departments of Selected Public Hospitals in Addis Ababa, Ethiopia: The Study Based on the Haddon Matrix," *BMC Emergency Medicine,* vol. 19, no. 2, 2019.

[66] S. Mutooro, E. Mutakooha and P. Kyamanywa, "A Comparison of Kampala Trauma Score II with the New Injury Severity Score in Mbarara University Teaching Hospital in Uganda," *East and Central African Journal of Surgery,* vol. 15, 2010.

Conflict of Interest

The authors declare that there is no conflict of interest.

This study analyzes the RTCs data acquired from the Road Traffic Injuries Research and Prevention Center (RTIRPC) focused on Karachi, Pakistan. The data used for analysis do not include sensitive information. The authors declare no conflicts of interest.

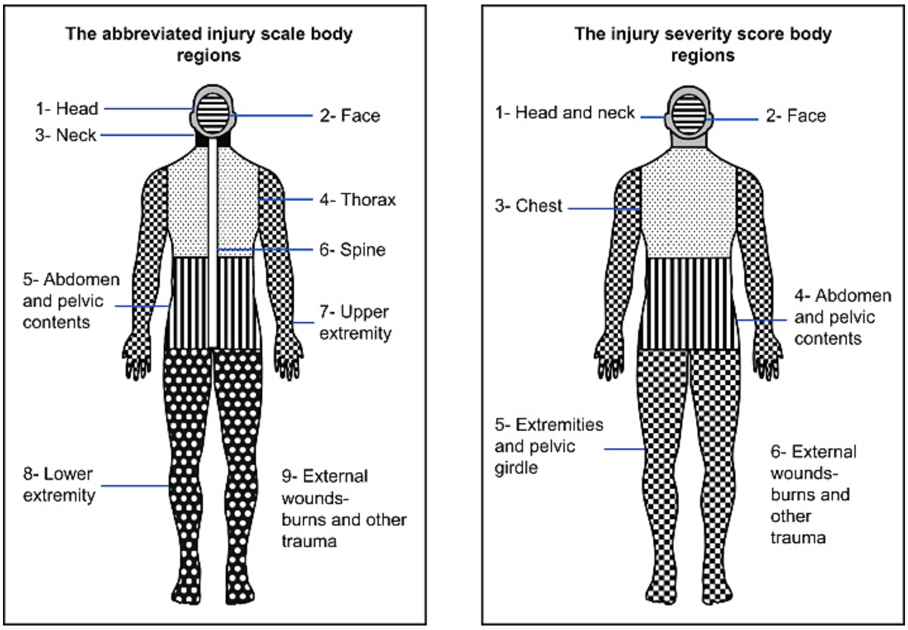


Figure 1: The Abbreviated Injury Scale and Injury Severity Score Body Regions

(Source: https://www.sciencedirect.comsciencearticlepiiS0007091221006528)

Table 1: Summary of the Relevant Past Literature

Title	Reference	Key Findings
Validating the Injury Severity Score (ISS) in Different Populations: ISS Predicts Mortality Better among Hispanics and Females	Bolorunduro, et al., 2011	• The ISS is widely used as a measure of injury severity • It effectively predicts trauma mortality based on multiple data sets • The ISS demonstrates strong discriminative ability across all groups, based on race and gender
Towards Better Measurement of Traffic Injuries – Comparison of Anatomical Injury Measures in Predicting Clinical Outcomes in Motorcycle Crashes	Wali, et al., 2022	• Despite its simplicity and clarity, the KABCO scale has significant limitations • The ISS is a more sophisticated scoring system than the KABCO scale, capable of accurately assessing overall injury severity and facilitating a more comprehensive evaluation
An Empirical Assessment of Factors Influencing Injury Severities of Motor Vehicle Crashes on National Highways of Pakistan	Hanif, et al., 2021	• Factors such as overspeeding, driver fatigue, driver negligence, driver age, type of vehicle (truck, rickshaw, single vehicle), road conditions (horizontal curve, potholes, night driving without road lights), time/day/month of crash occurrence, weather conditions (e.g., cloudy, clear) contribute to the injury severity in a crash
Prehospital Care and 24-hour Crash Injury Mortality Among Road Traffic Crash Victims in Addis Ababa	Mengstu, et al, 2021	• Without pre-hospital care, the chance of early death in RTCs is significantly higher • Key areas to focus on include reducing the time spent in the pre-hospital environment, using ambulance services, and increasing public awareness of pre-hospital care, particularly within the platinum 10-minute scene time and golden one-hour PHT
The Prehospital Time Impact on Traffic Injury from Hospital Fatality and Inpatient Recovery Perspectives	Sara et al, 2019	• The impact of PHT differs among observations and is positively associated with duration of hospital stay and Healthcare costs • Factors such as age and gender of the victim, crash type, hospital, and injury severity (i.e., AIS) significantly influence both the likelihood of mortality and the recovery rate of crash victims
Emergency Medical Service Response Time for Road Traffic Accidents in the Kingdom of Saudi Arabia: Analysis of National Data (2016–2020)	Thamer, et al., 2023	• Response time is significantly affected by various socio-demographic factors, such as geographical regions, causes of crash, age, gender, and nationality • Acquiring a thorough knowledge of these aspects is essential for optimizing efficiency during the PHT

Factors Affecting Prehospital Time Delay of the Injured Patients Arriving at the Emergency Department of Beni-Suef University Hospital in Egypt: A Cross-Sectional Study	Khalil, et al., 2021	• The delay in receiving medical care before reaching the hospital is associated with old age, living in rural areas, and the level of consciousness of crash victims • Implementing health education programs aimed at educating elderly individuals and those living in rural areas about the importance of minimizing PHT is necessary
Time to Reach Healthcare Facility and Hospital Exit Outcome among Road Traffic Accident Victims Attending a Tertiary Care Hospital, Puducherry	Antony, et al., 2021	• Various environmental and infrastructural factors, such as the day of the week, urban or rural location, specific crash details, and emergency response duration, significantly impact PHT
Factors Influencing Pre-Hospital Care Time Intervals in Iran: A Qualitative Study	Davoud, et al., 2018	• The EMS play a crucial role in reducing the PHT • Challenges associated with prompt response include the collaboration of the public, the allocation of EMS facilities, the accessibility of ambulances, and the availability of personnel
Pre-Hospital Trauma Care in Road Traffic Accidents in Kashan, Iran	Paravar, et al., 2013	• Trauma patients involved in RTCs on intercity roads have longer PHT and more serious injuries compared to those involved in RTCs on city streets • Consequently, this group requires more PHT-related measures
Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods	Lee et al, 2006	• EMS response times are most significantly influenced by the severity of RTCs • RTCs resulting in injuries or fatalities have EMS response times up to 20% less than crashes exclusively involving property damage • Total PHT during peak periods is greatly influenced by the day of the week, urban or rural location, off or opposing-lane crash location, number of vehicles involved, heavy vehicle involvement, and reaction time

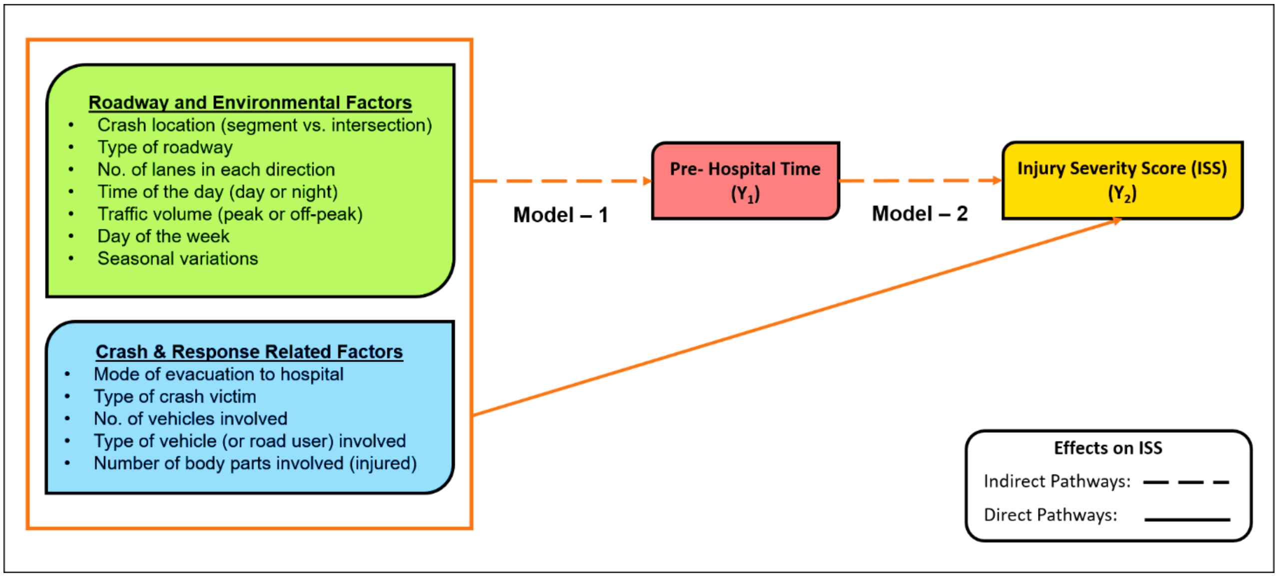
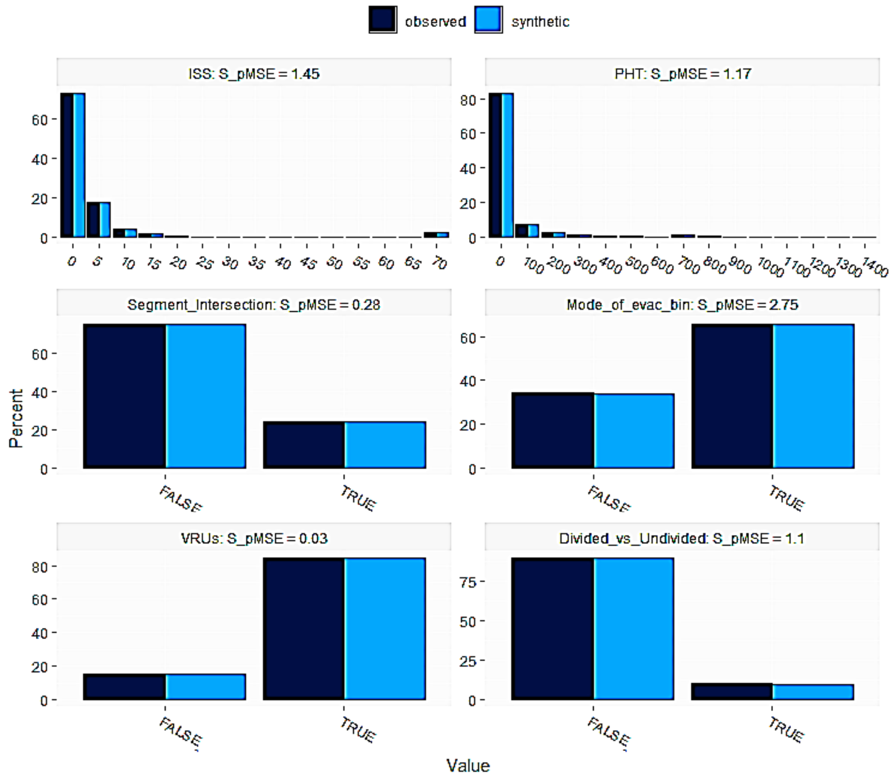


Figure 2: Conceptual Framework



Note: *False and true refer to 0 and 1 for the indicator variables*

Figure 3: Percentage-Wise Distribution of Variables - Observed (Actual) Versus Synthetic Data

Table 2: Descriptive Statistics - Actual Data versus Synthetic Data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Observed Data					
ISS	138,289	6.17	11.69	1	75
PHT (in minutes)	138,289	104.81	206.73	1	1439
Crash Location (0 if segment, 1 if intersection)	138,289	0.25	0.43	0	1
Mode of Evacuation (1 if ambulance, 0 otherwise)	138,289	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	138,289	0.86	0.34	0	1
Type of Roadway (0 if divided, 1 otherwise)	138,289	0.10	0.30	0	1
Synthetic Data					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
ISS	160,365	6.22	11.89	1	75
PHT (in minutes)	160,365	103.86	204.74	1	1439
Crash Location (0 if segment, 1 if intersection)	160,365	0.25	0.43	0	1
Mode of Evacuation (1 if ambulance, 0 otherwise)	160,365	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	160,365	0.87	0.33	0	1
Type of Roadway (0 if divided, 1 otherwise)	160,365	0.10	0.30	0	1

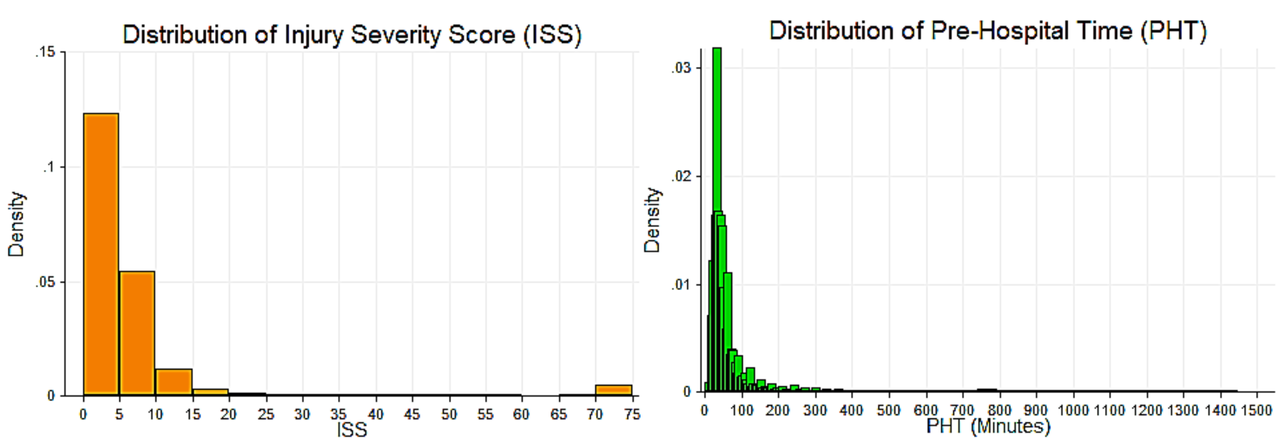


Figure 4: Distribution of ISS and Pre-hospital Time

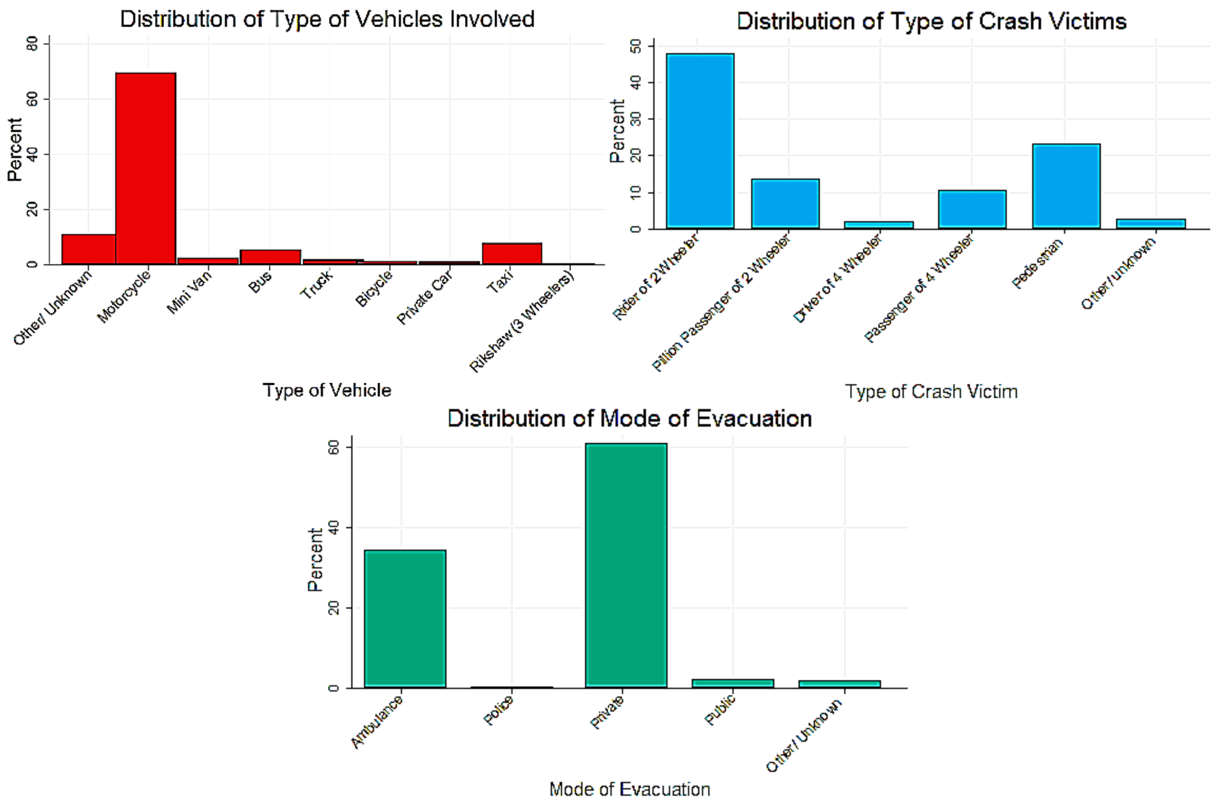


Figure 5: Distribution of Type of Vehicles Involved, Type of Crash victims, and Mode of Evacuation

Table 3: Descriptive Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variables					
ISS	298,654	6.20	11.80	1	75
PHT (in minutes)	298,654	104.30	205.66	1	1439
Independent Variables					
Roadway Environment and Traffic-Related Factors					
Crash Location (0 if segment, 1 if intersection)	298,654	0.25	0.43	0	1
Type of Roadway (0 if divided, 1 otherwise)	298,654	0.10	0.30	0	1
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	298,654	0.35	0.48	0	1
Time of the Day (0 if day, 1 otherwise)	298,654	0.37	0.48	0	1
Traffic Volume (0 if morning peak, 1 otherwise)	298,654	0.95	0.23	0	1
Day of the Week (1 if Friday, 0 otherwise)	298,654	0.13	0.34	0	1
Seasonal Variations (0 if summer,1 otherwise)	298,654	0.68	0.47	0	1

Crash and Response-Related Factors					
Mode of Evacuation (0 if ambulance, 1 otherwise)	298,654	0.66	0.47	0	1
Type of Crash Victim (1 if VRU, 0 otherwise)	298,654	0.87	0.34	0	1
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	298,654	0.35	0.48	0	1
Heavy Vehicles vs Other (1 if heavy vehicle i.e. truck or bus, 0 otherwise)	298,654	0.08	0.27	0	1
Number of Body Parts Injured	298,654	1.90	0.91	1	8

Table 4: Results of Model-1 (PHT Model)

PHT	Coef.	Std. Err.	t-stat	ME-1	ME-2	ME-3
Roadway Environment and Traffic-Related Factors						
Crash Location (0 if segment, 1 if intersection)	-31.3014	0.8740	-35.82	-21.53	-0.05	-15.20
Type of Roadway (0 if divided, 1 otherwise)	5.8517	1.4132	4.14	4.03	0.01	2.84
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-14.8500	0.8847	-16.79	-10.21	-0.03	-7.21
Time of the Day (0 if day, 1 otherwise)	23.5048	0.7820	30.06	16.17	0.04	11.41
Seasonal Variations (0 if summer,1 otherwise)	2.4386	0.8067	3.02	1.68	0.00	1.18
Crash and Response-Related Factors						
Mode of Evacuation (0 if ambulance, 1 otherwise)	-6.3341	0.8170	-7.75	-4.36	-0.01	-3.08
Type of Crash Victim (1 if VRUs, 0 otherwise)	-37.4407	1.2485	-29.99	-25.75	-0.06	-18.18
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	3.9627	0.7991	4.96	2.73	0.01	1.92
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	30.8792	1.5850	19.48	21.24	0.05	14.99
Number of Body Parts Injured	9.7848	0.4170	23.46	6.73	0.02	4.75
Constant	119.0316	1.7351	68.60	-	-	-
Sigma	205.4065	0.2678	-	-	-	-
Model Summary						
Log Likelihood	-1992007					
AIC	3984038					

BIC	3984165

Note: *The Variance Inflation Factors (VIF) were calculated to assess multicollinearity among variables, and the values for all the key regressors were less than 1.27 (well below the threshold of 10), indicating the absence of problematic collinearity.*

Table 5: Results of Model-2 (ISS Model)

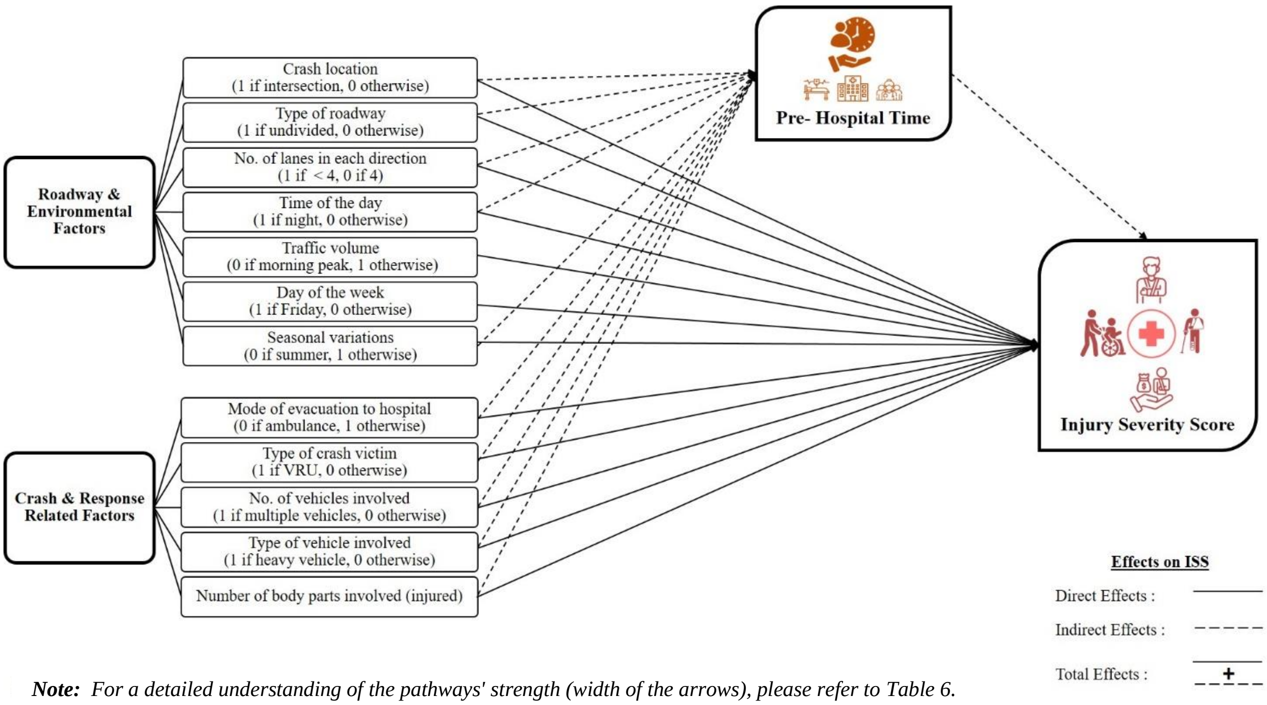
ISS	Coef.	Std. Err.	t-stat	ME-1	ME-2	ME-3
PHT	0.0111	0.0004	27.32	0.01	0.0003	0.004
c.PHT#c.PHT	-0.00001	0.0000004	-23.25			
Roadway Environment and Traffic-Related Factors						
Crash Location (0 if segment, 1 if intersection)	-0.6464	0.0612	-10.56	-0.36	-0.02	-0.27
Type of Roadway (0 if divided, 1 otherwise)	0.6556	0.0990	6.62	0.37	0.02	0.27
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-0.4880	0.0620	-7.87	-0.28	-0.01	-0.20
Time of the Day (0 if day, 1 otherwise)	0.5749	0.0555	10.36	0.32	0.02	0.24
Traffic Volume (0 if morning peak, 1 otherwise)	-1.4299	0.1159	-12.34	-0.81	-0.04	-0.59
Day of the Week (1 if Friday, 0 otherwise)	0.2037	0.0778	2.62	0.11	0.01	0.08
Seasonal Variations (0 if summer,1 otherwise)	-0.1559	0.0562	-2.77	-0.09	-0.01	-0.06
Crash and Response-Related Factors						
Mode of Evacuation (0 if ambulance, 1 otherwise)	-6.9258	0.0560	-123.58	-3.91	-0.19	-2.85
Type of Crash Victim (1 if VRUs, 0 otherwise)	0.7227	0.0865	8.35	0.41	0.02	0.30
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	1.0494	0.0556	18.87	0.59	0.03	0.43
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	2.2932	0.1087	21.09	1.29	0.06	0.94
Number of Body Parts Injured	3.6425	0.0295	123.28	2.05	0.10	1.50
Constant	0.6223	0.1647	3.78	-	-	-
Sigma	13.5519	0.0206	-	-	-	-
Model Summary						
Log Likelihood	-947745					

AIC	1895522
BIC	1895691

Note: *While values for the t-stat and MEs are reported up to two decimal places, values for the coefficients and standard error are reported up to four. However, to account for the first non-zero value after the decimal points, there are minor differences in how PHT and its squared term are reported. Moreover, the VIF values for all the key regressors are also less than 1.27 (well below the threshold of 10), indicating the absence of problematic collinearity.*

Table 6: Path Analysis Results: Direct, Indirect, and Total Effects of Key Variables

Independent Variables	Direct Effects	Indirect Effects	Total Effects
PHT	0.01	-	0.01
Roadway Environment and Traffic-Related Factors			
Crash Location (0 if segment, 1 if intersection)	-0.36	-0.22	-0.58
Type of Roadway (0 if divided, 1 otherwise)	0.37	0.04	0.41
Number of Lanes in Each Direction (0 if 4 lanes, 1 if less than 4 lanes)	-0.28	-0.10	-0.38
Time of the Day (0 if day, 1 otherwise)	0.32	0.16	0.48
Traffic Volume (0 if morning peak, 1 otherwise)	-0.81	-	-0.81
Day of the Week (1 if Friday, 0 otherwise)	0.11	-	0.11
Seasonal Variations (0 if summer,1 otherwise)	-0.09	0.02	-0.07
Crash and Response-Related Factors			
Mode of Evacuation (0 if ambulance, 1 otherwise)	-3.91	-0.04	-3.95
Type of Crash Victim (1 if VRUs, 0 otherwise)	0.41	-0.26	0.15
Number of Vehicles Involved (0 if single vehicle, 1 if multiple vehicles)	0.59	0.03	0.62
Heavy Vehicles vs Other (1 if heavy vehicle, 0 otherwise)	1.29	0.21	1.50
Number of Body Parts Injured	2.05	0.07	2.12



Note: *For a detailed understanding of the pathways' strength (width of the arrows), please refer to Table 6.*

Figure 6: Path Analysis: Direct and Indirect Effects of Key Variables on Injury Severity Score