UNIVERSIDAD
DE BURGOS

Escuela Politécnica Superior
Departamento de Ingeniería de Organización

TESIS DOCTORAL
Programa de Doctorado – Tecnologías Industriales e Ingeniería Civil

Estudio de la lesividad de los accidentes de tráfico en España. Modelización de los factores técnicos y humanos

Autor
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Burgos, noviembre de 2021

AUTORIZACIÓN PARA LA PRESENTACIÓN DE LA TESIS DOCTORAL

La Dra. Dña. Susana García Herrero y el Dr. D. Miguel Ángel Mariscal Saldaña, ambos miembros del Departamento de Ingeniería de Organización de la Universidad de Burgos

EXPONEN

Que la tesis doctoral titulada “Estudio de la lesividad de los accidentes de tráfico en España. Modelización de los factores técnicos y humanos” ha sido realizada por D. Juan Diego Febres Eguiguren dentro del programa de doctorado en “Tecnologías Industriales e Ingeniería Civil”, en el departamento de Ingeniería de Organización de la Universidad de Burgos, bajo la dirección de ambos.

Que autorizan a D. Juan Diego Febres Eguiguren a presentar el presente documento como memoria para optar al título de Doctor por la Universidad de Burgos.

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Burgos, 16 de noviembre de 2021

FINANCIACIÓN E INFORMACIÓN

El desarrollo del trabajo investigador de esta tesis doctoral ha sido financiado en distintos niveles por las siguientes entidades:

Fondo Europeo de Desarrollo Regional con la Junta de Castilla y León

- El proyecto titulado “Modelización mediante técnicas de machine learning de la influencia de las distracciones del conductor en la seguridad vial”, con referencia BU300P18, ha financiado parte de la difusión de los resultados científicos de la presente Tesis Doctoral.

Dirección General de Tráfico de España

La Dirección General de Tráfico (DGT), a través del proyecto SPIP2015-1852, ha cedido al grupo de investigación los datos de accidentes de tráfico con víctimas en España para su análisis e investigación. El dataset utilizado en la presente Tesis Doctoral incluye datos de accidentes de tráfico desde el año 2016 hasta el año 2019.

Universidad de Burgos

- La Universidad de Burgos ha subvencionado los servicios de asesoría en traducción de dos de las publicaciones científicas derivadas de esta investigación.

Universidad Técnica Particular de Loja

- La Universidad Técnica Particular de Loja ha subvencionado los gastos de difusión de una publicación científica de esta investigación, así como los gastos de manutención del doctorando durante sus estancias de investigación en la Universidad de Burgos.

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RESUMEN

Las lesiones y muertes causadas por los accidentes de tráfico se han convertido en un problema de salud pública a nivel mundial, de tal magnitud que han estado presentes en las estadísticas de la Organización Mundial de la Salud (OMS) y de varios organismos alrededor del mundo entre las diez primeras causas de fallecimiento por más de una década. Es por ello que, la Organización de las Naciones Unidas (ONU) ha incluido entre sus objetivos de desarrollo sostenible (ODS) la meta de reducir sus impactos a la mitad hasta 2030. A este objetivo se han unido varias organizaciones internacionales como la Unión Europea, el Gobierno de España y la Dirección General de Tráfico (DGT).

El análisis de datos y la modelización se ha transformado con la aparición del “Big Data”, la minería de datos y el aprendizaje automatizado. Si bien es cierto, estas disciplinas de la ciencia son relativamente nuevas, también es cierto que sus aportes han sido de gran utilidad para la toma de decisiones a todos los niveles, y parecen ser muy prometedoras conforme se avanza en sus estudios aplicados a las diferentes ramas de estudio, siendo este el caso del estudio de los accidentes de tráfico en la rama de la seguridad vial.

Esta Tesis Doctoral, considerando la problemática presentada por los accidentes de tráfico, así como las metodologías derivadas del análisis de datos y el aprendizaje automatizado, utiliza algoritmos de aprendizaje de redes bayesianas basados en técnicas de “machine learning” para modelizar la lesividad de los accidentes de tráfico de España, considerando variables relacionadas con factores humanos y técnicos que tienen lugar en el momento del accidente. El aporte metodológico de esta tesis es sólido, pues deja entrever en sus aportes científicos la bondad del aprendizaje de los algoritmos de redes bayesianas en el tratamiento de datos de los accidentes de tráfico, así como la correcta validación de los modelos teóricos y la red bayesiana generada por medio de la metodología del área bajo la curva del receptor (AUC).

El aporte específico de esta tesis se centra en las cinco contribuciones científicas realizadas sobre el estudio de la lesividad en los accidentes de tráfico en España, utilizando para ello la modelización a través de redes bayesianas. Estas contribuciones de forma general abordan, pero no se limitan, a: (i) un modelo que estudia la lesividad de los conductores en los accidentes de tráfico basados en el propósito del viaje, (ii) un modelo que analiza la lesividad de los conductores en los accidentes de tráfico según el uso de equipos de protección personal, (iii) un modelo para el análisis de la lesividad general de los usuarios de la vías a través del comportamiento inseguro de los conductores no alineados con las normas regulatorias de tráfico, (iv) un modelo que estudia la lesividad de los peatones basados en su comportamiento durante los accidentes de tráfico, (v) un modelo que estudia la lesividad general de los usuarios de las vías a través de las infracciones causadas por la conducción distraída de base tecnológica.

Palabras clave: accidentes de tráfico, análisis de datos, redes bayesianas, lesividad de usuarios de las vías, modelización y aprendizaje automatizado.

ESQUEMA GENERAL DE LA TESIS

El trabajo de investigación realizado se plasma en este documento de tesis siguiendo la estructura detallada en la figura 1. La primera sección está conformada por los capítulos uno y dos, donde se abordan los fundamentos teóricos, mientras que la segunda sección incluye los resultados del trabajo de investigación y se compone por los capítulos tres, cuatro, cinco, seis y siete, los cuales corresponden a cada uno de los artículos científicos publicados. Finalmente, la tercera sección corresponde a un solo capítulo, donde se abordan las conclusiones de todo el documento, las limitaciones del estudio y las futuras líneas de investigación.

El capítulo uno de introducción, aborda principalmente el estado del arte de los accidentes de tráfico y la lesividad en ellos, tanto alrededor del mundo, como en España, incluyendo también las formas de modelización de los factores y variables que están presentes en los accidentes de tráfico. Este capítulo, incluye también los objetivos del estudio, la motivación para realizar el mismo y un primer alcance de las contribuciones específicas en la investigación.

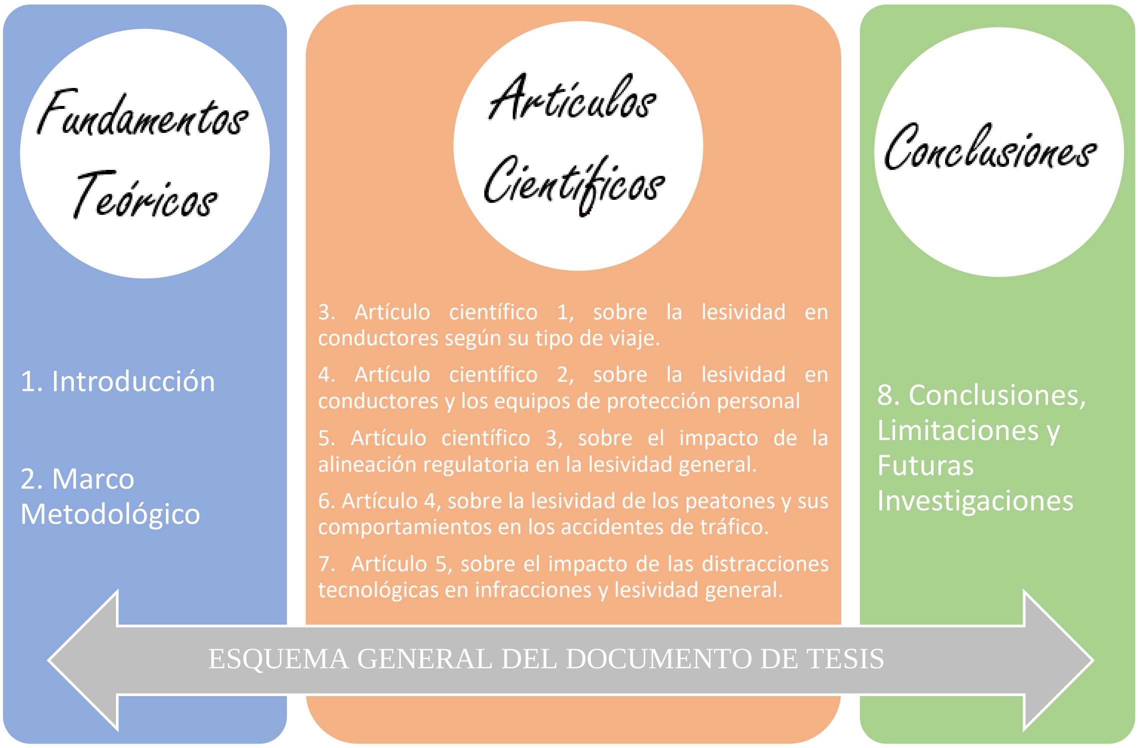
El capítulo dos de marco metodológico, aborda de forma general las técnicas del “machine learning” para la modelización de factores y variables a partir de conjuntos de datos extensos, centrándose en su fiabilidad y ventajas para los análisis de datos. De forma particular, el capítulo analiza el trabajo de modelización con los algoritmos de redes bayesianas, específicamente en el ámbito de los accidentes de tráfico y la lesividad provocada por los mismos, siendo esta metodología la que se ha utilizado en cada una de las publicaciones científicas. Se explica también el área bajo la curva AUC por sus siglas en inglés “Area Under the ROC Curve” como método de validación de los algoritmos de aprendizaje de redes bayesianas, y, finalmente se dedica un apartado a la explicación de los cuestionarios y las bases de datos utilizadas en toda la investigación.

En los capítulos comprendidos del tres al siete se expresan los resultados de esta Tesis Doctoral a través de los cinco artículos científicos publicados. Particularmente se analiza la lesividad de los accidentes de tráfico tanto para conductores y peatones, como para los usuarios en general de las vías. En estas publicaciones científicas, se generan modelos teóricos específicos para cada caso, incluyendo los factores humanos y técnicos a través de variables como las demográficas, las de comportamiento, circunstanciales, de infraestructura, vehiculares, y otras de gran importancia, con el objetivo de entender como el comportamiento de las mismas influye sobre la lesividad estudiada en los accidentes de tráfico en España. Para lograr esto, los modelos teóricos son llevados a la herramienta de cálculo de MatLab a través de un código único de programación del algoritmo de aprendizaje de redes bayesianas en cada modelo, y posteriormente validado por el AUC, obteniendo la interacción generada por las variables que componen el modelo y los diferentes resultados de probabilidad para las variables objetivos seleccionadas en su interacción con el resto de las variables de cada factor que se comprenden en el modelo teórico.

Finalmente, en el capítulo ocho, se abordan las conclusiones generales de toda la investigación, relacionando los resultados de los cinco artículos científicos, ya que las conclusiones específicas de cada trabajo se encuentran dentro de los mismos en el apartado de resultados. Para finalizar este documento de tesis, se inluyen dos apartados que ayudan a entender las limitaciones que tiene esta investigación y aportan los nuevos horizontes de estudio de esta línea de la ciencia.

Figura 1

Esquema general del documento de tesis



Fuente: Elaboración propia.

AGRADECIMIENTOS

A mis directores de tesis Dra. Dña. Susana García Herrero y Dr. D. Miguel Ángel Mariscal Saldaña, por todos los conocimientos impartidos y la ayuda que me han proporcionado durante este emocionante proceso de investigación. Les agradezco enormemente el tiempo que dedicaron para ayudar en mi formación, las enseñanzas específicas en materia de nuestro estudio y aquellas dirigidas a entender de mejor forma vuestra encantadora forma de ser en toda España. Gracias por impulsarme siempre en cada paso, por los ánimos y las exigencias en los momentos justos, por darme las herramientas necesarias para que este viaje haya sido una experiencia trasformadora, convirtiéndose en referentes a quienes seguiré permanentemente en la búsqueda de la ciencia. Finalmente, quiero agradecerles por todas las conversaciones con y sin café, por los eventos que pudimos disfrutar juntos, especialmente por hacerme sentir parte de sus vidas, de sus familias, en otras palabras, por haberme convertido en un amigo.

Agradecer a todos mis coautores, Dr. José M. Gutiérrez, Dr. Sixto Herrera, Dr. José M. López García, Dra. Wafa Boulagouas, Dr. Rachid Chaib, Dr. Méberek Djebabra, Dra. Fatemeh Mohamadi, Dra. Susana García Herrero y Dr. Miguel Ángel Mariscal Saldaña, por todos sus aportes científicos, sus ideas y su voluntad para lograr todas las publicaciones científicas que componen esta tesis. Quedo muy agradecido por aportar en tan diversas e interesantes formas en cada uno de nuestros trabajos en conjunto.

A todas las personas que conforman la Universidad de Burgos, por haber hecho de este templo del conocimiento un segundo hogar para mí. Les agradezco por haberme tratado siempre como un miembro más de la comunidad universitaria y apoyarme en cada paso nuevo que requería dentro de esta magnífica Universidad.

A la Dirección General de Tráfico, la Junta de Castilla y León, al Fondo Europeo de Desarrollo Regional, la Universidad de Burgos y a la Universidad Técnica Particular de Loja, por su apoyo constante en la generación de proyectos, la información otorgada a través de proyectos y las ayudas económicas sin las cuales no hubiese sido posible el desarrollo de esta investigación y de mi Tesis Doctoral.

A mi madre, mi padre y mi hermano, gracias por el apoyo, la fortaleza y las energías para hacer que este sueño de investigación sea posible. Gracias por siempre ser las personas que me invitan a soñar, las que siempre están presentes con el amor más puro que he podido conocer, las que nunca me dejan caer.

A ti, Alfonsina, por haberme apoyado incondicionalmente durante los momentos más difíciles de este estudio doctoral. Te agradezco por las fuerzas, los ánimos y la paciencia que me has dado durante todo este proceso.

Juan Diego Febres Eguiguren

CONTENIDO

INTRODUCCION

1. INTRODUCCIÓN

En el contexto global, las lesiones por accidentes de tráfico son las causantes de aproximadamente 1,3 millones de muertes cada año, así como de traumatismos no mortales, en una cifra que oscila entre los 20 y los 50 millones de personas por año, provocando en algunos casos discapacidades temporales o permanente (Organización Mundial de la Salud, 2021). En cambio, en Europa fallecieron 25.100 personas a causa de los accidentes de tráfico en 2018, y cerca de 135.000 padecieron heridas graves, mientras que el costo de los accidentes que se suscitaron se calcula en una cifra cercana a los 280.000 millones de euros anuales (2% del PIB de la Unión europea para ese año), a pesar de los esfuerzos por disminuir los accidentes de tráfico (Commission, 2019). Por otro lado, en el contexto nacional, las cifras son igualmente alarmantes, ya que España reporta 104.0801 accidentes de tráfico en 2019, donde 1.755 personas fallecieron, 8.613 resultaron heridas con hospitalización y 130.745 heridos sin hospitalización (Observatorio Nacional de Seguridad Vial, 2019).

En el proyecto mundial de la Organización de Naciones Unidas (ONU), el objetivo de desarrollo sostenible número 3 (Salud y Bienestar), habla en su meta 3.6 de reducir a la mitad las muertes y lesiones causadas por accidentes de tráfico para el año 2030 (Organización de Naciones Unidas, 2015). De igual forma los países alrededor del mundo se han sumado a esta meta a través de proyectos propios, sin embargo es una meta difícil de lograr, pues a pesar de los esfuerzos vemos incrementos en algunas tasas de siniestralidad, por ejemplo, en el informe "Las principales cifras de siniestralidad vial" emitido por la Dirección General de Tráfico de España (DGT) (Observatorio Nacional de Seguridad Vial, 2019), comentado anteriormente, se observa un incremento del 2% en accidentes con víctimas mortales en España al comparar el año 2018 con el año 2019.

Es claro entonces, que la reducción de accidentes de tráfico es un tema que los gobiernos en todo el mundo los han tomado con mucha seriedad, impulsando varios proyectos que permitan cumplir este importante objetivo. Es así, que esta tesis aborda el estudio de la lesividad de los accidentes de tráfico en España, aportando con avances científicos innovadores en el campo de la ciencia, el estudio de la probabilidad de accidentabilidad en diferentes circunstancias.

De forma general, esta tesis analiza los datos de accidentalidad recolectados por la Dirección General de Tráfico de España (DGT) a través de los formularios que los agentes de tráfico rellenan en el momento que sucede un accidente de tráfico con víctimas. El dataset utilizado para la presente tesis cuenta con los datos de accidentes de 2016, 2017, 2018 y 2019. Para su análisis se han utilizado técnicas de "machine learning" para comprender el comportamiento de los factores que intervienen en los accidentes de tráfico a través de la modelización de diversos escenarios. Es importante mencionar que la contribución científica de esta investigación es doble, ya que no solo aporta conocimiento sobre las condiciones de tráfico para la comunidad científica mundial, sino que también facilita a los organismos encargados del control de tráfico de España un análisis pormenorizado de sus propios datos. Esta información es útil para definir la política pública y los proyectos concientización ciudadana hacia la reducción de accidentes de tráfico.

Por otra parte, y a nivel más específico, esta investigación aporta cinco contribuciones científicas, que son concretamente los cinco artículos científicos que componen esta tesis. En particular, cada uno de ellos aplica la metodología de “Redes Bayesianas” con un algoritmo de aprendizaje específico para cada artículo, así como un modelo teórico único con variables específicas también para cada publicación; logrando así agrupar una gran cantidad de variables en la modelización de los factores técnicos y humanos estudiados en los accidentes de tráfico.

Específicamente, los problemas cubiertos en estos artículos incluyen: (i) el papel del propósito de viaje en las lesiones causadas por accidentes de tráfico, utilizando los datos oficiales de accidentes en España del año 2016 -artículo 1-; (ii) la influencia del uso del cinturón de seguridad en la gravedad de las lesiones de los conductores durante los accidentes de tráfico, utilizando los datos oficiales de accidentes en España ocurridos durante los años 2016 y 2017 -artículo 2-; (iii) la lesividad general de los usuarios de las vías a través de los comportamientos inseguros y los accidentes de tráfico que involucran a conductores sin permiso de conducir basados en la alineación regulatoria, utilizando los datos oficiales de accidentes en España de los años 2016, 2017 y 2018 -artículo 3-; (iv) la gravedad de las lesiones de los peatones en accidentes de tráfico basados en su comportamiento, utilizando los datos oficiales de accidentes en España ocurridos durante los años 2016, 2017, 2018 y 2019 -artículo 4-; (v) la influencia de las distracciones basados en tecnología sobre las infracciones de tráfico, y su impacto posterior en la gravedad de las lesiones en los usuarios de las vías durante los accidentes de tráfico, utilizando los datos oficiales de accidentes en España de los años 2016, 2017, 2018 y 2019 -artículo 5-.

1.1 MOTIVACIÓN

El análisis de grandes volúmenes de datos “big data” lleva algunos años transformando la ciencia. En las dos últimas décadas del siglo XX las ciencias como la astronomía y la genética empezaron a experimentar la revolución del tratamiento de grandes volúmenes de datos, y desde entonces este concepto se ha trasladado hacia casi todas las áreas de estudio en las que incursiona el ser humano (Mayer-Schönberger & Cukier, 2013).

En los ámbitos de la salud, el análisis de datos a través de cualquier técnica de Big Data está desempeñando un papel fundamental en la investigación sanitaria, aportando diversas herramientas y datos, que con el correcto manejo de cantidad, calidad, almacenamiento y análisis podría ayudar notablemente en la mejora de los resultados sanitarios (Góngora Alonso, 2017).

De la misma forma ocurre para la predicción de accidentes de tráfico, cuando la minería de datos permite proponer modelos para el análisis de los datos de accidentabilidad para la reducción de las tasas de siniestralidad (Henao-Pereira et al., 2020). Las lesiones causadas por accidentes de tráfico en la última década han ocupado entre la séptima y la décima posición en las estadísticas de las principales causas de muerte en el mundo (Organización Mundial de la Salud, 2020a).

Por los motivos expuestos, analizar con datos reales la siniestralidad vial, a partir de técnicas de análisis de datos, se convierte en una necesidad imperiosa para esta investigación. Es por ello que proyectos como “Modelización mediante técnicas de machine learning de la influencia de las distracciones del conductor en la seguridad vial. Diseño de un sistema integrado: simulador de conducción, eye tracker y dispositivo de distracción. Ref. BU300P18” soportado por el Fondo Europeo de Desarrollo Regional (FEDER) – Junta de Castilla y león, contribuyen notablemente a la consecución de las metas de reducción de accidentes de tráfico en España. Esta tesis es una contribución científica a esta prometedora forma de modelización, la cual, a través del análisis de datos de accidentes de tráfico y el conocimiento de los factores que impactan sobre los accidentes, aporta información valiosa para los agentes que deciden y definen las políticas de tráfico, y que tienen por objetivo reducir las altas cifras de lesividad en los accidentes de tráfico.

1.2 OBJETIVOS

El objetivo general de esta investigación se centra en el estudio de la lesividad de los accidentes de tráfico en España, utilizando para ello la modelización de los factores técnicos y humanos con técnicas de análisis de datos basados en “machine learning”. Es así, que la generación de modelos teóricos basados en la interacción de distintas variables que tienen lugar durante los accidentes de tráfico, son un aporte primordial para la comprensión de la lesividad en los usuarios de las vías cuando sucede un accidente de tráfico.

De forma particular, este objetivo general puede dividirse en cinco objetivos específicos que se materializan a través de los artículos científicos publicados, en la siguiente forma:

- Analizar la lesividad del conductor según su propósito de viaje considerando las variables relevantes de los factores técnicos y humanos en los accidentes de tráfico en España. (Artículo 1): Febres, J. D., Mohamadi, F., Mariscal, M. A., Herrera, S., & Garcia-Herrero, S. (2019). The Role of Journey Purpose in Road Traffic Injuries: A Bayesian Network Approach. Journal of Advanced Transportation, 2019, Article DOI: 6031482. 10.1155/2019/6031482.

- Estudiar la lesividad del conductor a través del uso del cinturón de seguridad y su interacción con las variables relevantes de los factores técnicos y humanos en los accidentes de tráfico en España. (Artículo 2): Febres, J. D., Garcia-Herrero, S., Herrera, S., Gutierrez, J. M., Lopez-Garcia, J. R., & Mariscal, M. A. (2020). Influence of seat-belt use on the severity of injury in traffic accidents. European Transport Research Review, 12(1), Article 9. DOI: 10.1186/s12544-020-0401-5.

- Comprender la influencia de los comportamientos inseguros de los conductores en la lesividad general de los usuarios de las vías, considerando las variables relevantes de los factores técnicos y humanos en los accidentes de tráfico en España. (Artículo 3): Boulagouas, W., Garcia-Herrero, S., Chaib, R., Febres, J. D., Mariscal, M. A., & Djebabra, M. (2020). An Investigation into Unsafe Behaviors and Traffic Accidents Involving Unlicensed Drivers: A Perspective for Alignment Measurement. International Journal of Environmental Research and Public Health, 17(18), Article 6743. DOI: 10.3390/ijerph17186743.

- Analizar la lesividad en los peatones desde una perspectiva del comportamiento del peatón, considerando las variables relevantes de los factores técnicos y humanos en los accidentes de tráfico en España. (Artículo 4): Febres, J. D., Mariscal, M. Á., Herrera, S., & García-Herrero, S. (2021). Pedestrians' Injury Severity in Traffic Accidents in Spain: A Pedestrian Actions Approach. Sustainability, 13(11), 6439. DOI: 10.3390/su13116439.

- Estudiar la influencia del uso de dispositivos con base tecnológica en la conducción distraída y su consecuente impacto en la lesividad general de los usuarios de las vías, considerando las variables relevantes de los factores técnicos y humanos en los accidentes de tráfico en España. (Artículo 5): García-Herrero, S., Febres, J. D., Boulagouas, W., Gutiérrez, J. M., & Mariscal Saldaña, M. Á. (2021). Assessment of the Influence of Technology-Based Distracted Driving on Drivers' Infractions and Their Subsequent Impact on Traffic Accidents Severity. International journal of environmental research and public health, 18(13), 7155. DOI: 10.3390/ijerph18137155.

Es importante recordar que, si bien cada artículo aporta a los objetivos específicos de la presente tesis, cada uno de los artículos tiene también sus propios objetivos específicos que responden a sus propias preguntas de investigación, los mismos que pueden identificarse en cada uno de los artículos publicados consultando la sección de resultados de este trabajo.

1.3ESTADO DEL ARTE

El estado del arte abordará el conocimiento previo desarrollado a esta tesis en áreas ligadas estrechamente a los accidentes de tráfico en su contexto global y local, los niveles de lesividad producida por los accidentes de tráfico, los factores y variables que inciden en los accidentes de tráfico, y finalmente, cuáles son las opciones de modelización de datos sobre los accidentes de tráfico, buscando comprender las variables relevantes que intervienen en estos accidentes y como contribuyen estas a la reducción de las tasas de lesividad.

LOS ACCIDENTES DE TRÁFICO EN EL CONTEXTO GLOBAL

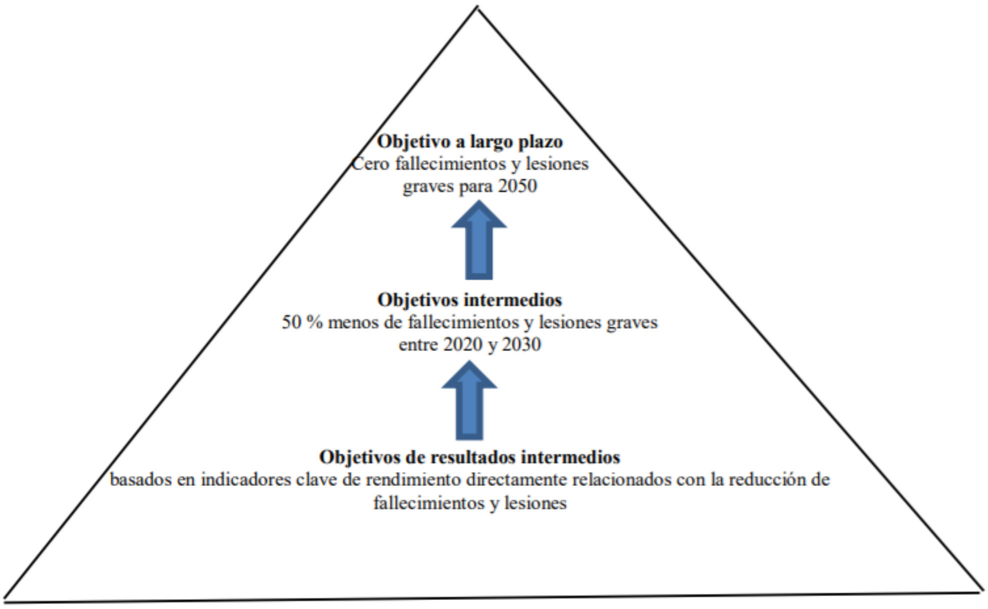
Los traumatismos generados por los accidentes de tráfico se han convertido en una de las causas de muerte más comunes alrededor del mundo, más precisamente se ha ubicado entre la sétima y la décima causa durante la última década (2011 – 2020), con un promedio actual de 1,3 millones de muertes anuales. El impacto ha sido tan grande, que la Organización de Naciones Unidas (ONU), ha incluido como parte de sus metas y objetivos de desarrollo sostenible la reducción de la tasa de accidentes de tráfico a la mitad para 2030 (Organización de Naciones Unidas, 2015), así como también la Organización Mundial de la Salud (2020b) en su último informe de julio de 2020, habla sobre el poder de las ciudades para la reducción de las tasas de mortalidad por accidentes de tráfico.

En Europa, según la Comisión Europea, a pesar del buen trabajo que se realiza en materia de seguridad vial, fallecieron 25.100 personas en 2018 a causa de accidentes de tráfico, y 135.000 resultaron gravemente heridas, un costo humano socialmente inaceptable para esta misma comisión (Comisión Europea, 2019). Incluso, un reciente informe económico que señala la Comisión Europea ha calculado un coste de 280.000 millones de euros anuales en los accidentes de tráfico dentro de la Unión Europea, donde además de lo mencionado, se evidencia que los avances en la reducción de la tasa de mortalidad en las vías se han estancado en los últimos años, y la prevención de lesiones graves ha avanzado aún menos.

El objetivo para 2050 según la comunicación de la Comisión Europea “Europa en movimiento: una movilidad sostenible para Europa: segura, conectada y limpia”, es lograr cero fallecidos en el transporte en las vías de la Unión Europea, y de igual forma debería suceder con las lesiones graves (Comisión Europea, 2018). Esta intención de reducir los accidentes y lesiones graves en las vías se propaga a lo largo de todo el mundo, y se planea realizar de una forma ordenada, paulatinamente y con metas claras, lo que se puede observar en la figura 2 para el caso de la Unión Europea.

Figura 2

Jerarquía de resultados del «Sistema Seguro» a escala de la UE



Fuente: Documento de trabajo de los servicios de la Comisión Marco de la política de la Unión Europea en materia de seguridad vial para 2021-2030, Comisión Europea, 2019.

Los accidentes de tráfico son eventos de naturaleza multicausal, es decir, que raramente es una sola causa la generadora de un accidente de tráfico, o en otras palabras una sola variable la causante del accidente (de Vicente Martínez, 2020). De ahí la necesidad de analizar la interacción de las distintas causas o variables que influyen en los accidentes de tráfico, para comprender de una mejor forma el evento global que significa un siniestro de esta naturaleza y sus posibles consecuencias en la salud de los usuarios de las vías alrededor del mundo.

Sin duda, la prevención de accidentes de tráfico no es tarea fácil para los entes reguladores estatales, ni para la sociedad en general. En un estudio de reducción de la gravedad de los accidentes de tráfico denominado “Reducing the severity of a traffic accident” (Dorokhin et al., 2020), sus autores concluyen que las restricciones administrativas e imposiciones reglamentarias no son suficientes para lograr este objetivo, y señalan la importancia de un enfoque integrado donde se menciona a las organizaciones de desarrollo y los procesos investigativos como pilares importantes para lograrlo.

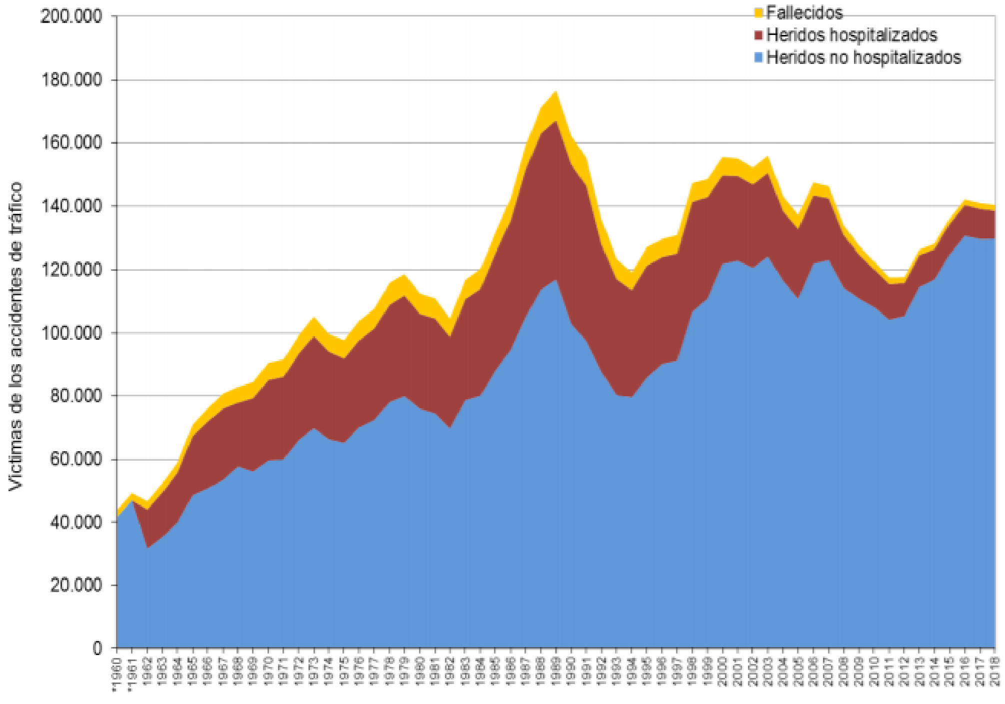
LOS ACCIDENTES DE TRÁFICO EN ESPAÑA

Según el informe ampliado de siniestralidad vial de España (Observatorio Nacional de

Seguridad Vial, 2018), las cifras de fallecidos por accidentes de tráfico han tenido una tendencia a incrementar desde el año 1960 que se mantienen registros, hasta llegar a 9.344 fallecidos en 1989 como el número más alto registrado en la historia. Desde el año 1989, las víctimas mortales por accidentes de tráfico se han reducido, alcanzado el número más bajo en 2013 con 1.680 fallecidos; sin embargo, durante los últimos años el promedio se ha mantenido con pequeñas alzas y bajas en las estadísticas, mostrando un aparente estancamiento en el anhelo de reducir las muertes causadas por accidentes de tráfico. Lo mencionado se puede apreciar en la figura 3.

Figura 3

Jerarquía de resultados del «Sistema Seguro» a escala de la UE



*1960 y 1961 sin separación entre heridos hospitalizados y no hospitalizados.

Fuente: Documento "Las principales cifras de la Siniestralidad Vial España 2018 - Edición ampliada", Observatorio Nacional de Seguridad Vial, 2018.

En la figura 3, se puede observar también las curvas relacionadas a los heridos hospitalizados y no hospitalizados. Para el año 1962 la relación entre los fallecidos, heridos hospitalizados y heridos no hospitalizados, era del 5%, 27% y 68% respectivamente, manteniéndose en proporción similar hasta el año 1998 (Observatorio Nacional de Seguridad Vial, 2018). En adelante las cifras de heridos hospitalizados ha ido reduciéndose, mientras que las de no hospitalizados ha crecido, sin embargo, al igual que con las cifras de fallecidos, el decremento en las estadísticas de los heridos hospitalizados se ha ido estabilizando con pequeñas diferencias, haciendo difícil reducirlas como se espera.

Un estudio realizado con datos de España entre los años 1975 a 2016, donde se relaciona la actividad económica y los accidentes de tráfico, se encontró que estos últimos tienen un comportamiento cíclico asimétrico, tanto para el mismo accidentes como para las lesiones causadas (García-Ferrer et al., 2020). También se pudo encontrar que políticas como el uso del cinturón de seguridad, ha permitido una reducción constante de las tasas de accidentabilidad desde 1992, sin embargo, algunas otras como los sistemas de penalización solo logran reducir estas tasas temporalmente.

Los costos directos (costos médicos, de reparación, administrativos, etc) y los indirectos (capacidad productiva, incapacidad permanente o parcial, etc) de los accidentes de tráfico son muy elevados (Observatorio Nacional de Seguridad Vial, 2018). A pesar de la discusión existente en la comunidad científica y la sociedad sobre asignar un costo a una vida humana, algunos autores que han realizado el ejercicio de costear íntegramente un accidente de tráfico, señalan que no puede obviarse el costo humano; por ejemplo, Rune Elvik (1995) señala la importancia de tomarlos en cuenta ya que pueden representar entre el 8% y el 88% del costo total del accidente, poniendo en evidencia que la conocida "regla del millón de euros" de la Comisión Europea no consideraba estos costos, mientras que en otros proyectos como por ejemplo, UNITE y HEATCO, recomiendan el valor de 1.5 millones de euros por accidente, donde si se consideran los costos humanos (Observatorio Nacional de Seguridad Vial, 2018).

Ya que el impacto de los accidentes de tráfico es tan alto frente al número de víctimas mortales, heridos hospitalizados y no hospitalizados, costos directos e indirectos y socialmente, las entidades regulatorias mundiales y españolas han puesto en marcha una serie de proyectos, estrategias y planes para la disminución de los accidentes de tráfico, por ejemplo, la Dirección General de tráfico de España cuenta con planes estratégicos de seguridad vial, planes territoriales, sectoriales, sistemas de seguro, formación vial y varias estrategias adicionales que le permitan alcanzar la meta de "cero fallecidos" por accidentes de tráfico (Dirección General de Tráfico, 2020a).

LA LESIVIDAD EN LOS ACCIDENTES DE TRÁFICO

La lesividad en los accidentes de tráfico se define como un índice de las lesiones causadas a las personas que se ven involucradas en el accidente de tráfico, los cuales podrían sufrir un nivel diferente de lesiones (desde ilesos hasta el fallecimiento), y ser susceptibles por ello de diferentes secuelas en el caso de poder reincorporarse a la vida cotidiana después del accidente (López, 2000).

En España, la Dirección General de Tráfico, considera a la lesividad como un elemento medible a través del grado de lesión en las personas víctimas de los accidentes de tráfico, dividiendo este grado o escala en cuatro partes: (i) Accidentados sin heridas, (ii) Heridos no hospitalizados, (iii) Heridos hospitalizados, y, (iv) Fallecidos (Observatorio Nacional de Seguridad Vial, 2018). Este grado de lesividad en los siniestros de tránsito, suele reportarse acompañado de una serie de variables que pueden agruparse en distintos factores, las mismas que suelen estar ligadas a las causas del accidente o no, pero que de alguna forma impactan en la lesividad; estas variables se comentarán en el siguiente apartado de “factores y variables que inciden en los accidentes de tráfico”.

El grado de lesividad, producto de las lesiones sufridas en los accidentes de tráfico impactan fuertemente en la posibilidad de supervivencia de una persona víctima en un accidente. Es así, que el estudio de las condiciones en las que suceden el accidente y las condiciones de atención médica de las personas involucradas en los accidentes de tráfico son determinantes para mejorar las probabilidades de reducir las lesiones o evitar el fallecimiento (Nikolić et al., 2001), aportando datos importantes sobre los diferentes tipos de lesiones y grado de lesividad para la prevención y reducción de tasas de lesionados y fallecidos en accidentes de tráfico.

En un estudio realizado sobre el desarrollo de modelos de previsión de traumatismos mortales por accidentes de tráfico, se informa que estos últimos ocurrieron en el 2,2% de la población, sin embargo representaron casi el 13% de todas las lesiones de esa población (Tan et al., 2014). El estudio considera que, si bien es cierto que la cantidad de muertes y años perdidos por accidentes de tráfico podría disminuir debido a la disminución de la cantidad de accidentes, también pronostica que las lesiones causadas por accidentes de tráfico podrían elevar estas mismas cifras entre el 2015 y el 2030.

El día mundial de la salud, que se celebra cada año por parte de la Organización Mundial de la Salud (OMS), fue por primera vez en 2004 dedicado principalmente a temas de seguridad vial. Desde entonces, la lesividad mediada a través de las lesiones causadas a los usuarios de las vías debido a los accidentes de tráfico ha cobrado gran importancia a nivel mundial, tanto así, que las lesiones por accidentes de tráfico han estado presentes entre las diez causas principales de muertes en el mundo por al menos una década, impulsando la necesidad no solo de reducir el número de accidentes de tráfico, sino también, de prevenir las lesiones causadas por estos accidentes (Organización Mundial de la Salud, 2004), en otras palabras, reducir el grado de lesividad en los usuarios de las vías durante los accidentes de tráfico.

Los traumatismos causados por los accidentes de tráfico, otra forma de denominar a las lesiones por estos accidentes, son aquellos que nos permiten medir también el grado de lesividad. Estos traumatismos son evitables, adoptando una serie de medidas de seguridad vial, comprometiendo a varios sectores como el transporte, la salud, la policía y la educación cimentada en la investigación. Por ello, la Organización Mundial de la Salud, trabaja en varios proyectos que impulsen el cumplimiento de esta meta, como su conjunto de medidas publicadas en 2017 en el informe denominado “Save Lives”, entre las cuales destacan la reducción de lesiones de la mano de un enfoque que nos permita conocer la situación actual de este índice alrededor del mundo (Organización Mundial de la Salud, 2017).

Se debe tener en cuenta que el grado de lesividad impacta de diferentes formas en los usuarios de las vías y la sociedad en general donde sucede el accidente de tráfico, provocando emergencias, daños morales, heridos leves y graves, fallecidos, rehabilitación, secuelas de diferentes tipos y daños económicos importantes en las economías de los países alrededor del mundo.

FACTORES Y VARIABLES EN LOS ACCIDENTES DE TRÁFICO

Analizar los factores y variables que influyen en los accidentes de tráfico, tanto en su ocurrencia como en su nivel de lesividad, resulta importante para realizar investigación en temas de seguridad vial. La Organización Mundial de la Salud, ha estudiado por años estos factores de riesgo, determinando los siguientes como los más relevantes: (i) enfoque de seguridad (tener en cuenta el error humano), (ii) la velocidad, (iii) la conducción bajo los efectos de alcohol y sustancias psicoactivas, (iv) falta de uso de equipo de protección (casco, cinturón de seguridad, sistemas de sujeción de niños), (v) distracciones durante la conducción, (vi) falta de seguridad de la infraestructura vial, (vii) seguridad de los vehículos, (viii) atención insuficiente tras colisiones, (ix) y cumplimiento insuficiente de las normas de tránsito (Organización Mundial de la Salud, 2021).

Un estudio sobre los factores de gravedad de los accidentes de tráfico desarrollado en Tailandia, concluye la importancia de estudiar y determinar todos los factores de riesgo que están asociados con los accidentes de tráfico y el grado de lesividad (Ditcharoen et al., 2018). Se concluye también, en este mismo estudio, que los factores pueden clasificarse en factores humanos, de carreteras, de vehículos y medio ambientales, siendo muy importante que los países traten de aportar información fiable en cada uno de ellos, pues las particularidades del tráfico pueden arrojar análisis diferentes en cada país, resultando importante que las comparaciones consideren los diferentes grados de riesgo asociados a cada factor en los accidentes de tráfico y la gravedad del mismo.

Las investigaciones de los factores y variables que influyen en los accidentes de tráfico y su grado de lesividad son muy numerosas, pues en algunos países las consecuencias de los accidentes de tráfico llegan a establecerse entre las 3 primeras causas de muerte. En los países clasificados como los más peligrosos en términos de accidentes de tráfico, estos últimos están relacionados con factores como la planificación deficiente o bajos estándares de seguridad, sin embargo, también se ven influenciados por los factores vehiculares, el control de velocidad, el uso de cascos y cinturones de seguridad, las variables del factor de comportamiento y el entorno de la carretera (Mohammed et al., 2019).

En España sucede algo similar al estudiar los factores y variables de mayor riesgo en los accidentes de tráfico, por ejemplo, en un estudio realizado sobre el impacto de las características provinciales en el número de víctimas de accidentes de tráfico (González et al., 2018), se determinó que variables como la velocidad, el uso de equipos de protección (casco y cinturón de seguridad), el volumen del tráfico, los puntos del permiso de conducción, la tasa de motorización, las condiciones de las carreteras, las condiciones ambientales, el comportamiento de los usuarios de las vías e incluso la inversión en infraestructura son influyentes en los accidentes de tráfico.

Sin embargo, el estudio de los factores y las variables que están inmersas en los accidentes de tráfico es muy grande, por lo que debe investigarse varias combinaciones posibles constantemente para un mejor entendimiento de estos. Es así que son muchas y muy diversas las variables que juegan un papel importante en los accidentes de tráfico, por ejemplo, la música es una variable influyente del comportamiento humano a la hora de conducir en conductores jóvenes, influyendo sobre las posibilidades de cometer infracciones de tránsito y tener un accidente (Catalina et al., 2020). De igual forma, algunas variables del factor demográfico (edad, género) o de transporte (tipo de vehículos, bicicleta, a motor eléctrico, caminando) son importantes de incluir en el análisis, es así, que en un estudio realizado en España sobre la severidad de las lesiones que sufren los ciclistas, se evidenció que la infraestructura para bicicletas exclusivamente, o de tráfico calmado (hasta 30 km/h), disminuye el riesgo de lesiones graves y fallecidos en accidentes de tráfico (Aldred et al., 2020).

LA MODELIZACIÓN A TRAVÉS DEL USO DE TÉCNICAS DE “MACHINE LEARNING”

En las últimas décadas, el manejo de datos se ha vuelto cada vez más importante, siendo aplicado en muchos campos de la ciencia y la sociedad, incluso muchas organizaciones dependen completamente del análisis de datos para continuar con sus operaciones. Es así, que se ha trabajado mucho para desarrollar diferentes tipos de distribuciones y tecnologías que sustenten el manejo de los datos de forma adecuada, incluyendo a la modelización dentro de estas (Oussous et al., 2018).

La modelización, es una técnica más antigua que el manejo de los datos a gran escala, sin embargo, se ha ajustado y aportado mucho al conjugar estas técnicas. Las redes computacionales, los sistemas de producción automatizados, el control de tráfico y los sistemas de comunicación e información son algunas de las pruebas de ello (Kofman, 2005). Es así que, existen muchas técnicas para poder atacar los problemas de simulación y modelización, como los algoritmos de aprendizaje.

Las técnicas de machine learning son un subcampo de la inteligencia artificial que tienen una fuerte relación con la estadística y la minería de datos, donde se emplean y desarrollan constantemente los algoritmos de aprendizaje, los cuales funcionan a partir de patrones que encuentran en los conjuntos de datos (Correa et al., 2008). Estos algoritmos de aprendizaje están en constante aprendizaje con los datos proporcionados, aportando resultados más certeros en menor tiempo, con la posibilidad de estar en constante evolución según las diferentes situaciones a la que se los exponga.

Las redes bayesianas son modelos probabilísticos gráficos de carácter acíclico y dirigido, que representan una serie de variables o también llamados nodos y sus independencias de condiciones probabilísticas (Neapolitan, 2004). Estas redes, utilizan los algoritmos de aprendizaje mencionados para comprender las interacciones de las variables según los datos proporcionados y poder realizar la inferencia requerida. Es así, que la modelización a través de técnicas de "machine learning", y más específicamente a través del uso de redes bayesianas, ha demostrado generar algoritmos fiables de predicción en la clasificación e interpretación de los datos del modelo (Correa et al., 2008).

1.4 METODOLOGÍA

La finalidad de esta tesis, como se indica en el título, consiste en estudiar el comportamiento de la lesividad ocurrida en los accidentes de tráfico dentro de España, considerando el comportamiento de los factores humanos y técnicos que transcurren durante el accidente, y por ende del grupo de variables influyentes en diversos casos. Como hemos visto anteriormente, el estudio de los accidentes de tránsito es una prioridad a nivel mundial, de Europa y de España, y que el uso de la modelización y sus herramientas ha demostrado ser eficiente para el estudio de este campo de la ciencia (Sánchez Molina et al., 2018), el enfoque seleccionado es apropiado para el cumplimiento de los objetivos de la investigación.

Como se había mencionado previamente la modelización a través del uso de técnicas de "machine learning" es una forma muy eficiente de realizar modelización a partir de grandes conjuntos de datos. Esta forma de análisis de datos pertenece a una rama de la inteligencia artificial, permitiendo a los ordenadores aprender de su propio algoritmo generado, para obtener respuestas más fiables en el tratamiento de datos (Hinestroza Ramírez, 2018). Dentro de esta gran herramienta denominada "machine learning", existen varias técnicas que permiten el procesamiento de datos, es decir diferentes tipos de algoritmos que permiten procesar los datos a gran escala, cada uno de ellos con características y especificaciones únicas.

El aprendizaje autónomo de los ordenadores es vital en los procesos del "machine learning" y se produce a través de diversos tipos de agrandes algoritmos, como lo son: (i) Algoritmos de aprendizaje supervisado, (ii) Algoritmos de aprendizaje sin supervisión, y, (iii) Algoritmos de aprendizaje por refuerzo (Hinestroza Ramírez, 2018). De forma más específica, algunos de los algoritmos de aprendizaje automático usados más frecuentemente, y con buenos resultados en el análisis de datos son: (i) Algoritmos de agrupación, (ii) Algoritmos de regresión, (iii) Algoritmos de árbol de decisión, (iv) Algoritmos bayesianos, (v) Algoritmos de redes neuronales, (vi) Algoritmos de aprendizaje profundo.

Los algoritmos de redes bayesianas se basan en técnicas de agrupamiento, por lo cual existen muchas opciones de trabajo, sin embargo, entre las opciones más comunes se encuentran algoritmo k-means y el modelado de mezclas Gausianas, el algoritmo de aprendizaje estructural y el de aprendizaje de intervalos (Hernández Leal, 2011). La posibilidad de análisis con estos algoritmos de redes bayesianas permite obtener información fiable sobre la red creada para el conjunto de variables analizadas. Para mayor detalle de la metodología empleada en esta tesis consulte a fondo el capítulo de Marco metodológico y los capítulos de metodología de cada uno de los artículos científicos presentados en la sección de contribuciones científicas.

1.5 CONTRIBUCIONES CIENTÍFCAS

Como se mencionó en el apartado 1.2 de este trabajo, la investigación se realizó basada en su objetivo general de estudiar la lesividad en los accidentes de tráfico en España, y particularmente en sus objetivos específicos de estudiar esta misma lesividad en escenarios de modelización distintos, donde se combinan importantes variables de los factores humanos y técnicos que intervienen en un accidente de tráfico. Es así, que las contribuciones de este documento científico están basadas en las contribuciones científicas específicas de los artículos científicos, los cuales juntos permiten tener una mirada global del escenario de la lesividad en los accidentes de tráfico de España.

LISTADO DE CONTRINUCIONES CIENTÍFICAS

En este apartado se describe de forma breve los aportes científicos a la investigación en materia de accidentabilidad de tráfico de cada uno de los cinco artículos que forman parte de este documento, así como la contribución general de toda la tesis. Para conocer más detalladamente las contribuciones específicas y general, puede consultar cada uno de los artículos científicos en el capítulo de resultados, así como el capítulo de conclusiones al final de este documento.

ARTÍCULO 1: THE ROLE OF JOURNEY PURPOSE IN ROAD TRAFFIC INJURIES: A BAYESIAN NETWORK APPROACH

- Aporta un modelo teórico para el estudio de la lesividad en los conductores según su tipo de viaje, incluyendo una red bayesiana de la interacción de las variables representadas en el modelo para los factores técnicos y humanos.
- De forma general el estudio muestra que la probabilidad de sufrir accidentes de tráfico con lesiones graves para los conductores se encuentra en los viajes realizados con motivos de ocio, esto debido a la estrecha relación que tienen variables el exceso de velocidad, la falta de uso de equipo de protección personal y las distracciones cuando las personas se encuentran más relajadas, a diferencia de cuando se encuentran trabajando o trasladándose al trabajo.

ARTÍCULO 2: INFLUENCE OF SEAT-BELT USE ON THE SEVERITY OF INJURY IN TRAFFIC ACCIDENTS

- Aporta un modelo teórico para el estudio de la lesividad en los conductores basado en el uso del cinturón de seguridad, incluyendo una red bayesiana de la interacción de las variables representadas en el modelo para los factores técnicos y humanos.
- En forma general este estudio confirma que la falta de uso de cinturón de seguridad eleva considerablemente la probabilidad de un grado de lesividad alto durante los accidentes de tráfico para los conductores, relacionando esta condición con variables influyentes como la velocidad, el tipo de accidente, el comportamiento, entre otras. El estudio incluye también una comparativa del trabajo de la red bayesiana con la técnica de regresión logística.

ARTÍCULO 3: AN INVESTIGATION INTO UNSAFE BEHAVIORS AND TRAFFIC ACCIDENTS INVOLVING UNLICENSED DRIVERS: A PERSPECTIVE FOR ALIGNMENT MEASUREMENT

- Aporta un modelo teórico para el estudio de la lesividad en general de los usuarios de las vías, basados en el comportamiento de los conductores con licencias de conducir no válidas, incluyendo una red bayesiana de la interacción de las variables representadas en el modelo para los factores técnicos y humanos.
- El tercer artículo de esta tesis, se evidencia que existe una estrecha relación entre la conducción sin licencia o licencia inválida y el comportamiento arriesgado de los conductores durante la conducción, por ende con el alineamiento hacia las condiciones regulatorias de tráfico. Es así, que, en los hallazgos encontrados, se puede evidenciar que la lesividad en general de los usuarios de las vías, se ve mayormente afectada con accidentes que causan heridas graves o mortales cuando los conductores involucrados tienen problemas con su licencia de conducir.

ARTÍCULO 4: PEDESTRIANS’ INJURY SEVERITY IN TRAFFIC ACCIDENTS IN SPAIN: A PEDESTRIAN ACTIONS APPROACH

- Aporta un modelo teórico para el estudio de la lesividad de los peatones durante los accidentes de tráfico, incluyendo una red bayesiana de la interacción de las variables representadas en el modelo para los factores técnicos y humanos.
- En general este estudio aporta información valiosa sobre el comportamiento de los peatones durante los accidentes de tráfico, poniendo en evidencia que existe una estrecha relación entre el grado de lesividad de los peatones y su comportamiento en las vías. Los hallazgos señalan que los comportamientos arriesgados de los peatones incrementan las probabilidades de lesiones graves o mortales.

ARTÍCULO 5: ASSESSMENT OF THE INFLUENCE OF TECHNOLOGY-BASED DISTRACTED DRIVING ON DRIVERS' INFRACTIONS AND THEIR SUBSEQUENT IMPACT ON TRAFFIC ACCIDENTS SEVERITY

- Aporta un modelo teórico para el estudio de la lesividad en general de los usuarios de las vías, basados en las distracciones de base tecnológica de los conductores, incluyendo una red bayesiana de la interacción de las variables representadas en el modelo para los factores técnicos y humanos
- El último artículo de este aporte científico, se evalúa las infracciones de tránsito bajo la influencia de las distracciones de base tecnológica, y su subsecuente impacto en la lesividad global de los usuarios de las vías. El estudio pone en evidencia un fuerte vínculo entre la conducción distraída basada en la tecnología y las infracciones aberrantes y de velocidad, las cuales tienen un impacto directo en el grado de lesividad sufrido por los usuarios de las vías durante los accidentes de tráfico.

Realizando un compendio de las cinco aportaciones científicas a través de los artículos de investigación publicados, se puede evidenciar las relaciones que tienen los factores humanos y técnicos modelados en esta tesis sobre e grado de lesividad en conductores, peatones y usuarios en general de las vías cuando ocurre un accidente de tráfico, poniendo en evidencia las condiciones de mayor riesgo. Estas condiciones, junto con las variables que las afectan, se pueden consultar detalladamente en el capítulo de conclusiones.

MARCO METODOLÓGICO

2. MARCO METODOLÓGICO

La presente tesis aborda el estudio de la lesividad derivada de los accidentes de tráfico en España a través de la modelización de los factores técnicos y humanos que se suscitan durante los accidentes, analizando la relación de las variables que suceden en dichos eventos a través de los modelos teóricos generados. Para lograr este estudio, se utilizaron los datos derivados de los formularios durante los accidentes de tráfico por los agentes de la Dirección General de Tráfico de España (DGT) entre los años 2016, 2017, 2018 y 2019.

Para la selección de variables, el procesamiento de datos y la validación de los resultados se utilizaron varios métodos y técnicas de investigación como: (i) método científico, (ii) modelización a través técnicas de “machine learning”, puntualmente los algoritmos de aprendizaje de redes bayesianas, (iii) técnica de validación del área bajo la curva ROC (AUC). La explicación general de cada uno de estos métodos y técnicas las encontramos en los siguientes apartados dentro de este capítulo de marco metodológico, mientras que los detalles puntuales de la aplicación de estos métodos para cada modelo de las contribuciones científicas, se encuentra en el capítulo de contribuciones científicas.

2.1 MÉTODO CIENTÍFICO

El estudio de la ciencia es sin duda muy antiguo en nuestro mundo, y a pesar de que según John Gribbin cualquier fecha elegida para datar el inicio de la historia de la ciencia resultará arbitraria, él mismo narra en su libro de historia de la ciencia al siglo XVI como un posible punto de partida de este proceso llamado ciencia (Gribbin, 2005).

La obtención de conocimiento científico válido a través del uso de técnicas y prácticas de investigación se define como método científico, y a pesar de no existir un solo método para el estudio de todas las ramas de la ciencia, el método científico aborda muchas opciones de estudio con particularidades específicas para cada rama (Andersen & Hepburn, 2015). Actualmente, una gran parte de la ciencia sigue investigándose bajo el paraguas de este método, a pesar de que existen diversas corrientes que también sugieren un cambio radical en el estudio de la ciencia a través de diversos métodos.

Ya que el conocimiento de cualquier fenómeno que sucede en nuestro universo no puede ser adquirido de forma totalitaria a través de la ciencia en vista de la complejidad de los sistemas y sucesos en el universo, los investigadores seleccionan un limitado grupo de variables para estudiarlas, es decir la generación de un modelo más simple de lo que busca estudiar o comprender (Rosenblueth, 1971). Es así que las variables son consideradas la unidad fundamental del método científico, aquellas con características propias que las distinguen de otras y son susceptibles de cambio en diversas circunstancias; es entonces que a partir de ellas se construyen las hipótesis, las cuales se demuestran o no en función de los modelos experimentales que se diseñan para cada caso de investigación (Amiel Pérez, 2007). Estas variables tienen diversas clasificaciones, como cuantitativas y cualitativas, o, discretas y continuas, a las cuales se les aplica diversas técnicas para procesar sus datos, en el caso puntual de esta tesis, se aplican los algoritmos de redes bayesianas.

Las etapas del método científico pueden ser estudiadas de diferentes formas, en el caso de Herrera y Sacasas (2010) proponen las siguientes: (i) La existencia de un problema, el cual debe ser formulado desde un comienzo, e incluso puede obtenerse después de un largo trabajo investigativo, (ii) La búsqueda, recolección y análisis de la información, procurando que la misma sea lo más completa posible hasta la fecha de inicio de la investigación, (iii) La formulación de la hipótesis o conjetura, que debe buscar la solución del problema planteado o explica la esencia del mismo a través de las cosas que se desconocen hasta la esa fecha.

En este sentido, esta tesis aplica el método científico en dos situaciones distintas. En primera instancia, para la definición de la metodología de aplicación en procesamiento de datos, realizando una búsqueda completa de las posibles técnicas de procesamiento actuales con mejores resultados para el procesamiento de datos a gran escala, y por lo que se evidenció en el capítulo introductorio así como en los análisis previos a los aportes científicos realizados, las redes bayesianas aportan una gran fiabilidad en la obtención de resultados al procesar modelos con grandes cantidades de datos. Las redes bayesianas son explicadas de forma más extensa en el apartado 2.2 y en las contribuciones científicas.

En segunda instancia, el método científico se aplicó en la selección de variables para cada uno de los modelos teóricos de las contribuciones científicas de la siguiente forma:

- En la búsqueda del problema para cada modelo teórico planteado, se realizó una extensa búsqueda de la accidentabilidad de tráfico en España y el mundo, centrándose en las condiciones, factores y variables que causaban los altos grados de lesividad en los accidentes de tráfico, los cuales son ya conocidos por generar altas cifras de siniestralidad a nivel mundial. Los hallazgos más importantes, así como toda la información recolectada, fue utilizada para la proposición de cada modelo teórico a ser evaluado.
- Una vez con el panorama claro de las variables a utilizar para el estudio general del problema, así como puntual de cada aporte científico, se realizó la búsqueda de la información fiable y oficial de datos de accidentabilidad en España, contando con la fuente oficial del Gobierno Español a través de la Dirección General de Tráfico en un proyecto conjunto mencionado previamente para la obtención de datos. El posterior análisis y validación de datos se cumple con la técnica de “machine learning” a través de algoritmos de redes bayesianas y el área bajo la curva (AUC) seleccionadas en la aplicación general del método científico.

- Finalmente, siguiendo el método científico, y a través de la extensa revisión bibliográfica sobre trabajos de estudio de accidentes de tráfico, se aplica la formulación de hipótesis en busca no de una solución al problema de accidentabilidad, sino más bien de explicar la esencia del problema con información científica nueva a través del estudio de lesividad durante los accidentes de tráfico para cada modelo planteado.

La aplicación del método científico en cada una de sus etapas en esta tesis, da paso a la utilización de las redes bayesianas como elemento de procesamiento de los datos de accidentabilidad en España y sus técnicas de validación de modelos, los cuales se describen en los siguientes apartados.

2.2 TÉCNCIAS DE MACHINE LEARNING Y MODELIZACIÓN

La inteligencia artificial ha demostrado actualmente un gran potencial para el procesamiento de datos a través de la minería de datos y la estadística, y parte de ello son las técnicas de “machine learning”, desarrollando constantemente nuevos algoritmos de aprendizaje a partir de patrones encontrados en el análisis de datos (Correa et al., 2008). Es así que la modelización con el uso de las técnicas de “machine learning” es un campo prometedor en el estudio de distintas ramas de la ciencia que cuentan con suficientes datos para comprender sucesos como los accidentes de tráfico.

En los campos de la inteligencia artificial, el aprendizaje automático se convierte en una parte vital, el mismo que trabaja a través de árboles de aprendizaje automáticos y sus métodos de cálculo de álgebra matricial (Zhang, 2020). Los principales objetivos de los aprendizajes automáticos de la inteligencia artificial es la selección de características y análisis de componentes principales, así como la correlación canónica que ofrece el aprendizaje supervisado o no supervisado.

Los algoritmos de aprendizaje automático en “machine learning” aprenden el funcionamiento de los modelos con la interpretación de los parámetros, en forma de pesos, o también con estructuras en forma de árboles, guiados por funciones de puntuación o pérdidas que minimizan el rango de la respuesta, de tal forma que en cada repetición el modelo se capacita hasta poder predecir los resultados de nuevas instancias (Molnar, 2020). Para lograr esto, el proceso general que siguen estos algoritmos son: (i) Recopilación de datos, lo cuales deben contener el resultado que se desea predecir y las variables adicionales que desean incluirse en el análisis (entre mayor es la cantidad de datos con la que se cuenta es mejor); (ii) Ingresar los datos al algoritmo de aprendizaje automático diseñado para el modelo planteado, tomando en cuenta la importancia de que estos datos estén correctamente organizados; (iii) Usar el modelo con nuevos datos, para luego integrar el modelo en un solo proceso.

Los modelos de aprendizaje automático implementados son capaces de procesar tareas complejas en tiempos reducidos, ofreciendo resultados confiables y consistentes, y además, permiten copiarse infinitamente y replicarse en nuevos máquinas para su uso en diferentes situaciones y lugares (Molnar, 2020). Una desventaja del uso de algoritmos de aprendizaje es que los modelos que se crean son cada vez más complejos, necesitando de millones de datos para crear sus redes, dificultando en gran medida la comprensión de estos modelos en su totalidad.

En esta tesis, son las redes bayesianas las técnicas utilizadas para la modelización de los factores humanos y técnicos en el estudio de la lesividad en los accidentes de tráfico en España. El funcionamiento metodológico de los algoritmos de redes bayesianas, así como la validación de los modelos teóricos que se ejecutan en el algoritmo, se explican en los dos apartados siguiente.

REDES BAYESIANAS

Las redes bayesianas son modelos gráficos probabilísticos que están basados en grafos acíclicos dirigidos (DAG, por su significado en inglés “directed acyclic graph”) que combinan las teorías de probabilidad y los grafos, siendo así como su proceso de aprendizaje se vuelve más eficiente en cuanto a la distribución probabilística conjunta de un problema multivariado que involucre variables o eventos discretos (Castillo et al., 1997; Koller & Friedman, 2009).

La estructura generada por el grafo (DAG) define la dependencia, sea esta de carácter condicional o no, entre las variables del modelo; mientras que estas dependencias que se reflejan en el grafo definen la factorización de la distribución de probabilidad conjunta (JPD, por su significado en inglés “Joint Probability Distribution”) en la siguiente ecuación:

Ecuación 1

Función de probabilidad conjunta de la red bayesiana

$$p(x_1, x_2, \dots, x_n) = \prod_{i=1}^{n} p(x_i | \pi_i)$$

Fuente: “Sensitivity Analysis in Discrete Bayesian Networks”, Castillo, E., Gutierrez, J. M., & Hadi, A. S. (1997).

En la ecuación 1 las variables consideradas en el modelo de la función de probabilidad conjunta de la red bayesiana se ven representadas en (x_1, x_2,…,x_n), mientras que π_i son el conjunto de padres de la variable x_i dada por el grafo acíclico dirigido (DAG). (Castillo et al., 1997). Este proceso permite al investigador obtener una red gráfica representada de esta función de probabilidad conjunta, facilitando la interpretación de las dependencias entre variables del modelo.

Cuando el grafo (DAG) y la función de probabilidad conjunta (JPD) han sido obtenidas para una variable del modelo, y según se evidencian nuevos conocimientos para cada variable del modelo, este conocimiento se propaga fácilmente por toda la red bayesiana y facilita la obtención de nuevas probabilidades o inferencias(Neapolitan, 2004). Es así, que particularmente la sensibilidad de la variable objetivo seleccionada se puede cuantificar debido a los cambios de las probabilidades dados en los diferentes escenarios predefinidos por las diversas posibilidades de combinaciones del resto de variables de la red. Además, se debe mencionar que los bayes clasificadores, se pueden obtener definiendo el umbral de probabilidad por encima y por debajo de las condiciones de la variable objetivo seleccionada para el estudio.

En esta tesis se ha utilizado las redes bayesianas como metodología de análisis de datos en los modelos propuestos para cada publicación científica, usando para los cálculos el conjunto de herramientas de Bayes Net (Murphy, 2001; "Toolbox, F.M.,") y MeteoLab (Gutiérrez, 2004) para Matlab (Matlab, 2014). De forma general, se ha obtenido un clasificador ligado a la lesividad para cada modelo específico de las contribuciones científicas, determinando el grado de lesión en una serie de rangos específicos en cada modelo. En el apartado de publicaciones científicas, se encuentra detallado específicamente el uso de la metodología de redes bayesianas para cada modelo propuesto en esta tesis.

VALIDACIÓN DE REDES BAYESIANAS MEDIANTE AUC

Una vez que el algoritmo de aprendizaje automático de la red bayesiana se ha entrenado con los datos proporcionados, y se encuentra listo para procesar datos y arrojar información de probabilidades, este debe sr validado para comprobar la eficiencia del modelo planteado y la fiabilidad de los resultados que arrojará. Para lograr esto, se debe evaluar la habilidad del clasificador que se designa en el estudio o modelo creado.

En el caso de esta tesis y de sus contribuciones científicas se ha utilizado la técnica de validación cruzada, partiendo la muestra de datos 10 veces, es decir el 10% de los datos para cada segmento partido. En cada uno de estos segmentos se obtiene un modelo considerando el restante 90% de los datos de la muestra, obteniendo una predicción para los casos del segmento seleccionado, obteniendo en esta iteración 11 muestras de prueba, una por cada segmento partido, y el onceavo que sería la predicción completa para la unión de los diez segmentos de la muestra (Berrar, 2019).

Cada muestra de las pruebas realizadas en los 10 segmentos se evalúa utilizando el área bajo la curva ROC (AUC) (Fawcett, 2006), la cual aporta una medida estándar de precisión total para los clasificadores probabilísticos y binarios que varían entre 0,5 y 1, siendo de suposición aleatoria los valores de 0.5 y de rendimiento perfecto los valores de 1 que se obtienen en la onceava validación por AUC (Hanley & McNeil, 1982).

2.3 BASES DE DATOS

Para el procesamiento de datos a través de los algoritmos de aprendizaje automático es necesario contar con la mayor cantidad de información posible para las predicciones de cada modelo (Correa et al., 2008). Es así, que en el caso de esta tesis se ha tomado para las diferentes contribuciones científicas, todos los datos disponibles de accidentes de tráfico en España proporcionados por la Dirección General de Tráfico (DGT) a través del proyecto “SPIP2015-1852” mantenido con la Universidad de Burgos.

Los datos utilizados para el procesamiento a través de las redes bayesianas fueron recolectados por los agentes de tráfico de la DGT a través del formulario de accidentes de tráfico con víctimas (Dirección General de Tráfico, 2020b) en cada uno de los accidentes de tráfico suscitados en España (ver Anexo A). Es importante mencionar que los datos son recolectados en el mismo formulario por todas las comunidades de España desde 2016, pues previo a este año la Comunidad Autónoma de Cataluña y el País Vasco tenían un registro diferente para los accidentes de tráfico, es por ello que los datos tomados para esta tesis y sus contribuciones científicas se realiza desde el año 2016 en adelante, tomando siempre todo el conjunto de datos disponibles hasta la fecha de cada estudio.

La última base de datos utilizada para esta investigación cuenta con un registro de 410,974 accidentes de tráfico en España de los años 2016, 2017, 2018 y 2019, donde se registraron un total de 7,201 fallecidos y 557,519 heridos hospitalizados y no hospitalizados. Estas bases de datos se encuentran divididas en 5 secciones: (i) base de datos de accidentes, (ii) base de datos de conductores, (iii) base de datos de peatones, (iv) base de datos de pasajeros, y, (v) base de datos de vehículos. Cada una de las bases de datos cuenta con sus propias variables obtenidas a través del formulario de accidentes de tráfico con víctimas, arrojando la posibilidad de trabajar con cientos de miles de datos en cada base.

Las bases de datos se pueden relacionar entre ellas a través de la variable “ID de accidente”, la misma que tiene un registro único para cada accidente de tráfico, es decir que todos los datos asociados a ese accidente se encuentran registrados bajo esa codificación única, lo que permite a los algoritmos de aprendizaje automático buscar los datos solicitados en cada análisis a través de las 5 bases de datos basados en los registros únicos para cada accidente, y apoyándose también en las variables “ID del vehículo” e “ID del peatón” para identificar información importante en las bases de datos onde se repite el “ID del accidente” debido a que se ven involucrados varios vehículos, conductores o peatones. Es así qué, las variables que se deseen estudiar, como por ejemplo en el caso de esta tesis que se centra en el estudio de la lesividad, es factible encontrar de forma sencilla y precisa todos los datos asociados a la variable de lesividad estudiada en los diferentes modelos planteados. Se puede consultar más sobre la adquisición de datos para cada modelo en el capítulo de contribuciones científicas.

PUBLICACIONES CIENTÍFICAS

3. ARTÍCULO 1: THE ROLE OF JOURNEY PURPOSE IN ROAD TRAFFIC INJURIES: A BAYESIAN NETWORK APPROACH

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Journal: JOURNAL OF ADVANCED TRANSPORTATION

Published: 2 December 2019

Accesible at: https://doi.org/10.1155/2019/6031482

3.1 ABSTRACT

Introduction. Road traffic injuries are now regarded as the eighth leading cause of death globally. For example, in 2016, 102,362 traffic injuries took place in Spain in which 174,679 drivers suffered injuries. these findings necessitated the development of the current study which focuses on the prime factors that cause this type of injuries. The aim of this study, therefore, is to explore the behavioral factors that entail a higher risk of suffering either a serious or a fatal injury for drivers. Methods. The findings are based on information and data provided by “Dirección General de Tráfico” (DGT) in Spain on traffic injuries that occurred in the year 2016. Reviewing a wide range of the literature, the authors identified the most influential variables and created a model using the Bayesian networks. The variables that define the model are grouped into four factors: vehicle factor, road factor, circumstantial factor and human factor. Results. The results suggest that the principal variables that determine a higher probability of serious or fatal injuries in traffic injuries are: lack of using appropriate safety accessories, high-speed violations, distractions as well as errors. Finally, the research shows the severity probability based on reason of displacement (“in itinere” on business, or in leisure).

3.2 INTRODUCTION

Road traffic injuries are one of the main causes of death in the world (Yasmin et al., 2014) (Hamalainen, 2009). Every year 1.24 million. people die on the world’s roads and between 20 and 50 million. people are injured, making road traffic accidents the eighth cause of death globally (OMS).

Studies argue that around 10% of road traffic injuries take place when the driver is traveling in the course of work; while a further 18% of injuries take place while a driver is traveling to or from work, i.e., commuting (Charbotel et al., 2010). A bus driver injured in the course of driving for work would be seen as such. A cross Europe, it is estimated that 40% of traffic injuries happen during commute or business journeys. In Spain, in this regard, in 2016 there were 566,235 injuries associated with traveling to/from work in which 64,737 cases were road traffic injuries occurring during business or work travel, accounting for more than 11.4% of the total (OECT).

In this study the journey purpose is classified into three groups: “in itinere” refers to commute—journeys or travel from home to work and vice versa, on business refers to when a driver travels for work-related purposes, and in leisure refers to when a driver travels for pleasure.

The variables that influence the occurrence of a traffic injury can be divided and defined in four groups: demographic factor, human factor, vehicle factor, and circumstantial factor. Nevertheless, the focus of the current research is mainly on the human factor. Human factor has been considered the main cause of traffic injuries as highlighted by Mazankova (Mazankova, 2017).

Sabey and Taylor (Sabey & Taylor, 1980) suggest that the behavior that the driver adopts in front of the steering wheel has become an important factor in the principal cause of promoting traffic injuries. For that reason, several theories have been developed in which they have explained possible risk behaviors behind the steering wheel. One of these theories is denominated “the zero-risk theory” which discusses the existence of a risk threshold above which the danger is not perceived (Summala, 1988). This theory considers that the reasons and emotions play an important role in the driver behavior.

If we extrapolate “the zero-risk theory” as suggested by Salminen and Lähdeniemi (Salminen & Lähdeniemi, 2002) to the traffic that occurs during the workday, some of these reasons could be argued as the time pressure, work pressure as well as excessive workload and tiredness.

The time saving is argued as a main reason by Summala (Summala, 1988), which can trigger an increase in speed (assuming higher risk) to meet the objective (arrive early). Tiredness behind the wheel is one of the risk factors that has been highlighted by Bener, Yildirim (Bener et al., 2017). Driving throughout long periods of time without rest phases makes driving a monotonous task, reducing the ability of driver to drive safely until dangerous limits (Dozza, 2013). Kim and Chung (Kim & Chung, 2019) explain the role of job satisfaction in relation to the number of traffic accidents, and Wishart, Somoray (Wishart et al., 2017) suggest strategies should be developed in order to encourage positive work driving safety climate at work. Finally, issues associated with family or work conflicts which in the majority of the cases result in biological imbalances also often trigger a reduction in resting hours as well as drowsiness and subsequently add to risk factors (Salminen & Lähdeniemi, 2002) (Mitchell et al., 2004) (Pylkkonen et al., 2015)

Another relevant variable presented in different campaigns of the Direción General de Tráfico is the lack of using appropriate safety accessories. Many authors consider the lack of using helmet or seat belt as the main risk factors in work-related injuries (Naevestad et al., 2015) (Naevestad et al., 2015). Several authors have taken into account the gender, age, labor sector, and economic remuneration received in order to identify which population groups are most propense to suffering a traffic injury (Machado-Leon et al., 2016; Mitchell et al., 2014).

Regarding gender, studies argue that male gender is more involved in injuries than the female gender. The main reason for such conclusion is that sectors with higher frequency indices are the transport and distribution sectors that are generally run by men. However, these studies highlight that women suffer more work-related traffic injuries during their displacement than men (MAPFRE, 2015).

Studies conducted in relation to age factor demonstrate that young drivers overestimate their driving abilities, using risk maneuvers (Abele et al., 2018). The aging process involves the biological and psychological system deterioration, and it is considered that it starts around 45–50 year old. From the point of view of driving, this loss is focused on the sense of sight, slowing down the speed of perception and response to stimuli and the reduction of muscle strength (Holliday, 1995).

To this end, we can conclude that speed is one of the most influential behaviors of the driver that causes fatal injuries (Scherrer, 2008; Wu & Xu, 2017). Little increases in speed highly increment the risk of an injury and the severity of the injury (Aarts & van Schagen, 2006). An increased speed means a greater kinetic energy; therefore, in the case of an impact, this energy is absorbed by the vehicle, its passengers, and the element against which it interacts, encoring the number and the severity of injuries. A driver traveling at a high speed lengthens the reaction distance, defined as the distance traveled by the vehicle before the driver reacts to a danger. The pressure of arriving to work on time can cause some reckless and careless manners of drivers such as reaching high speed, which could result in more injury-prone in the roads (Mitchell et al., 2004), (Naevestad et al., 2015), (Newnam et al., 2004), (Chen et al., 2015).

To conclude, the key point of this study is to establish a probabilistic model based on Bayesian networks. Such analysis was conducted in order to predict the risk of suffering an injury in function of displacement reasons: whether “in itinere”, on business, or in leisure trips and others. The model narrows down its focus on four groups of factors including demographic factors, vehicle factors, circumstantial factors, and human factors. Thus, the model determines those drivers’ behaviors that entail a greater risk of suffering an injury. Therefore, research directly focusing on a systematic relation-ship between the journey purpose and harmfulness of drivers while taking into account these four groups of factors in road traffic injuries in a Spanish context remains limited in the field. To this end, the justification behind conducting this research was to address this gap in the field and aims to add to the existing knowledge as well as the literature around the topic.

3.3 MATERIAL AND METHODS

3.3.1 DATA BASE ACQUISITION

The data base used to develop this study has been provided by the Dirección General de Tráfico (DGT). Institution on charge to register the traffic injuries in Spain.

In Spain, when a traffic accident occurs, the agents of the authority in charge from the surveillance and control of traffic, within the scope of their respective competences, send the information related to traffic accidents to the National Registry of Victims of Traffic

Accidents. This information includes the information concerning the traffic accidents with victims, and through the form, this information is included in the annex of the official document BOE-A-2014-12411 (Tránsito, 2016) . The micro-data set used in this study has three tables: general table, vehicles table, and drivers table, which gather information about the traffic injuries that happened in 2016. In that year, 102,362 injuries took place in which 172,971 drivers were implicated (Tránsito, 2016). This research specifically focuses on those drivers whom harmfulness is known, and at the same time the study focuses on the type of their known displacement. The degree of severity of such drivers has been defined as: fatal (FI), seriously injured (SI), lightly injured (LI), and unhurt (U). These drivers are registered by traffic police as drivers who were taking a journey either to go to work from home or vice versa to home from work. They also could be registered as drivers who were driving for work purposes or driving was their job. Finally, they could be registered as traveling for leisure and pleasure purposes. Taking this harmfulness of the driver and cause of displacement aspects into account, the final dataset includes a total of 66,253 drivers.

To this end, the sampling technique employed in this study is a systematic sampling method. The authors have excluded the data for traffic accidents in 2016 in which the purpose of the journey and the driver harmfulness were not reported by (DGT). Utilizing data from the sample population collected by (DGT) and employing a Bayesian network, the current study focuses on four relevant variables and discusses results in which the study highlights the importance of relationship between drivers’ behaviors in road traffic injuries with the level of drivers’ harmfulness.

3.3.2 STUDY VARIABLES

The variables that contribute to the occurrence of a traffic injury and result in driver harmfulness can be assembled into four groups: demographic factors, vehicle factors, circumstantial factors, and human factors.

Each of these factors in turn includes a series of variables, with their corresponding states.

(i) Demographic factors: combination of the gender and the age of the driver.

(ii) Vehicle factors: type of vehicles.

(iii) Circumstantial factors: type of trips or reasons for displacements, type of roads or zones and distance or kilometers of travel.

(iv) Human factors: the behavioral factors, or modifiable factors by the driver. These could include wearing a seat belt, wearing a helmet, the speed violation as well as distraction and errors made by the driver.

(v) Study variable: driver harmfulness represents driver injury severity.

This study focuses mainly on the human factor, being considered as the principal cause of traffic injuries (between 70% and 90%) (Blanco, 2013).

3.3.3 BAYESIAN NETWORK

In order to characterize the dependences between the different factors and the target variable, the probabilistic graphical models (PGMs) have been considered. Several studies have previously employed Bayesian network in their analysis of traffic accidents to express certain relationships between the different factors (Zou & Yue, 2017) (de Ona et al., 2011). These models are based on a graph in which each node represents a variable or factor and each link between variables represents a dependence between them. These dependences/independences let us to factorize the joint probability distribution (JPD), which is the second element of these models, dramatically reducing the number of parameters of our model and, as a result, simplifying the learning and inference processes. In addition, the graph obtained is a visual and easily interpretable tool to illustrate the factors affecting our target variable. In particular, in our study, we have considered the discrete Bayesian networks (Castillo et al., 1997) in which the graph of the model is a directed acyclic graph (DAG). The link's direction introduces two additional concepts in the nodes of our model, parents and children, depending on whether the arrow departs or points to the node, respectively. As a result, the JPD can be expressed mathematically as

$$p(x_{1,}x_2,\ldots,x_n) = \prod_{i=1}^{n} p(x_i|\pi_i), \tag{1}$$

where π corresponds to the parents of $x_{1,}$ being the BN the model defined by both the DAG and the corresponding JPD in Equation (1).

Once the Bayesian network has been defined, the probability of any node or set of nodes given any information on the state of the others variables (evidence) can be efficiently obtained by using both the factorization and the DAG (inference), letting us to analyze the impact of each of the variables in the injury severity grade suffered by the driver. As an example, we could have some evidence about the motive of the displacement, the age, and the gender with which we can determine the probability of a serious injury in the accident by means of the expression:

$$p(\text{harmfulness}|\text{Type of Trip} \cap \text{Age} \cap \text{Gender}) = \frac{p(\text{harmfulness intersect Type of Trip} \cap \text{Age} \cap \text{Gender})}{p(\text{Type of Trip} \cap \text{Age} \cap \text{Gender})}. \quad (2)$$

Moreover, from the definition of the Bayesian network, a natural classifier for the injury severity can be obtained defining a threshold for the probability above/below of which serious/no injury is assigned. To evaluate this classifier, the receiver operating characteristic (ROC) curve was considered. This technique was introduced in the clinical investigation by two radiologists which allow us to represent the true positives

(sensitivity) based on false positives (specificity) (Hanley & McNeil, 1982). This area enclosed under the curve (AUC) allows to evaluate the model. This area can take values between 0 (perfect predictor of the contrary state) and 1 (perfect predictor), corresponding the 0.5 value to a random prediction (unreliable model).

3.4 RESULTS AND DISCUSSION

3.4.1 THEORY MODEL

The proposed model can be appreciated in Figure 1.

Below is the list of the factors and the interactive variables with their definitions that contributed to the development of our model (please see Figure 2. Theory model). The factor vehicle refers to the type of vehicle variable that has been discretized in six groups: cars, bikes, motorcycles, buses and coaches, trucks and others.

The demographic factor included two types of variables: age and gender. The variable “gender” remains the same as mentioned in the questionnaire. However, the variable “age” has been grouped into four groups: less than 18, 18 to 24, 25 to 60, and over 60.

The human factor has been grouped in five types of variables: seat belt, helmet, speed, distraction, and error. The variables seat belt and helmet indicate if the driver was using such safety accessories in the moment of the accident. The speed variable has the same four states as shown in the questionnaire; the first state is “none” and indicates that the driver was driving in the correct speed, the second group indicates if the speed was inadequate, the third state shows when the driver was driving over the limit speed allowed, and the fourth state indicates if driver was driving the vehicle too slow—below the standards. Finally, the group of the variables’ errors and distraction indicates that the driver did not make any error or distraction. On the other hand, the state “yes” indicates the contrary. All the errors and distractions included in the analysis are shown in the section of comments in Table 1.

The circumstantial factor has been grouped into two types of variables: zone and type of trip. The variable type of road or zone remains in the same four types as in the questionnaire filled by the police (road, crossing, street, and highway). The variable type of trip shows the cause of displacement in three groups including “in itinere,” on business and in leisure. Another variable taken into consideration is the distance that the driver undertakes. The variable shows the same three groups with the answers that drivers answered the transport policemen. The distances are categorized as: local (less than 50 km), medium (between 50 km and 200 km), and long distance (more than 200 km).

Lastly, the objective variable, is the object of the study, injury severity, has been created considering the severity of the driver’s injury. This variable has two values: firstly “light” if the driver was slightly injured, and secondly kill serious injuries “KSI” if the driver was either fatally injured or seriously injured. It would be worth mentioning here that this study focuses merely on injury severity for the driver himself or herself.

3.4.2 VALIDATION

A k-fold cross-validation approach, with k=10, was considered to evaluate the model. This method divides the data into 10 folds including the 10% of the sample (i.e., ~6625 data for each fold). For each fold the other 90% of the sample (~59628 data) is used as training data to predict the sample included in the corresponding fold, used as test data. This procedure was performed ten times in order to ensure that all data with no exceptions were calculated since it has been part of the training and testing analysis. The area under the curve indicates the ability to determine the probability of suffering whether it was a major, a fatal, a minor, or an unharmed injury. In this case, the AUC is in a range of (0.767–0.801).

3.4.3 INITIAL PROBABILITIES OF SERIOUS INJURY IN A TRAFFIC INJURY

A sensitivity analysis of each of the variables carried out in this study is to determine the initial probability of death or major injury for the drivers versus minor injury in each of its states. A sensitivity analysis of each of the variables is also carried out to determine the initial probability of death or serious injury (KSI risk) for the drivers versus slight injury in each of its states. The results are shown in Table 1.

After carrying out the sensitivity analyses, showing the initial probabilities, we can argue that the most influential variables are respectively as follows: the type of vehicle, distance, age, seat belt, and, finally, speed.

It is important to take into account the interrelation that may exist between the different variables. Therefore, the Bayesian network presents their strong point for their ability to extract knowledge through the search of the joint probabilities of all the variables among themselves.

The factors that contribute to the severity of accidents are related to each other and do not act on merely. As a result, the accident occurs with complex interactions between road user behavior, vehicle factors, road geometric characteristics, and environmental factors (Xu et al., 2018).

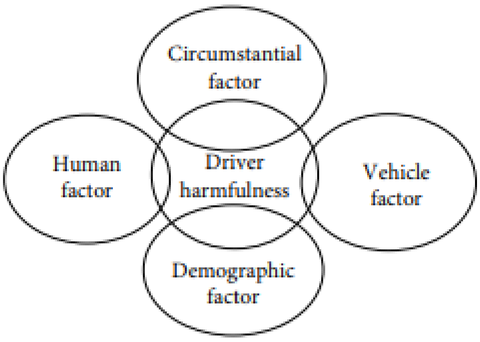


FIGURE 1: Principal risk factors.

This is important; however, the result of the analysis con-ducted in this study employing the Bayesian network (presented in Figure 1) gives us information on how all these variables are interrelated with each other (Figure 3).

3.4.4 PROBABILITY OF SERIOUS TRA—C ACCIDENT BASED ON THE CAUSE OF DISPLACEMENT AND THE BEHAVIOR OF THE DRIVER

To analyze the influence of displacement reason in the harmfulness in the accident, a sensitivity analysis has been done to establish driver's harmfulness probability in function of two evidence (see Table 2). The first evidence, in all analysis carried out, is always the type of trip, and the second evidence is in relation to one of these human behavior variables: seat belt, helmet, speed, distraction, and errors.

Not wearing safety accessories including seat belt and helmet results in serious accidents. That reaches levels of 19.9% and 13.0%, respectively. Focusing on the type of displacement, not wearing a seat belt, "in itinere," on business, and leisure, the figures are shown as 19.1%, 17.4%, and 19.3%, respectively. A cross-tabulation test illustrated in Table 1 examined the relationship between speed variables and type of trip. The test was statistically significant and illustrated 0.202, the worst figure, suggesting that there is a highly significant relationship between "exceeding speed" and "travel for leisure purpose" for serious injuries. Specifically, if we keep our focus on the type of trip, exceeding speed on pleasure trips is the factor that mostly determines the probability of suffering a serious and/or fatal accident. These probabilities account for 17.5% in "in itinere" trips, 15.9% in on business trips, and 20.2% in leisure trips.

These possible distractions made by the drivers are using mobile phones, focusing on GPS devices, being distracted by radio and music, smoking while driving, and some other types of distractions. On the other hand, the errors made by the drivers are related to making mistakes in terms of not paying enough attention to traffic signs, to other vehicles, to the pedestrians, and so on. The results show the probability of death or major injury in an accident based on these variables and the reasons for displacement.

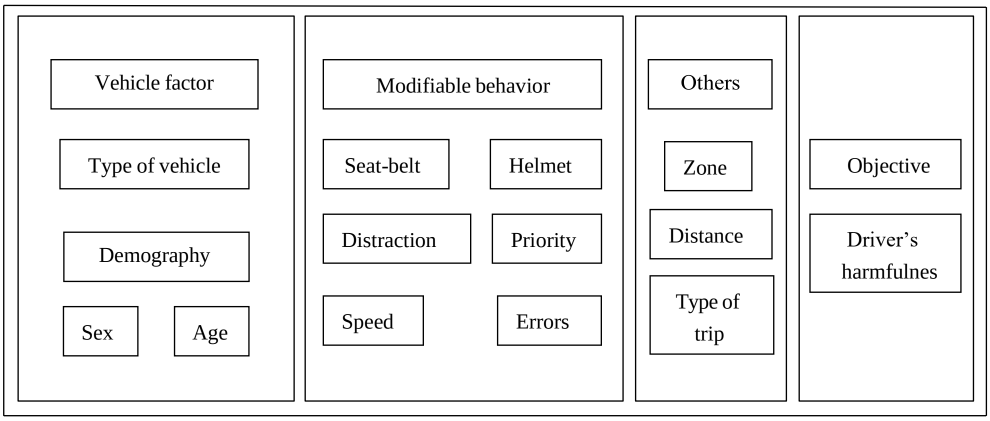


FIGURE 2: Theory model.

Distractions and errors, provoke very similar probabilities of suffering a serious and/or a fatal accident. This fact was also verified in several studies as mentioned by Cordazzo, Scialfa (Cordazzo et al., 2014). However, if we analyze the probability of distraction and error depending on the type of trip, the results suggest that the highest chances of suffering a serious and/or a fatal accident occur in leisure trips (7.5% and 6.7%). This might be due to the fact that drivers on leisure trips may drive on the routes that are less familiar with and they are likely to be more distracted by other factors such as talking to their fellow travelers.

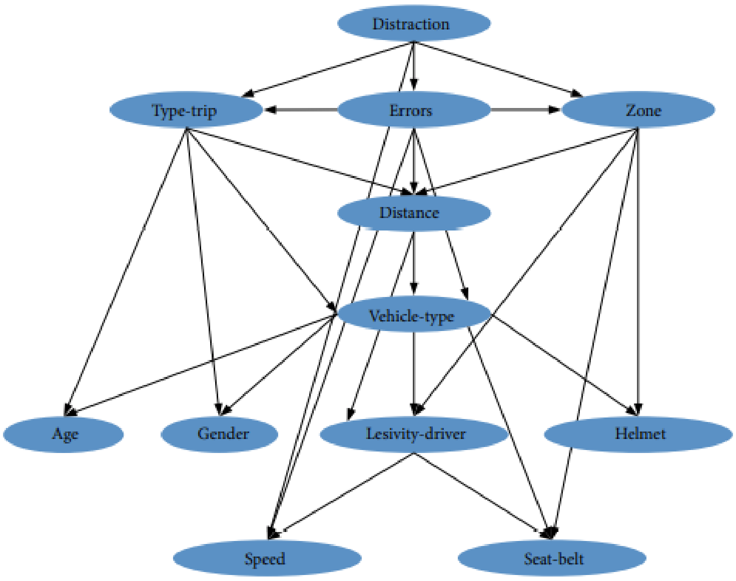


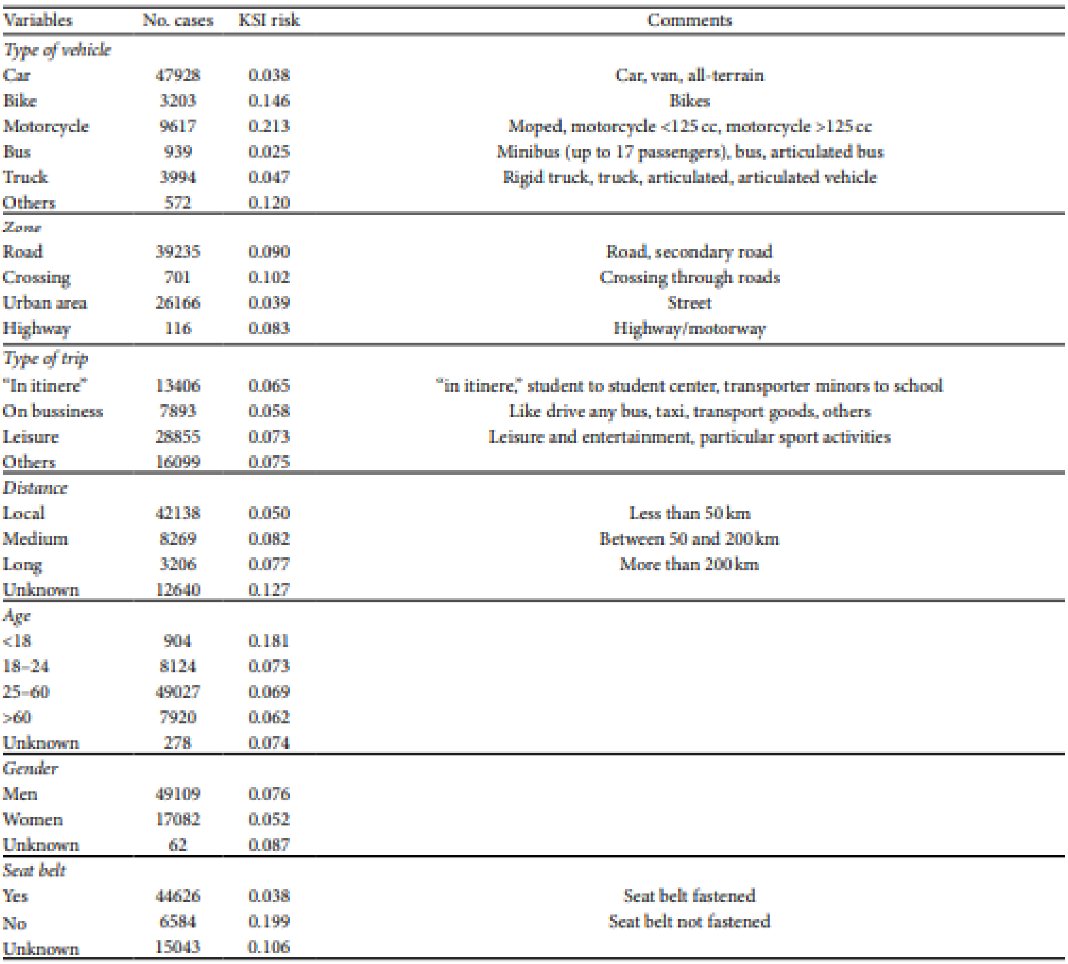
FIGURE 3: Bayesian network. Processed by the authors.

Table 3 shows the relative probability of having a distraction or errors in function of the purpose of displacement.

Depending on the type of trips taken by drivers, different probabilities of getting distracted or making mistakes during the trip are shown in Table 3. As the table illustrates, the probability to make a mistake due to the errors is higher than mistakes due to distractions. This is quite evident in leisure trips, reaching a probability of 42.4% of making an error. Likewise, the probability to make a mistake due to distraction is bigger in leisure trips reaching a probability of 17.8%. This suggests that the reasons highlighted earlier resonate well with these findings.

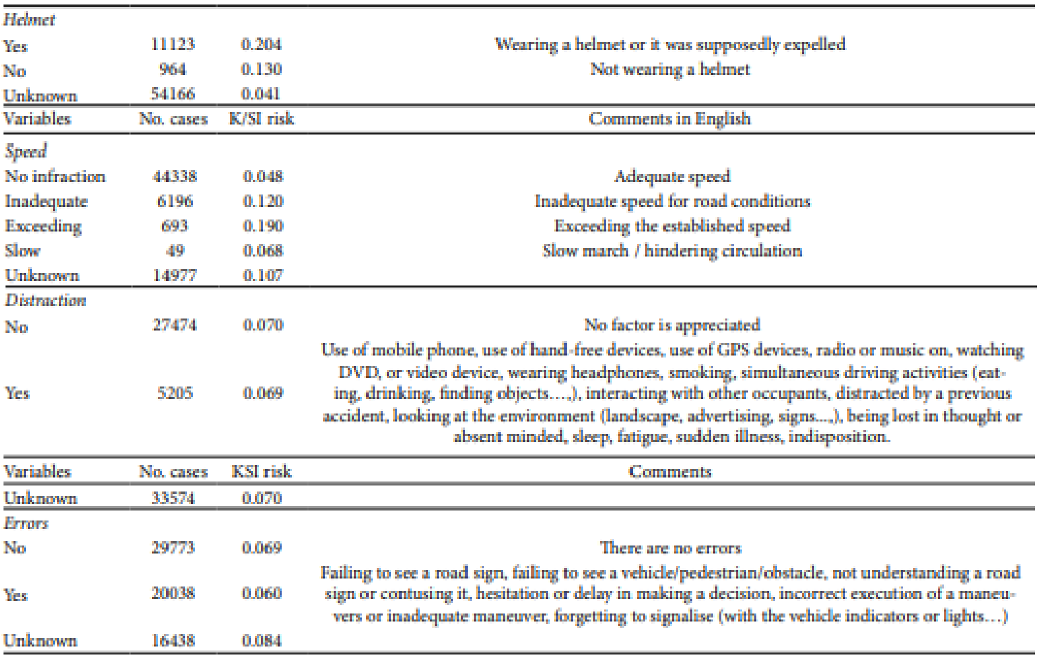
On the other hand, business trip is less probable to result in high-risk accidents. This is in keeping with the work of de Oliveira, Petroianu (de Oliveira et al., 2015) who explain how recklessness while driving a motorcycle could be argued as the main cause of traffic accidents. In their study only 7% of displacement with motorcycles was for work. Our analysis shows similar results as motorcycles are used on business with a probability of 8.2%.

Table 1: Number of cases and a priori probability of the severity of the injury based on behavior variables. Processed by the authors.



Variables	No. cases	KSI risk	Comments
Type of vehicle			
Car	47928	0.038	Car, van, all-terrain
Bike	3203	0.146	Bikes
Motorcycle	9617	0.213	Moped, motorcycle <125 cc, motorcycle >125 cc
Bus	939	0.025	Minibus (up to 17 passengers), bus, articulated bus
Truck	3994	0.047	Rigid truck, truck, articulated, articulated vehicle
Others	572	0.120	
Zone			
Road	39235	0.090	Road, secondary road
Crossing	701	0.102	Crossing through roads
Urban area	26166	0.039	Street
Highway	116	0.083	Highway/motorway
Type of trip			
"In itinere"	13406	0.065	"in itinere," student to student center, transporter minors to school
On bussiness	7893	0.058	Like drive any bus, taxi, transport goods, others
Leisure	28855	0.073	Leisure and entertainment, particular sport activities
Others	16099	0.075	
Distance			
Local	42138	0.050	Less than 50 km
Medium	8269	0.082	Between 50 and 200 km
Long	3206	0.077	More than 200 km
Unknown	12640	0.127	
Age			
<18	904	0.181	
18–24	8124	0.073	
25–60	49027	0.069	
>60	7920	0.062	
Unknown	278	0.074	
Gender			
Men	49109	0.076	
Women	17082	0.052	
Unknown	62	0.087	
Seat belt			
Yes	44626	0.038	Seat belt fastened
No	6584	0.199	Seat belt not fastened
Unknown	15043	0.106	

Table 1: Continued



Helmet			
Yes	11123	0.204	Wearing a helmet or it was supposedly expelled
No	964	0.130	Not wearing a helmet
Unknown	54166	0.041	
Variables	No. cases	K/SI risk	Comments in English
Speed			
No infraction	44338	0.048	Adequate speed
Inadequate	6196	0.120	Inadequate speed for road conditions
Exceeding	693	0.190	Exceeding the established speed
Slow	49	0.068	Slow march / hindering circulation
Unknown	14977	0.107	
Distraction			
No	27474	0.070	No factor is appreciated
Yes	5205	0.069	Use of mobile phone, use of hand-free devices, use of GPS devices, radio or music on, watching DVD, or video device, wearing headphones, smoking, simultaneous driving activities (eating, drinking, finding objects…,), interacting with other occupants, distracted by a previous accident, looking at the environment (landscape, advertising, signs...,), being lost in thought or absent minded, sleep, fatigue, sudden illness, indisposition.
Variables	No. cases	KSI risk	Comments
Unknown	33574	0.070	
Errors			
No	29773	0.069	There are no errors
Yes	20038	0.060	Failing to see a road sign, failing to see a vehicle/pedestrian/obstacle, not understanding a road sign or confusing it, hesitation or delay in making a decision, incorrect execution of a maneuvers or inadequate maneuver, forgetting to signalise (with the vehicle indicators or lights…)
Unknown	16438	0.084	

3.4.5 PROBABILITY OF SERIOUS TRAFFIC ACCIDENT BASED ON THE CAUSE OF DISPLACEMENT AND THE TYPE OF VEHICLE, ZONE AND DISTANCE

To analyze the probability of KSI risk, a sensitivity analysis has been conducted to establish the probability in function of two evidence (see Table 4). In our study, based on our findings, we argue that where a car driver experiences an injury, in 3.8% of cases, the injury is whether serious or mortal. The risk is somewhat higher for truck drivers, at 4.7%. the other two vehicular modes with elevated KSI risk are, respectively, cycles, at 14.6%, and motorcycles, at 21.3%. However, focusing on the type of trips, it is important to emphasize that 14.8% of the serious and/or fatal accidents occur in displacement for pleasure when the vehicle used is a bicycle. Concerning motorcycles, the “in itinere,” on business, and leisure displacements, the figures show higher probability of suffering a serious and/or a fatal accident demonstrating 20.1%, 21.6%, and 20.2%, respectively.

In general, the risks of suffering a serious and/or a fatal accident for road users are less harmful when they travel on urban areas as Olszewski, Szagala (Olszewski et al., 2019) mentioned in their study. Table 4 confirms the figure 3.9% of having a serious accident on street, especially on business displacements, which reaches 2.7%. In contrast to this, the analysis shown in Table 4 confirms that the highest probability of suffering a serious and/or a fatal accident occurs on the motorways with 10% in leisure journeys.

The last variable in Table 4 is the distance. It can be noted that among the local displacements, medium and long range, are mid-range displacements that cause more risk to drivers (8.2%). Within these medium-range trips, pleasure trips are the most dangerous trips, reaching the figure 10.3%, in comparison with local displacement for business travels that shows the figure 4.2%.

Leisure trips, as presented in the table, encompass the higher risk of suffering a serious and/or a fatal accident in trips in comparison with the others. These results are consistent with the findings by Bellos et al. (2019). In their article, Bellos et al. explain that the risk of suffering accidents in general is increased with the tourists who drive during holiday periods, those who are obviously doing leisure trips. These article highlights that this may be due to the increase in vehicles during the tourist season and also because tourists do not know the city nor its traffic regulations or signage (Bellos et al., 2020).

The data presented in Table 4 demonstrates an elevated severity risk for road users, those who are involved in leisure-related “in itinere” journeys. As the table indicates, the severity risk for road user leisure travelers is at 9.5%, indicating a higher frequency than the other trip purposes.

3.4.6 PROBABILITY OF A SERIOUS TRAFFIC ACCIDENT BASED ON THE REASON FOR DISPLACEMENT, AGE AND GENDER

A sensitivity analysis examined the age and gender of the driver in relation to the cause for displacement. The analysis presents the probability of having a serious or fatal accident. Table 5 illustrates these analyses.

As in previous studies, the results confirm how men are more likely to have more serious accidents on the road (Regev et al., 2018). On the other hand, focusing on the reason for the displacement, the test revealed that there is a big difference in KSI risk in function of the age and gender in relation to the cause of displacement. First, as the figures show man drivers over 25-year-old have the highest probabilities of having a serious accident in leisure trips (8.1% in leisure in comparison with 5.5% for business). Looking at the table, however, it becomes apparent that, young drivers (less than 18-year-old), regardless of their gender whether a woman or man, reach the highest prob-abilities on business trips (20.1% for men and 18.7% for women). According to Korpinen and Paakkonen (Korpinen & Paakkonen, 2012), younger people tend to have more accidents while on their mobile phones (distraction, in our study).

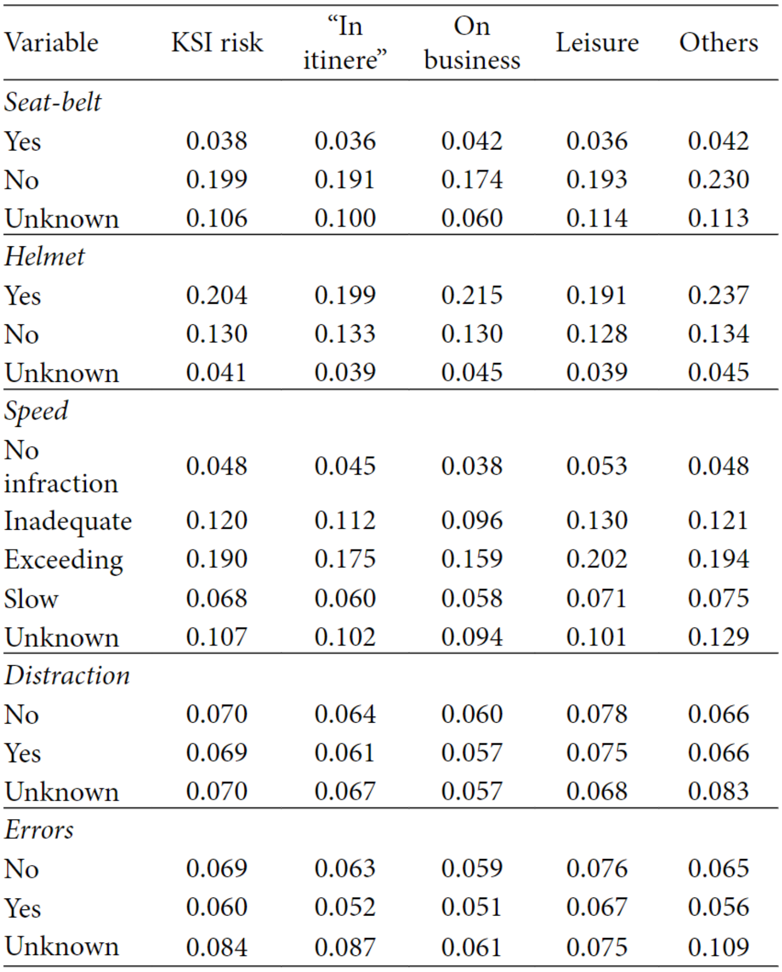
3.5 CONCLUSIONS

In the year 2016, in Spain, 177,356 vehicles and 172,972 drivers were involved in traffic accidents resulting in 102,362 traffic injuries. The focus of this study was, therefore, on drivers who were injured in traffic accidents, and the focus shifted on their harmfulness in relation to the type of trips they were under-taken. Therefore, the dataset for this study includes a total number of 66,253 drivers.

According to the dataset, out of the 66,253 initial drivers involved in a traffic accident, only 4,542 were seriously injured (6.8%). According to the analysis carried out in this study, the high probability to suffer a serious injury in leisure purpose was (7.3%), “in itinere” (6.5%), and on business (5.8%). Based on these results, it can be argued that there is in general a greater probability of having accidents in leisure trips. These data resemble with the article published by Mitchell, Bambach (Mitchell et al., 2014), where the authors conclude that factors such as alcohol, speed and fatigue are less likely to be involved in accidents when they are associated with business issues.

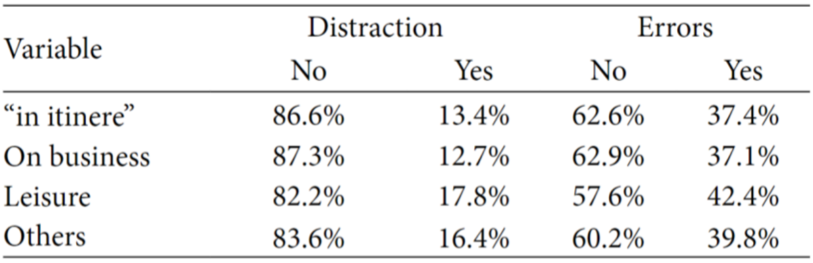
The main risk factors involved in road traffic injuries were, respectively, driving a motorcycle (21.3%), not wearing a seat belt (19.9%), exceeding speed limit (19.0%), drivers under 18-year-old (18.1%), not wearing a helmet (13.0%), while crossing.

Table 2: Probabilities of suffering a serious accident, depending on the type of displacement and the different variables of the human factor. Processed by the authors.



Variable	KSI risk	“In itinere”	On business	Leisure	Others
Seat-belt					
Yes	0.038	0.036	0.042	0.036	0.042
No	0.199	0.191	0.174	0.193	0.230
Unknown	0.106	0.100	0.060	0.114	0.113
Helmet					
Yes	0.204	0.199	0.215	0.191	0.237
No	0.130	0.133	0.130	0.128	0.134
Unknown	0.041	0.039	0.045	0.039	0.045
Speed					
No infraction	0.048	0.045	0.038	0.053	0.048
Inadequate	0.120	0.112	0.096	0.130	0.121
Exceeding	0.190	0.175	0.159	0.202	0.194
Slow	0.068	0.060	0.058	0.071	0.075
Unknown	0.107	0.102	0.094	0.101	0.129
Distraction					
No	0.070	0.064	0.060	0.078	0.066
Yes	0.069	0.061	0.057	0.075	0.066
Unknown	0.070	0.067	0.057	0.068	0.083
Errors					
No	0.069	0.063	0.059	0.076	0.065
Yes	0.060	0.052	0.051	0.067	0.056
Unknown	0.084	0.087	0.061	0.075	0.109

Table 3: Probabilities of distracting or making mistakes during driving depending on the type of displacement made by the drivers. Processed by the authors



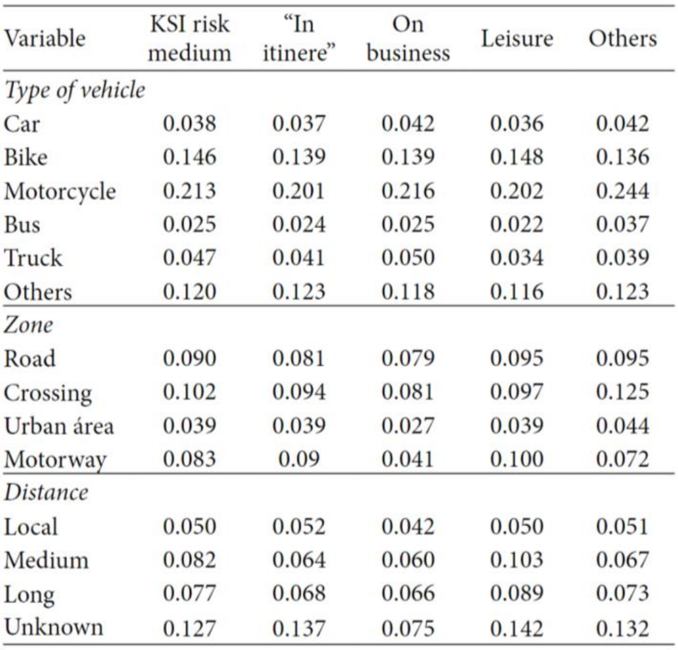
Variable	Distraction		Errors	
	No	Yes	No	Yes
“in itinere”	86.6%	13.4%	62.6%	37.4%
On business	87.3%	12.7%	62.9%	37.1%
Leisure	82.2%	17.8%	57.6%	42.4%
Others	83.6%	16.4%	60.2%	39.8%

road (10.2%), driving a medium distance (8.2%), being distracted (6.9%), and finally making a mistake (6.0%).

The findings of the current study, according to the type of vehicle, suggest that motorcycles account for a probability of 21.3% of suffering a serious or fatal. These results are consistent with the results of the study conducted by de Oliveira, Petroianu (de Oliveira et al., 2015), and these authors argue that recklessness of motorcyclists while driving is the main cause of traffic accidents. Also, the authors emphasize that besides motorcycles, bicycle cyclists have a high probability of suffering a serious accident, reaching (14.0%) and coinciding with the result of our study (14.6%).

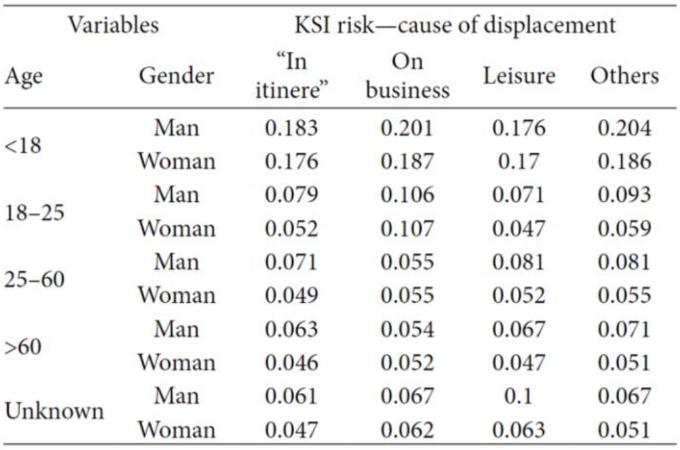
Regarding the sex and age of the driver, the masculine gender is the sex with greater probability to suffer a serious injury and/or a fatal one. Young man drivers (<18) are in particular affected on business trips with a (20.1%) of probability. This is while young women drivers represent the (18.7%) of probability. Another important factor concerning the gen-der and age is that the lower risk of suffering serious and/or a fatal accident occurs in the age range above 60-year-old.

Table 4: Probabilities of suffering a serious accident, depending on the type of displacement and distraction or errors made by the driv-ers. Processed by the authors.



Variable	KSI risk medium	“In itinere”	On business	Leisure	Others
Type of vehicle					
Car	0.038	0.037	0.042	0.036	0.042
Bike	0.146	0.139	0.139	0.148	0.136
Motorcycle	0.213	0.201	0.216	0.202	0.244
Bus	0.025	0.024	0.025	0.022	0.037
Truck	0.047	0.041	0.050	0.034	0.039
Others	0.120	0.123	0.118	0.116	0.123
Zone					
Road	0.090	0.081	0.079	0.095	0.095
Crossing	0.102	0.094	0.081	0.097	0.125
Urban área	0.039	0.039	0.027	0.039	0.044
Motorway	0.083	0.09	0.041	0.100	0.072
Distance					
Local	0.050	0.052	0.042	0.050	0.051
Medium	0.082	0.064	0.060	0.103	0.067
Long	0.077	0.068	0.066	0.089	0.073
Unknown	0.127	0.137	0.075	0.142	0.132

Table 5: Probabilities of suffering a serious accident, based on the reason of displacement, age and gender. Processed by the authors



Variables		KSI risk—cause of displacement			
Age	Gender	“In itinere”	On business	Leisure	Others
<18	Man	0.183	0.201	0.176	0.204
	Woman	0.176	0.187	0.17	0.186
18–25	Man	0.079	0.106	0.071	0.093
	Woman	0.052	0.107	0.047	0.059
25–60	Man	0.071	0.055	0.081	0.081
	Woman	0.049	0.055	0.052	0.055
>60	Man	0.063	0.054	0.067	0.071
	Woman	0.046	0.052	0.047	0.051
Unknown	Man	0.061	0.067	0.1	0.067
	Woman	0.047	0.062	0.063	0.051

Another important factor that is considered in the current study is the behavior of the driver. The main risk factor associated with driver’s behavior in relation to displacement is not wearing a seat belt, in the case of “in itinere” displacement representing (19.1%) and for business trips (17.4%). Exceeding the speed limit is another factor associated with driver’s behavior in the case of displacement reaching (20.2%) in leisure trips. In relation to the driver’s behavior, it is further observed that the probability of having a serious and/or a fatal accident due to making mistakes or being distracted is not so high. The result shows an average of (5.7%) for mistakes and (6.4%) for distractions. Nevertheless, the probability of committing an error or distraction during driving is high, which reaches an average of (38.99%) for mistakes and (14.6%) for distractions.

Finally, a sensibility analysis was conducted in order to identify the probability of serious accidents as to what extent they determine the cause of displacement, the zone as well as distance. The higher probabilities of suffering a serious and/or a fatal accident according to the zone are in leisure trips in motorway (10%), on business and “in itinere” in crossing areas (8.1% and 9.4% respectively). This is while displacements caused by driving long distance reach (6.8%) “in itinere” trips and (6.6%) on business trips, on the other hand, in the case of leisure trips the high probability occurrence in medium distance reaching (10.3%).

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

ACKNOWLEDGMENTS

We would like to thank the Dirección General de Tráfico (DGT) for providing us with the necessary data for conducting this study (SPIP2015-1852). e MICRODATOS_ACCIDENTES_2016, MICRODATOS_CONDUCTORES_ 2016, and MICRODATOS _VEHICULOS_ 2016 used to support the findings of this study were supplied by the Dirección General de Tráfico (DGT) and so cannot be made freely available. Requests for access to these data should be made to DGT, C/ Josefa Valcarcel, 28 y 44, 28071 Madrid, España. This work is part of the research project "Modelización mediante técnicas de machine learning de la influencia de las distracciones del conductor en la seguridad vial. Diseño de un sistema integrado: simulador de conducción, eye tracker y dispositivo de distracción. Ref. BU300P18" supported by funds from FEDER (Fondo Europeo de Desarrollo Regional - Junta de Castilla y León).

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(DOI: 10.1155/2019/6031482)

4. ARTÍCULO 2: INFLUENCE OF SEAT-BELT USE ON THE SEVERITY INJURY IN TRAFFIC ACCIDENTS

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Journal: European Transport Research Review

Published: 10 february 2020

Accesible at: https://doi.org/10.1186/s12544-020-0401-5

Keywords: Road traffic injuries, Seat belt, Bayesian networks, Traffic accidents, Human and conditioning factors

4.1 ABSTRACT

Background: About 1.35 million people died in traffic accidents around the world in 2018, make this type of accidents the 8th cause of death in the world. Particularly, in Spain, there were 204,596 traffic accidents during 2016 and 2017, out of which 349,810 drivers were injured. The objective of this study was to understand to what extent seat belt non-use and human factors contribute to drivers injury severity. Methodology: The results are based on the information and 2016–17 data provided by the Spain national traffic department "Dirección General de Tráfico" (DGT). The discretization model and Bayesian Networks were developed based on important variables from the literature. These variables were classified as, human factor, demographic factor, conditioning factor and seat belt use. Results: The results showed that failure to wear the seat belt by drivers are likely to increase the risk of fatal and sever injury significantly. Moreover, distraction and road type road can contribute to the accident severity.

4.2 INTRODUCTION

Road traffic accidents are considered as one of the major life-threatening problems in the world that cause significant financial losses and long-term psychological problems. Every year, around 1.35 million people die on the road globally, making this the eighth cause of death globally, and the first leading cause of death in children and young adults aged 5 to 29 (Organization, 2018). From the literature, the human factors contributing to the road traffic accidents include speeding, driving under the influence of alcohol and drugs, distraction and failure to wear seat belts and child restraint systems.

According to the Spain national traffic department "Dirección General de Tráfico"

(DGT), in 2014, there were around 91,570 traffic accidents which resulted in 1688 fatalities, 9574 hospitalized injuries and 117,058 non hospitalized injuries. As 24% of the fatalities in car and vans were because of seat belt non-use, DGT aimed to reduce this figure by changing the driver's behavior and raising awareness about the importance of the use of seat belts and child restraint system through various campaigns(Vial, 2019).

Previous research efforts investigated the role of human behavior in seat belt use (Beck et al., 2019). They reported that in the United States, there is generally higher compliance with the seat belt regulations, however it is used more in the front seats than in the rear seats. It is also found that people who use public or private road transport (rear seats) in regions with less legal obligations are in need of mechanisms to promote their knowledge regarding the use of seat belt.

Furthermore, Høye (Hoye, 2016) showed that seatbelt use can reduce fatal and non-fatal injuries in front and rear seat occupants by 60% and 44% respectively. In addition, it has been found that drivers without seatbelt are 8.3 times more likely to sustain fatal injury and 5.2 times more likely to sustain serious injury compared to the drivers who use seat belts. Bedard, Guyatt, Stones, and Hirdes (Bedard et al., 2002) reported that the risk of death in traffic accident is conditioned on driver's characteristics and vehicle model. That is, women, elderly drivers, speeding, seat belt non-use, and recent model year vehicles are associated with an increased risk of fatality. Also, they found that left lateral impact is more likely to result in fatal injury than front impact. Moreover, J. M. Kim et al. (Kim & Chung, 2019) reported that seat belt non-use, the driver age, the vehicle degree of deformation and the side collisions are positively associated with the serious traffic accident. Vallibhakara, Plitpolkarnpim, Suriyawongpaisal, and Thakkinstian (Paibul Suriyawongpaisal, 2018) evaluated the socioeconomic factors affecting seatbelt use in Thailand. They found that people in urban and metropolitan areas tend to use seat belt more than people in rural areas. Also, gross provincial product, level of literacy and law penalty were found to be positively associated with seat belt use.

In addition to seat belt use, previous works showed that other factors corresponding to the driving behaviors such as overtaking, errors and distraction can contribute to the severity of traffic accidents (Cardamone et al., 2017; de Ona et al., 2014; Febres et al., 2019). Kaplan and Prato (Kaplan & Prato, 2012) found that drivers beyond the age of 55, female drivers, age and risky driving are likely to increase the risk of fatality. J.-K. Kim, Ulfarsson, Kim, and Shankar (Kim et al., 2013) reported the same results except that the male drivers have higher risk of fatality than female drivers. Moreover, alcohol consumption was found to increase the risk of fatality significantly.

From the methodological standpoint, numerous authors have analyzed accident severity using different methods. Zong, Xu, and Zhang (Zong et al., 2013) assessed the performance of Bayesian Networks and Regression Models in accident severity modeling. Their results showed that the Bayesian Networks outperformed the regression models and they are more suitable for the prediction of the accident severity. Previous works demonstrated that Bayesian Networks method gives validated and reliable results and it is an optimum method for assessing the probability of injury from a traffic accident (de Ona et al., 2013; Zong et al., 2013).

To this end, the aim of this study is to establish a probabilistic model based in Bayesian networks in order to predict the risk of injury and fatal injury in a traffic accident as a function of seat belt use, demographic factors, human factors, and conditioning factors (the type of vehicle, the type of road, the type of collision and the visibility of the driver).

4.3 DATA COLLECTION

Data used in this study obtained from the Spain national traffic department (Tránsito, 2016), that collects data from the police accident reports. The database was restricted by the type of vehicle the driver was driving during the traffic accident, focusing only on those vehicles that have a seat belt. Taing these two conditions, the final database includes a total of 349,810 drivers. Driver injury severity (Accident severities) have been defined as: Fatal (FI), seriously injured (SI), lightly injured (LI), and unhurt (U). Also, as seen in Fig. 1, variables used in this study have been grouped into four factors: human factors (e.g., speed infringements, distraction), driver's characteristics (e.g., age and gender), conditioning factors (vehicle type, road type, collision type and the visibility of the driver) and seat belt use, the latter belongs to the human factors, but it

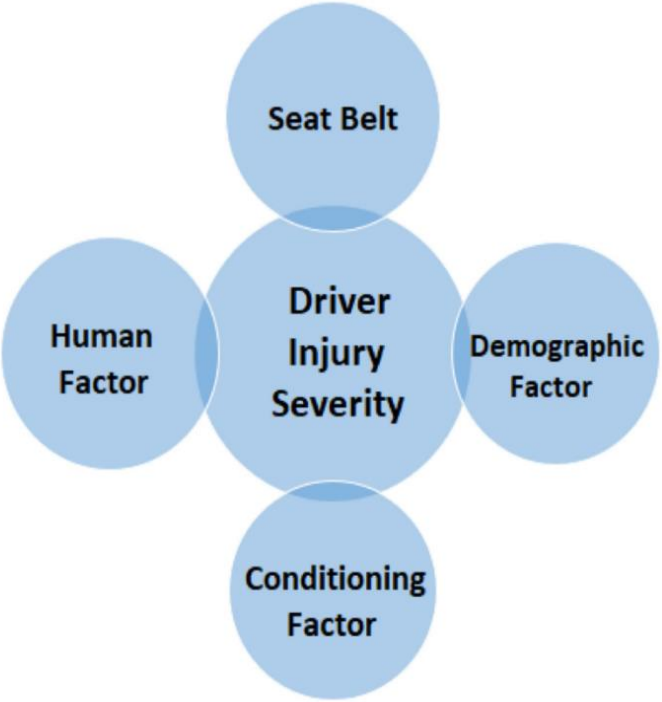


Fig. 1 Principal risk factors

has been studied separately. Figure 1, depicts the potential risk factors that can affect the driver's accident severity.

4.4 METHODOLOGY

4.4.1 FACTORS USED IN DISCRETIZATION MODEL

Figure 2 shows a list of factors in the discretization model. The seat belt factor refers to the drivers that have access to use the seat belt depending on the type of car they drive; this variable is very important as it only limits the study to the vehicles that have a built-in safety belt (For example, data related to motorcycle accidents, bikes accidents, etc. were not considered). The demographic factors included 2 types of variables: age and gender. The variable 'gender' remains the same as mentioned in the police accident report. However, the variable 'age'has been grouped into four different age groups; less than 25, 26 to 40, 41 to 60, and over 60.

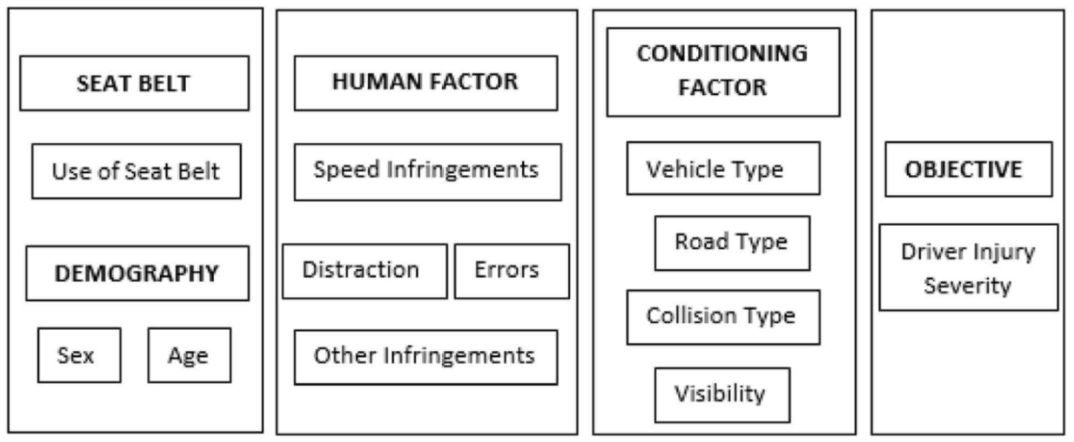


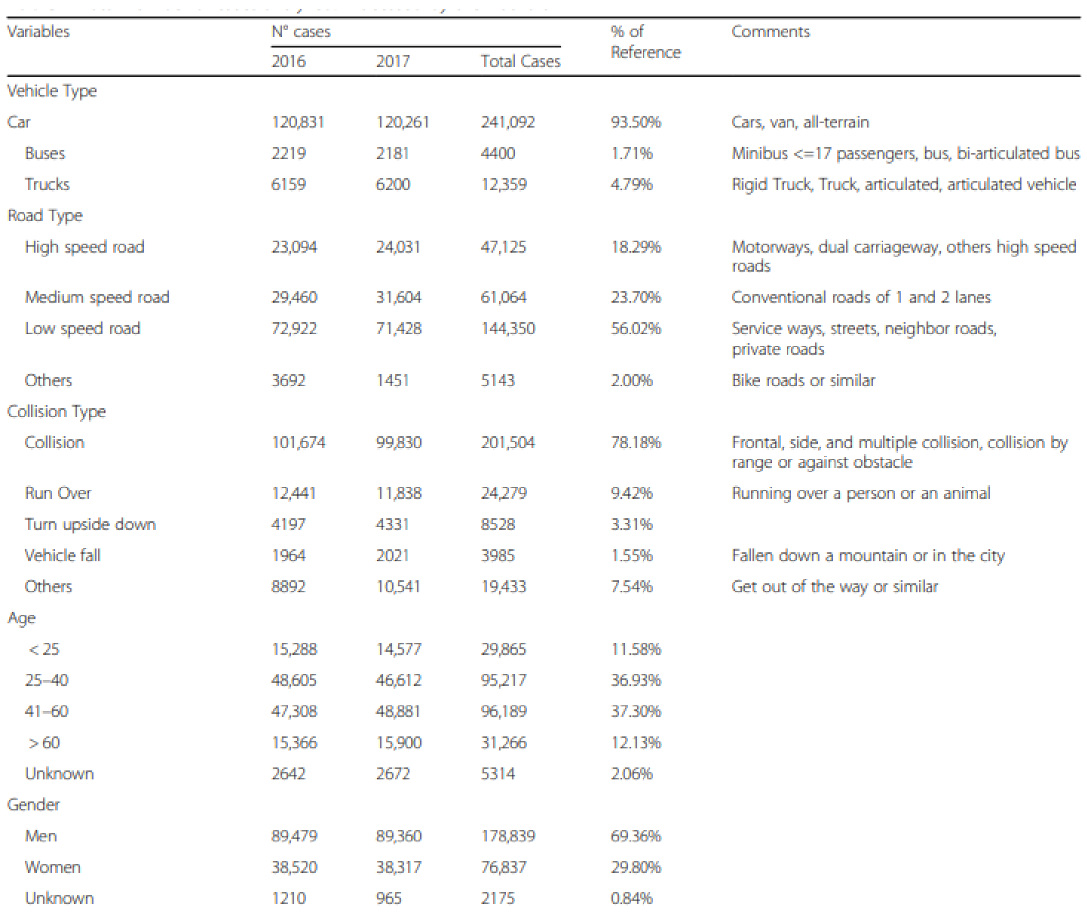
Fig. 2 Factors used in discretization Model

The human factor has been grouped in 4 class variables: speed infringements, distraction, errors and other type of infringements. The variable "speed infringements" has the same four states as shown in the police accident report; the first state is (a) none, indicating that the driver was driving with proper speed. (b) inadequate speed, that refers to exceeding speed in relation to the road condition, for example, a speed limit on a roadway might be 50 km/hr., but driving 45 km/hr. on icy roads could be dangerous. (c) over speed limit, which refers to the situation that the driver was driving over the allowable limit speed. (d) below the standard, that is the driver was driving the vehicle too slow. The group of the variables "errors" and "distraction" indicate that the driver did not make any error or were not distracted (errors occurs when the drivers do not see a traffic sign, a vehicle, a pedestrian, an obstacle, etc.). Finally, the variable "other type of infringements", has also four states; (a) the first sate is 'none' which indicates that the driver didn't commit a specific infringement. (b) the second group indicate that the driver disrespected traffic signals. (c) the third state shows that the driver disrespected traffic norms. (d) fourth state indicates if the driver makes a reckless maneuver. All the errors and distractions included in the analysis are shown in the section of comments in Table 1.

The conditioning factor has been grouped in 4 types of variables: Vehicle type, road type, collision type and the visibility of the driver. The variable vehicle type has been discretized in 3 groups: cars, buses and trucks as they have built-in safety belt. The road type variable indicates that in what type of road occurs the traffic accident, is grouped in high-speed road, medium speed road and low speed road. The variable collision type is grouped in four states that are: collision, run over, turn upside down and vehicle fall. Finally, the variable visibility has been discretized in adequate visibility, inadequate visibility and unknown. All these variables have specific content that are shown in Table 1.

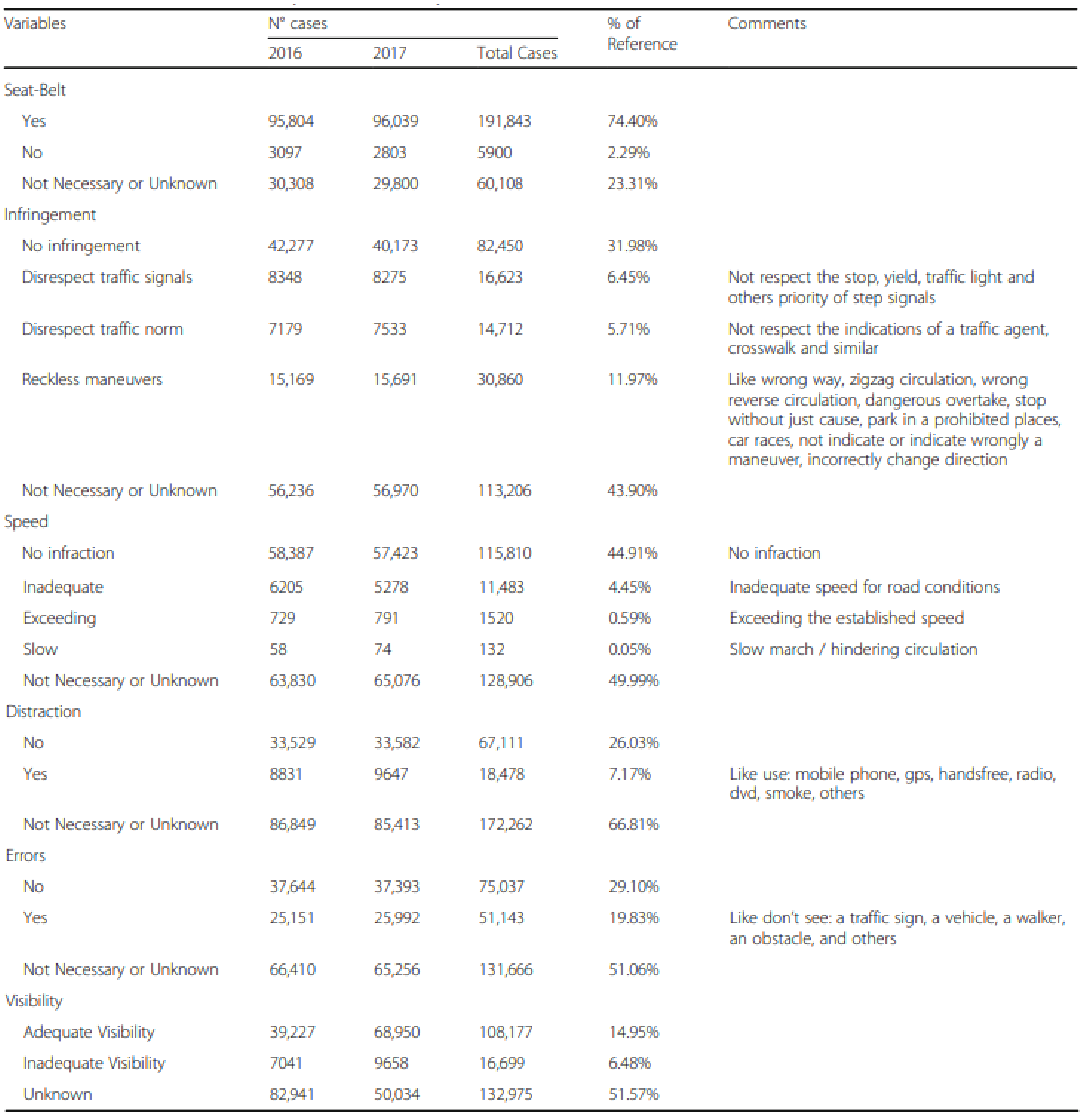
Lastly, the dependent variable is driver’s injury severity. Although MAIS3+ index measures the severity of injuries and is internationally recognized, in this study a variable is created that measures the severity of injuries from the data provided by the DGT. This variable has two values: firstly ‘light’ if the driver was slightly injured or unhurt, and secondly ‘KSI’ if the driver was either killed or seriously injured. It is noteworthy to mention that this study merely focus on driver’s injury severity in relation to the seat belt use.

Table 1: Total number of cases analyzed. Processed by the Authors



Variables	N° cases			% of Reference	Comments
	2016	2017	Total Cases		
Vehicle Type					
Car	120,831	120,261	241,092	93.50%	Cars, van, all-terrain
Buses	2219	2181	4400	1.71%	Minibus <=17 passengers, bus, bi-articulated bus
Trucks	6159	6200	12,359	4.79%	Rigid Truck, Truck, articulated, articulated vehicle
Road Type					
High speed road	23,094	24,031	47,125	18.29%	Motorways, dual carriageway, others high speed roads
Medium speed road	29,460	31,604	61,064	23.70%	Conventional roads of 1 and 2 lanes
Low speed road	72,922	71,428	144,350	56.02%	Service ways, streets, neighbor roads, private roads
Others	3692	1451	5143	2.00%	Bike roads or similar
Collision Type					
Collision	101,674	99,830	201,504	78.18%	Frontal, side, and multiple collision, collision by range or against obstacle
Run Over	12,441	11,838	24,279	9.42%	Running over a person or an animal
Turn upside down	4197	4331	8528	3.31%	
Vehicle fall	1964	2021	3985	1.55%	Fallen down a mountain or in the city
Others	8892	10,541	19,433	7.54%	Get out of the way or similar
Age					
< 25	15,288	14,577	29,865	11.58%	
25–40	48,605	46,612	95,217	36.93%	
41–60	47,308	48,881	96,189	37.30%	
> 60	15,366	15,900	31,266	12.13%	
Unknown	2642	2672	5314	2.06%	
Gender					
Men	89,479	89,360	178,839	69.36%	
Women	38,520	38,317	76,837	29.80%	
Unknown	1210	965	2175	0.84%	

Table 1: Total number of cases analyzed. Processed by the Authors (Continued)



Variables	Nº cases			% of Reference	Comments
	2016	2017	Total Cases		
Seat-Belt					
Yes	95,804	96,039	191,843	74.40%	
No	3097	2803	5900	2.29%	
Not Necessary or Unknown	30,308	29,800	60,108	23.31%	
Infringement					
No infringement	42,277	40,173	82,450	31.98%	
Disrespect traffic signals	8348	8275	16,623	6.45%	Not respect the stop, yield, traffic light and others priority of step signals
Disrespect traffic norm	7179	7533	14,712	5.71%	Not respect the indications of a traffic agent, crosswalk and similar
Reckless maneuvers	15,169	15,691	30,860	11.97%	Like wrong way, zigzag circulation, wrong reverse circulation, dangerous overtake, stop without just cause, park in a prohibited places, car races, not indicate or indicate wrongly a maneuver, incorrectly change direction
Not Necessary or Unknown	56,236	56,970	113,206	43.90%	
Speed					
No infraction	58,387	57,423	115,810	44.91%	No infraction
Inadequate	6205	5278	11,483	4.45%	Inadequate speed for road conditions
Exceeding	729	791	1520	0.59%	Exceeding the established speed
Slow	58	74	132	0.05%	Slow march / hindering circulation
Not Necessary or Unknown	63,830	65,076	128,906	49.99%	
Distraction					
No	33,529	33,582	67,111	26.03%	
Yes	8831	9647	18,478	7.17%	Like use: mobile phone, gps, handsfree, radio, dvd, smoke, others
Not Necessary or Unknown	86,849	85,413	172,262	66.81%	
Errors					
No	37,644	37,393	75,037	29.10%	
Yes	25,151	25,992	51,143	19.83%	Like don't see: a traffic sign, a vehicle, a walker, an obstacle, and others
Not Necessary or Unknown	66,410	65,256	131,666	51.06%	
Visibility					
Adequate Visibility	39,227	68,950	108,177	14.95%	
Inadequate Visibility	7041	9658	16,699	6.48%	
Unknown	82,941	50,034	132,975	51.57%	

4.4.2 BAYESIAN NETWORKS

Bayesian Networks (Castillo et al., 1997) are probabilistic graphical models (Koller & Friedman, 2009)based on a directed acyclic graph (DAG) which combine graphs and probability theories to efficiently learn the joint probability distribution of a multi-variate problem involving discrete variables. On the one hand, the graphical structure given by the DAG defines the dependence (conditional or no) between the different variables considered in the model. On the other hand, these dependences reflected in the DAG define a factorization of the Joint Probability Distribution (JPD):

$$p(x_1, x_2, x_3, \ldots, x_n) = \prod_{i=1}^{n} p(x_i|\pi_i) \tag{1}$$

Equation1 stands for the Joint Probability Function of the Bayesian Network, where [x1,...,xn] are the variables considered in the model and π, are the set of parents of the variable x given by the DAG. Finally, the DAG gives us a graphical and easily interpretable representation of the dependences between the variables.

Once the DAG and the JPD are obtained from the data (Neapolitan, 2004), as new knowledge is evidenced for one or several variables of the model, it is then easily propagated to the rest of the BN to get the new probabilities (inference). In particular, the sensibility of the target variable to different pre-defined scenarios, given by combinations of the rest of variables, can be quantified by the changes of the corresponding probabilities. Moreover, a Bayes Classifier (BC) can be obtained by defining a probability threshold above/below of which the severity is considered serious/light.

All the calculations in this study have been done usingthe Bayes Net (Murphy, 2001) and MeteoLab (Gutiérrez, 2004) Toolboxes forMatlab (Matlab).

4.4.3 LINEAR LOGISTIC REGRESSION

For the sake of the comparison, a linear logistic regression (Kadilar, 2016; Kononen et al., 2011; Zong et al., 2013)is considered as benchmark to assess the performance of the Bayesian network. The proposed logistic regression model is a maximum-likelihood method commonly used for a binary classification problem and is given in eq. (2):

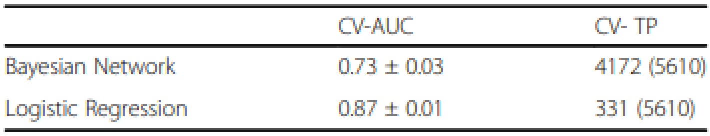
$$\mathrm{logit}(\mathrm{p}) = \log\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \cdot x_i \tag{2}$$

where p is the probability of driver being severely in-jured, and xi(i = 1,...n) refer to the variables consideredin the model.

4.4.4 VALIDATION

In order to evaluate the skill of the obtained classifier, a10-fold cross validation approach has been considered defining a partition of the sample in 10-folds containing the 10% of the total sample. For each fold a model is obtained considering the other 90% of the sample, which issued to obtain a prediction of the fold’s cases. As a result, 11 test-samples are obtained, one per fold and the latest one considering the prediction of the complete sample obtained by joining the 10 folds. Each test- sample was evaluated by using the Area Under the ROC (Fawcett, 2006)Curve (AUC), a standard measure of overall accuracy (Hanley & McNeil, 1982) for probabilistic and binary classifiers that varies from 0.5 (random guess) to 1 (perfect performance),obtaining 11 AUC values.

Table 2 AUC values and True Positives from Cross Validation (CV). Processed by authors



	CV-AUC	CV- TP
Bayesian Network	0.73 ± 0.03	4172 (5610)
Logistic Regression	0.87 ± 0.01	331 (5610)

4.5 RESULTS AND DISCUSSION

This section presents the predictions of the probability of injury and fatal injury in a traffic accident as a function of seat belt use, demographic factors, human fac-tors, and conditioning factors (type of vehicle, type of road, type of collision and the visibility of the driver). The validation of the Bayesian Network model and its corresponding graph are discussed in section 4.1. The initial probabilities are presented in section 5.2, and the sensitivity analysis results based on the Bayesian network are discussed in section 5.3 through section 5.6.

4.5.1 VALIDATION AND GRAPH

Table 2 shows the results from the Bayesian Network and Logistic Regression models and their performance have been compared using AUC including the 10-foldcross cross validation approach, and the number of True Positives (TP) given by the two methods.

Comparison of results indicates that, in spite of the better performance of the logistic regression in terms of AUC, this method strongly underestimates the number of accidents in which the drivers sustained severe injuries whereas the Bayesian Network is able to identify most of these cases. However, this can penalize the over-all accuracy as reflected by the AUC. Moreover, the resulting Bayesian Network model is unique in a way that it allows to perform sensitivity analysis and to realize the variations in the risk of driver’s injury severity due to changes in other independent variables. In contrast, as the proportion of drivers with fatal/severe injury in accident dataset is low, use of logistic regression would result in biased parameter estimates and subsequently inaccurate sensitivity analysis. Additionally, including many variables with different states to the logistic model would increase the complexity of the analysis and limit the interpretability of the results. As a result, the Bayesian Network model is used as a preferred model in the rest of the paper.

The uncertainty of the predictions obtained with the Bayesian model is based on the cross-validation step de-scribed in Section 3.4. However, the overall prediction ability of the model may not be consistent with the specific cases considered in the sensitivity analysis. To address this issue, the measure of fit (the percentage of the observations that is correctly predicted by the model) for each subsample related to each sensitivity analysis has been estimated and evaluated using cross-validation procedure. In this sense, the measure of fit estimated for severe injuries falls between 84% and 91% whereas for no injuries it falls between 87% and 95%,reflecting the uncertainty of the predictions.

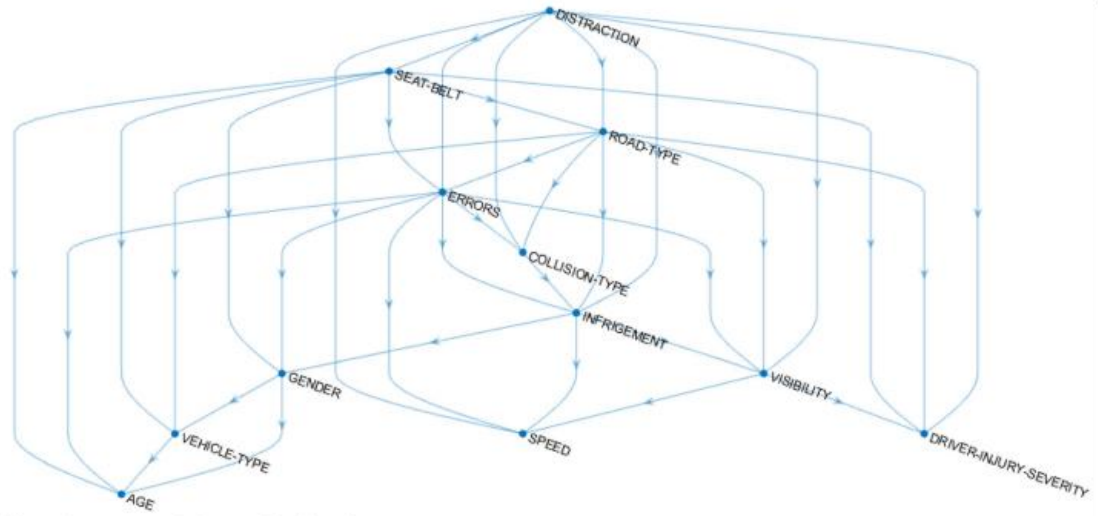


Fig. 3 Bayesian network. Processed by the authors

As shown in Fig.3, the Bayesian Network graph depicts the significant dependencies among the variables. For example, seat belt, road type, visibility and distraction, are the only variables directly related to the dependent variable, driver injury severity. Hence, a joint analysis of is carried out on these four variables.

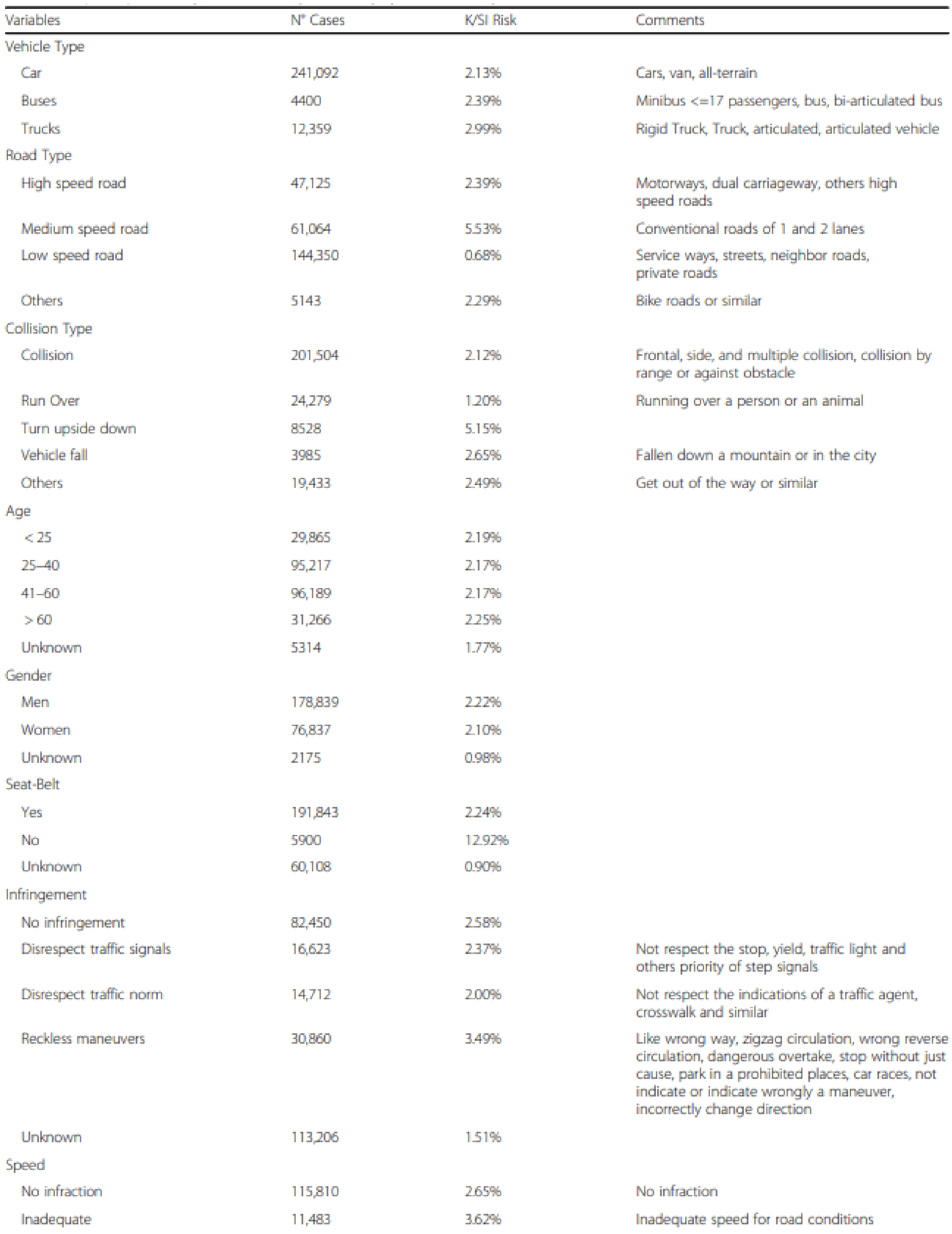
As indicated in Fig.3, The graph represents the inter-actions among all the variables and gives information about how these variables relate to each other. This demonstrates that the network takes information from the whole data.

4.5.2 INITIAL PROBABILITIES OF SERIOUS INJURY IN A TRAFFIC ACCIDENT

The study starts with a sensitivity analysis, based on the Bayesian model, to estimate the initial probabilities of suffering a serious or fatal injury for the drivers (which his called risk probability “KSI Risk”) compared to minor injuries in each of the variables and model States. The results for each variables and states are summarized in Table 3.

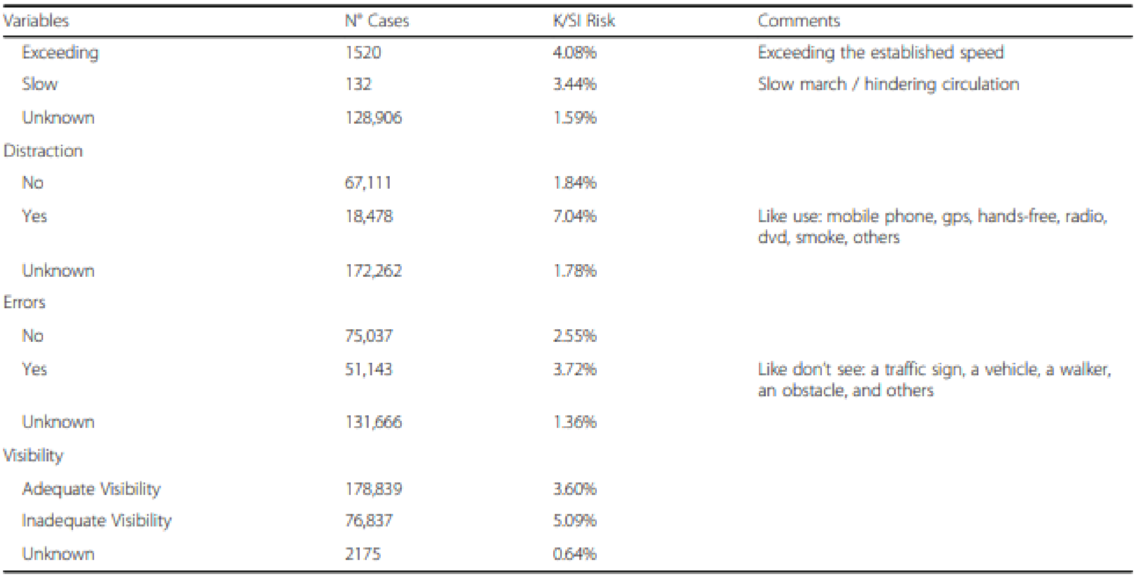
By getting the initial probabilities from the sensitivity analysis, the most influential variables are as follows: Seat Belt (especially those who do not use seat-belt),Distraction (especially the group of drivers with distractions), Road type (especially the group of medium and high speed roads), Visibility (especially with inadequate visibility), and Speed (especially those who exceeded the speed limits). The ‘a priori’ probabilities of suffering a serious and / or fatal injury in a traffic accident reach its highest level (12.92%) because of seat belt non-use (this does not account for the effects of other variables yet). This finding reinforces the study argument that seat belt use is the most influential variable.

Table 3 A priori probability of the severity of the injury. Processed by the Authors



Variables	N° Cases	K/SI Risk	Comments
Vehicle Type			
Car	241,092	2.13%	Cars, van, all-terrain
Buses	4400	2.39%	Minibus <=17 passengers, bus, bi-articulated bus
Trucks	12,359	2.99%	Rigid Truck, Truck, articulated, articulated vehicle
Road Type			
High speed road	47,125	2.39%	Motorways, dual carriageway, others high speed roads
Medium speed road	61,064	5.53%	Conventional roads of 1 and 2 lanes
Low speed road	144,350	0.68%	Service ways, streets, neighbor roads, private roads
Others	5143	2.29%	Bike roads or similar
Collision Type			
Collision	201,504	2.12%	Frontal, side, and multiple collision, collision by range or against obstacle
Run Over	24,279	1.20%	Running over a person or an animal
Turn upside down	8528	5.15%	
Vehicle fall	3985	2.65%	Fallen down a mountain or in the city
Others	19,433	2.49%	Get out of the way or similar
Age			
< 25	29,865	2.19%	
25–40	95,217	2.17%	
41–60	96,189	2.17%	
> 60	31,266	2.25%	
Unknown	5314	1.77%	
Gender			
Men	178,839	2.22%	
Women	76,837	2.10%	
Unknown	2175	0.98%	
Seat-Belt			
Yes	191,843	2.24%	
No	5900	12.92%	
Unknown	60,108	0.90%	
Infringement			
No infringement	82,450	2.58%	
Disrespect traffic signals	16,623	2.37%	Not respect the stop, yield, traffic light and others priority of step signals
Disrespect traffic norm	14,712	2.00%	Not respect the indications of a traffic agent, crosswalk and similar
Reckless maneuvers	30,860	3.49%	Like wrong way, zigzag circulation, wrong reverse circulation, dangerous overtake, stop without just cause, park in a prohibited places, car races, not indicate or indicate wrongly a maneuver, incorrectly change direction
Unknown	113,206	1.51%	
Speed			
No infraction	115,810	2.65%	No infraction
Inadequate	11,483	3.62%	Inadequate speed for road conditions

Table 3 A priori probability of the severity of the injury. Processed by the Authors



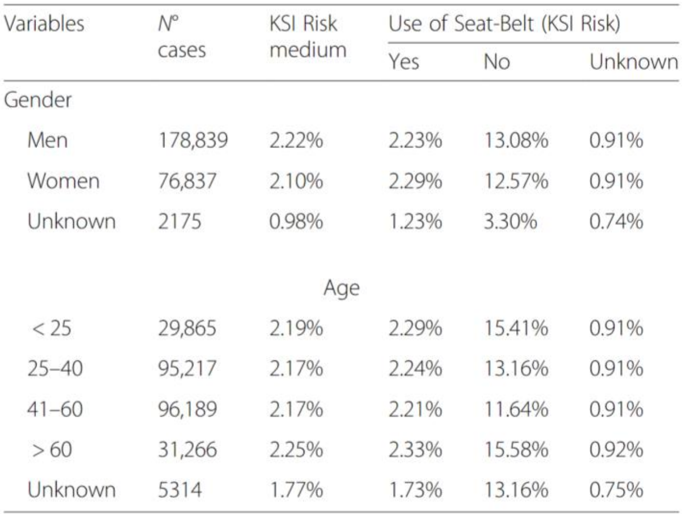
Variables	N° Cases	K/SI Risk	Comments
Exceeding	1520	4.08%	Exceeding the established speed
Slow	132	3.44%	Slow march / hindering circulation
Unknown	128,906	1.59%	
Distraction			
No	67,111	1.84%	
Yes	18,478	7.04%	Like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
Unknown	172,262	1.78%	
Errors			
No	75,037	2.55%	
Yes	51,143	3.72%	Like don't see: a traffic sign, a vehicle, a walker, an obstacle, and others
Unknown	131,666	1.36%	
Visibility			
Adequate Visibility	178,839	3.60%	
Inadequate Visibility	76,837	5.09%	
Unknown	2175	0.64%	

The other variables which are associated with high serious/fatal injury probabilities are driving distractedly(7.04%), road type, specifically conventional roads with 1and 2 lanes (5,53%), rollover accident (5,15%), inadequate visibility (5,09), speeding (4.08%) and making errors while driving (3,72%), implying that the drivers without seat belt are likely to have a fatal or serious in-jury when the vehicle is rollover or when they drive on medium speed roadway.

4.5.3 PROBABILITY OF SERIOUS INJURY IN A TRAFFIC ACCIDENT BASEDON THE USE OF SEAT BELT AND THE DEMOGRAPHIC FACTOR

In this section demographic variables such as gender and age have been used to estimate the KSI probabilities given seat belt use. From Table 4, it can be understood that seat belt non-use would increase the risk of fatal or serious injury in men, women and all age groups more than 5 times, compared to seat belt use. Specifically, for “gender”, the higher risk of suffering a serious and / or fatal injury is associated with the male drivers without seat belt, reaching (13.08%). As with “age”, drivers under 25 and over 60 who do not use seat belts are more likely to sustain fatal or serious injury in a traffic accident. While driver between 41 and 60 have higher risk of fatality or serious injury compared to other age groups.

Table 4. Probabilities of suffering a serious injury, depending on the use of seat belt and the different variables of the demographic factor. Processed by the Authors.



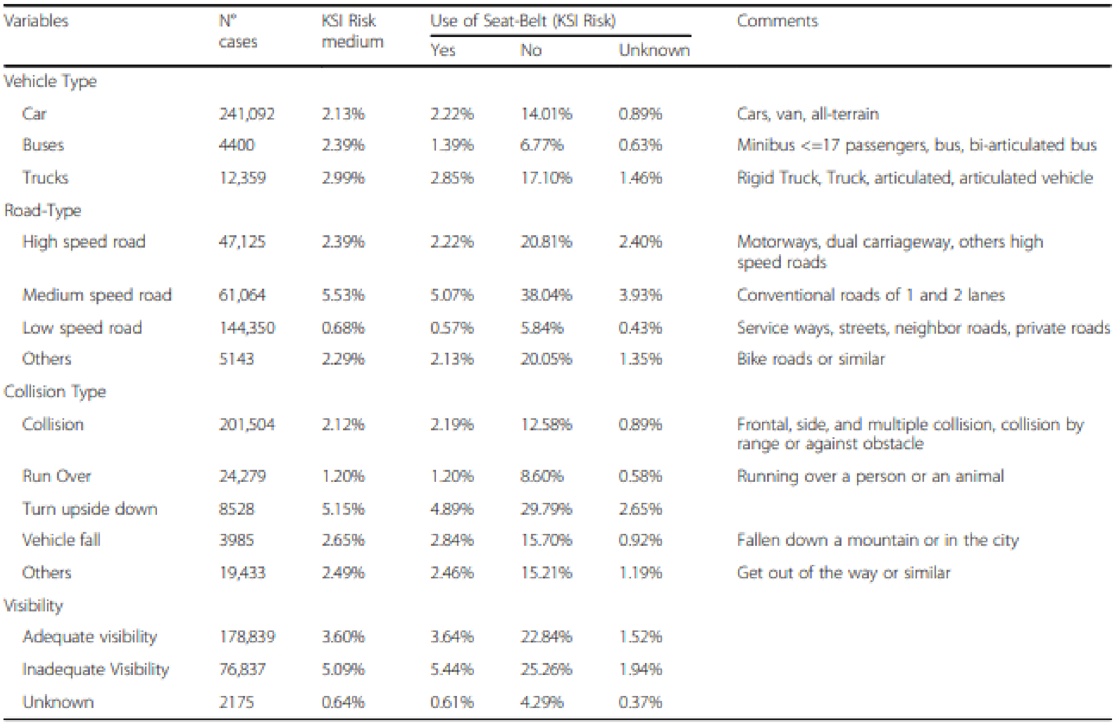
Variables	N° cases	KSI Risk medium	Use of Seat-Belt (KSI Risk)		
			Yes	No	Unknown
Gender					
Men	178,839	2.22%	2.23%	13.08%	0.91%
Women	76,837	2.10%	2.29%	12.57%	0.91%
Unknown	2175	0.98%	1.23%	3.30%	0.74%
Age					
< 25	29,865	2.19%	2.29%	15.41%	0.91%
25–40	95,217	2.17%	2.24%	13.16%	0.91%
41–60	96,189	2.17%	2.21%	11.64%	0.91%
> 60	31,266	2.25%	2.33%	15.58%	0.92%
Unknown	5314	1.77%	1.73%	13.16%	0.75%

4.5.4 PROBABILITY OF SERIOUS INJURY IN A TRAFFIC ACCIDENT BASEDON THE USE OF SEAT BELT AND THE CONDITIONING FACTOR

To analyze the probability of a serious and / or fatal in-jury (KSI risk) based on conditioning factor and seat belt use, a sensitivity analysis was carried out with respect to the variables “vehicle type”, “road type”, “collision type” and “visibility” in all its states.

As shown in Table 5 the difference between the prob-ability of suffering a serious and / or fatal injury in a traffic accident with and without seat belt use are significant. As with “vehicle type”, truck drivers without safety belt have the highest risk of fatality and serious injury (please refer to the comments in Table 5). While bus drivers without seat belt are in lower risk of fatality or serious injury. One possible reason is that, on average, the bus drivers may travel slower compared to truck and car drivers as they carry may passengers. Also, for the “road type “variable, the two states, high and medium speed roads are found to contribute to the risk of injury and fatality of drivers who do not use seat belt. For the variable “collision type”, it is clearly evident that a turn upside down traffic accident is the most dangerous situation and unbelted drivers would have an increased risk of fatality /serious injury (up to 29.79%). This could be reasonable as the risk of ejection for unbelted drivers would be high in rollover crashes. Also, from the results, “vehicle fall “is the second dangerous type of collision that threaten the life of driver who do not use seat belt. Finally, for “visibility” variable, in the two states, the prob-ability of suffering a serious injury increases dramatically.

Table 5. Probabilities of suffering a serious injury, depending on the use of seat belt and the different variables of the conditioning factor. Processed by the Authors



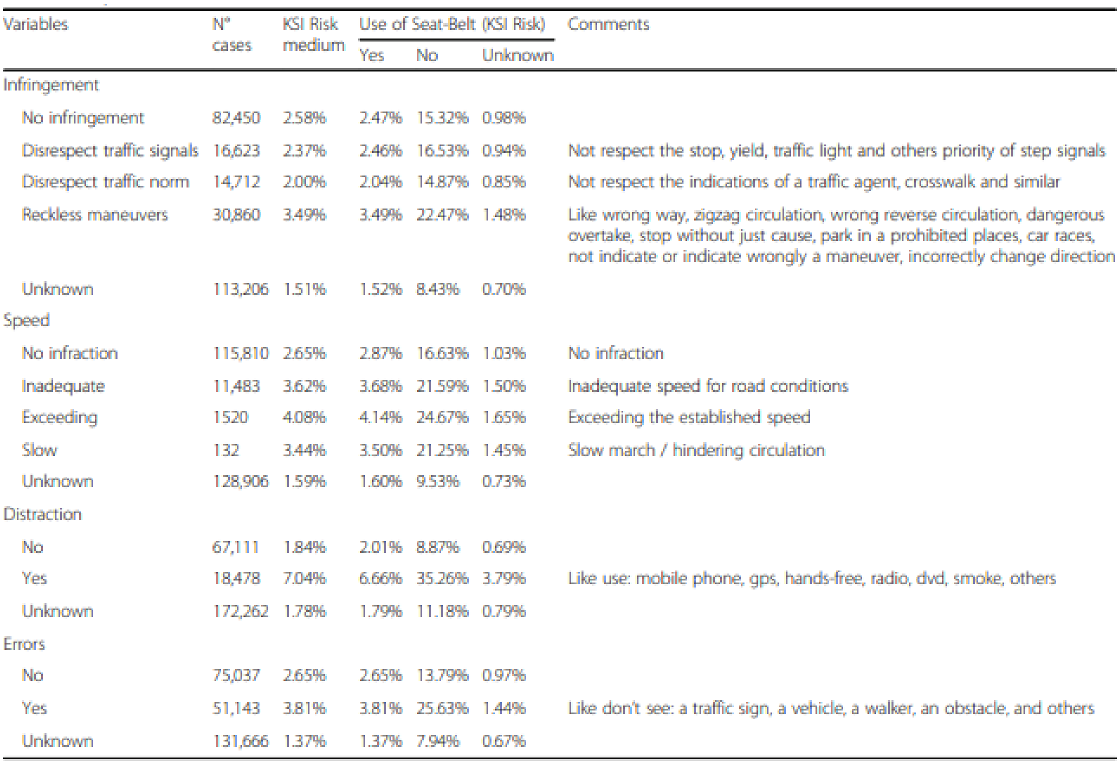
Variables	N° cases	KSI Risk medium	Use of Seat-Belt (KSI Risk)			Comments
			Yes	No	Unknown	
Vehicle Type						
Car	241,092	2.13%	2.22%	14.01%	0.89%	Cars, van, all-terrain
Buses	4400	2.39%	1.39%	6.77%	0.63%	Minibus <=17 passengers, bus, bi-articulated bus
Trucks	12,359	2.99%	2.85%	17.10%	1.46%	Rigid Truck, Truck, articulated, articulated vehicle
Road-Type						
High speed road	47,125	2.39%	2.22%	20.81%	2.40%	Motorways, dual carriageway, others high speed roads
Medium speed road	61,064	5.53%	5.07%	38.04%	3.93%	Conventional roads of 1 and 2 lanes
Low speed road	144,350	0.68%	0.57%	5.84%	0.43%	Service ways, streets, neighbor roads, private roads
Others	5143	2.29%	2.13%	20.05%	1.35%	Bike roads or similar
Collision Type						
Collision	201,504	2.12%	2.19%	12.58%	0.89%	Frontal, side, and multiple collision, collision by range or against obstacle
Run Over	24,279	1.20%	1.20%	8.60%	0.58%	Running over a person or an animal
Turn upside down	8528	5.15%	4.89%	29.79%	2.65%	
Vehicle fall	3985	2.65%	2.84%	15.70%	0.92%	Fallen down a mountain or in the city
Others	19,433	2.49%	2.46%	15.21%	1.19%	Get out of the way or similar
Visibility						
Adequate visibility	178,839	3.60%	3.64%	22.84%	1.52%	
Inadequate Visibility	76,837	5.09%	5.44%	25.26%	1.94%	
Unknown	2175	0.64%	0.61%	4.29%	0.37%	

4.5.5 PROBABILITYOF SERIOUS INJURY IN A TRAFFIC ACCIDENT BASED ON THE USE OF SEAT BELT AND THE HUMAN FACTOR

In this section four types of variables, including “infringement”, “speed”, “distraction” and “errors” were considered to estimate the probability of a serious and /or fatal injury (KSI risk) given seat belt use. From Table 6, comparison of the estimated probabilities under seat belt use and non-use conditions shows that un-belted drivers significantly have higher risk of fatality or serious injury compared to belted drivers.

For the variable “infringement”, unbelted drivers making reckless maneuvers or failing to comply with traffic signal have higher risk of fatality or injury. That’s because this action generally lead to serious accident (e.g., side accidents). In the specific case of speed infringements, the drivers committed any speed infringements have higher risk probabilities than drivers who complied with speed limits. Especially driving over the speed limit is the most dangerous situation if the driver does not use the seat belt. In the case of the “distraction” and “error”, drivers who drive distractedly or with errors will have higher risk of fatality than drivers who drive without distraction or mis-takes. However, such risk would be increased significantly if the driver does not use the seat belt.

Table 6 Probabilities of suffering a serious injury, depending on the use of seat belt and the different variables of the human factor. Processed by the Authors

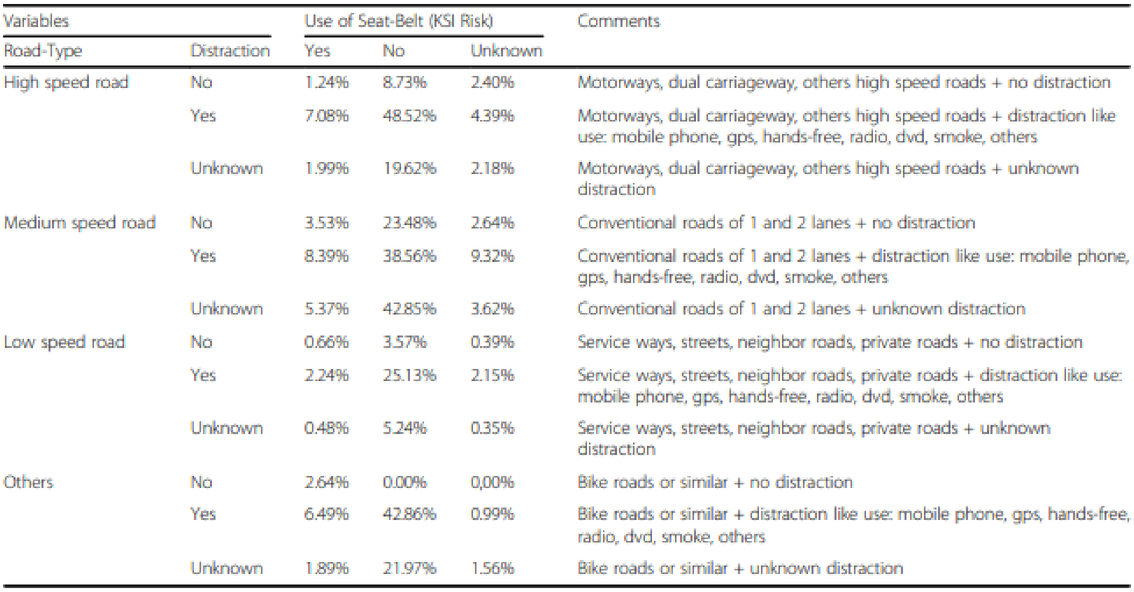


Variables	N° cases	KSI Risk medium	Use of Seat-Belt (KSI Risk)			Comments
			Yes	No	Unknown	
Infringement						
No infringement	82,450	2.58%	2.47%	15.32%	0.98%	
Disrespect traffic signals	16,623	2.37%	2.46%	16.53%	0.94%	Not respect the stop, yield, traffic light and others priority of step signals
Disrespect traffic norm	14,712	2.00%	2.04%	14.87%	0.85%	Not respect the indications of a traffic agent, crosswalk and similar
Reckless maneuvers	30,860	3.49%	3.49%	22.47%	1.48%	Like wrong way, zigzag circulation, wrong reverse circulation, dangerous overtake, stop without just cause, park in a prohibited places, car races, not indicate or indicate wrongly a maneuver, incorrectly change direction
Unknown	113,206	1.51%	1.52%	8.43%	0.70%	
Speed						
No infraction	115,810	2.65%	2.87%	16.63%	1.03%	No infraction
Inadequate	11,483	3.62%	3.68%	21.59%	1.50%	Inadequate speed for road conditions
Exceeding	1520	4.08%	4.14%	24.67%	1.65%	Exceeding the established speed
Slow	132	3.44%	3.50%	21.25%	1.45%	Slow march / hindering circulation
Unknown	128,906	1.59%	1.60%	9.53%	0.73%	
Distraction						
No	67,111	1.84%	2.01%	8.87%	0.69%	
Yes	18,478	7.04%	6.66%	35.26%	3.79%	Like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
Unknown	172,262	1.78%	1.79%	11.18%	0.79%	
Errors						
No	75,037	2.65%	2.65%	13.79%	0.97%	
Yes	51,143	3.81%	3.81%	25.63%	1.44%	Like don't see: a traffic sign, a vehicle, a walker, an obstacle, and others
Unknown	131,666	1.37%	1.37%	7.94%	0.67%	

4.5.6 PROBABILITY OF SERIOUS INJURY IN A TRAFFIC ACCIDENT BASEDON THE USE OF SEAT BELT AND THE MOST INFLUENTIAL VARIABLESIN DRIVER INJURY SEVERITY

As explained in the section 4.2, seat belt use, distraction and road type, are the variables most directly related to the driver injury severity. Hence, this section presents a simultaneous analysis of these influential factors summarized in Table7. Starting with the "high speed road "state from "road type "variable, it can be observed that the higher risk of fatality (which is associated with probability of 48.52%)occurs when a driver has a distraction, does not use the seatbelt and is driving in a high speed road, like a motorway or similar (please observe the comments in Table7). As 48.52% is the highest value in this study, therefore this would be one of the most dangerous situation in a traffic accident. In contrast, when the driver is unbelted, has a dis-traction and is deriving on low speed road, the risk of fatal-ity or serious injury would be as low as 25%. This implies that the lower the driving speed the lower the impact speed which can reduce the risk of severe injury.

Table 7 Probabilities of suffering a serious accident, depending on the use of seat belt and the most influential variables in driver injury severity. Processed by the Authors



Variables		Use of Seat-Belt (KSI Risk)			Comments
Road-Type	Distraction	Yes	No	Unknown	
High speed road	No	1.24%	8.73%	2.40%	Motorways, dual carriageway, others high speed roads + no distraction
	Yes	7.08%	48.52%	4.39%	Motorways, dual carriageway, others high speed roads + distraction like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
	Unknown	1.99%	19.62%	2.18%	Motorways, dual carriageway, others high speed roads + unknown distraction
Medium speed road	No	3.53%	23.48%	2.64%	Conventional roads of 1 and 2 lanes + no distraction
	Yes	8.39%	38.56%	9.32%	Conventional roads of 1 and 2 lanes + distraction like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
	Unknown	5.37%	42.85%	3.62%	Conventional roads of 1 and 2 lanes + unknown distraction
Low speed road	No	0.66%	3.57%	0.39%	Service ways, streets, neighbor roads, private roads + no distraction
	Yes	2.24%	25.13%	2.15%	Service ways, streets, neighbor roads, private roads + distraction like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
	Unknown	0.48%	5.24%	0.35%	Service ways, streets, neighbor roads, private roads + unknown distraction
Others	No	2.64%	0.00%	0,00%	Bike roads or similar + no distraction
	Yes	6.49%	42.86%	0.99%	Bike roads or similar + distraction like use: mobile phone, gps, hands-free, radio, dvd, smoke, others
	Unknown	1.89%	21.97%	1.56%	Bike roads or similar + unknown distraction

4.6 CONCLUSIONS

This study aimed to analyze the driver’s injury severity as a function of seat belt use and other human factors.

Analysis of data showed that the high probability ‘apriori’ of serious and fatal injury, 12.92%, happens when the driver does not use the seat belt. In addition to “seatbelt”, the variables that are directly connected with the driver injury severity are “distraction” and “road type” which have a priori probability of risk of 7.04% and5.53% respectively.

Regarding the demographic factor (sex and age), male drivers and the drivers under 25 and over 60 years old are more likely to suffer a serious and / or a fatal injury in a traffic accident. As with male drivers, being under25 or over 60 and failing to wear the seat belt can in-crease the risk of death or severe injury to 15,41% and15.58% respectively. For conditioning factor, the most worrisome case is when the driver is driving on a medium speed road without seat belt. Among the “collision type” and “vehicle type” States, the risk of sustaining a serious injury increases when the traffic accident is a “turn upside down “and the driver is driving a “truck”. Also, when the drivers do not wear a seat belt, the prob-ability of suffering a serious/fatal injury increases significantly, which is consistent with previous study [4]. In addition to “seat belt use”, distraction and high-speed road are the most influential variables when the driver is not using the seat belt. These findings are consistent with previous works conducted around the world, implying that human factors along with other factors such as road and vehicle type are the major causes of road accident (Yaacob et al., 2018).

The majority of previous works on traffic safety adopted frequentist approaches (e.g., multivariate regression, logit models, etc.) to assess the impact of “seat belt use “in combination with other factors on injury severity. In this research, we compared the performance of the Logistic Regression and Bayesian Network using their estimated AUCs. In spite of the better performance of the Logistic Regression in terms of AUC (0.87 for Logistic Regression versus 0.73 for Bayesian Network), the Bayesian Network better estimates the number of accidents in which the drivers sustained severe injuries (4172 of 5610 for Bayesian Network versus 331 of 5610for Logistic Regression). Moreover, the proposed Bayesian Network model provides the probabilities for injuryvseverity while accounting for the interactions among the variables (especially influential variables such as seat belt use, distraction, and road type).

This study’s findings can be used by transportation authorities and decision makers in order to establish effect-ive policies. For example, it is recommended to; (a) use incentive and educational programs for young and old adults to promote their awareness about the seat belt use, (b) obligate the car manufacturers to equip the vehicles with seat belt interlock devices to prevent the car from being started unless front seat occupants have fastened their safety belts, (c) obligate the car manufactures to reduce the risk of distraction from electronic systems in vehicles, and (d) increase the security checkpoints and roadside cameras on high-speed roadways.

ACKNOWLEDGEMENTS

We would like to thank the Traffic Department (Dirección General de Tráfico)for providing us with the data used in this study and for its help through theSPIP2015-1852 research project. Also, we would like to thank the Regional Government of Castilla y León (Junta de Castilla y León) for funding this re-search project BU300P18.

AUTHORS CONTRIBUTIONS

Conceptualization: SG-H and JDF; Data curation: SG-H, SH and JF; Funding acquisition: SG-H; Investigation: SG-H, JDF and JMG; Supervision: JMG and SG; Writing: JDF, SG-H and SH; Writing–review & editing: JRL-G and MÁM. All authors read and approved the final manuscript.

FUNDING

This research is part of the project “Modelización mediante técnicas demachine learning de la influencia de las distracciones del conductor en laseguridad vial”, with the reference BU300P18 and supported by funds from FEDER (Fondo Europeo de Desarrollo Regional - Junta de Castilla y León).

AVAILABILITY OF DATA AND MATERIALS

The institution in Spain on charge to register the road traffic accidents and the injuries derived from them is the “Dirección General de Tráfico (DGT)”.This institution provide the data base used in this study. The microdata files can be obtained through the following link: http://www.dgt.es/es/seguridad-vial/estadisticas-e-indicadores/ficheros-microdatos-accidentalidad/

COMPETING INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication title “Influence of the seat-belt use on the severity of the injury in traffic accidents”. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

REFERENCES

(DOI: 10.1186/s12544-020-0401-5)

5. ARTÍCULO 3: AN INVESTIGATION INTO UNSAFE BEHAVIORS AND TRAFFIC ACCIDENTS INVOLVING UNLICENSED DRIVERS: A PERSPECTIVE FOR ALIGNMENT MEASUREMENT. A PERSPECTIVE FOR ALIGNMENT MEASUREMENT

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Journal: International Journal of Environmental Research and Public Health

Published: 16 September 2020

Accesible at: https://doi.org/10.3390/ijerph17186743

Keywords: alignment; regulatory; behaviors; drivers; Bayesian; network; traffic; accidents; unlicensed; unsafe

5.1 ABSTRACT

Road traffic plays a vital role in countries' economic growth and future development. However, traffic accidents are considered a major public health issue affecting humankind. Despite efforts by governments to improve traffic safety, the misalignment between the policy efforts and on-ground infringements, distractions and breaches reflect the regulatory failure. This paper uses the Bayesian network method to investigate unsafe behaviors and traffic accidents involving unlicensed drivers as a perspective for the regulatory alignment assessment. The findings suggest that: (1) unlicensed drivers are more likely to have unsafe driving behaviors; (2) the probability of being involved in a severe traffic accident increases when the drivers are unlicensed and decreases in the case of licensed drivers; (3) young drivers are noticeably more likely to engage in unsafe behaviors, usually leading to serious injuries and deaths, when their driving licenses are invalid; (4) women are more likely to engage in right-of-way violations and to have collisions with no serious injuries, contrary to unlicensed men drivers, who are involved in other types of traffic accidents resulting inserious injuries.

5.2 INTRODUCTION

Traffic safety has become a major public health concern all around the world (Alghuson et al., 2019; S. Useche et al., 2018; Uzondu et al., 2019). The traffic safety problem is multidimensional, and many risk factors, i.e., technical factors (vehicles), environmental factors (the road and infrastructures), human factors (the road users) and their interactions, contribute to causing crashes (Das et al., 2015; Luo et al., 2020; Oviedo-Trespalacios &

Scott-Parker, 2018) Generally, two approaches to traffic safety studies have been established so far (Hong et al., 2020; Seibokaite et al., 2020). The first approach focuses on advancing engineering and enhancing traffic infrastructures, and the second approach is interested in the driver's individual factors

and driving behaviors. Indeed, these two approaches are complementary to each other within the systems perspective of Vision Zero (Kim et al., 2017). This global vision is conditioned by the efficiency of the abovementioned approaches and involves a mix of initiatives to address safe mobility issues, i.e., vehicle safety, safety of infrastructures and promotion of road users' behaviors (Safarpour et al., 2020; Tingvall & Haworth, 1999).

In recent years, governments all around the world have undertaken several initiatives to enhance the traffic safety through (Castillo-Manzano & Castro-Nuno, 2012; Wang et al., 2013): (1) preventive measures in terms of education and information (i.e., communication campaigns and road safety advertisements); (2) corrective or sanctioning measures (i.e., coactive dissuasion and severe criminal penalties); (3) softer regulations based on economic sanctions (i.e., fines and insurance payments); and (4) license deprivation sanctions (i.e., suspension or withdrawal). Although the fundamental purpose of these regulations is to manipulate the conditions to change drivers' behaviors and improve the results, the misalignment between policy efforts and breaches and on-ground traffic accidents reflects regulatory failure (Payani & Law, 2020), hence the importance of the regulatory alignment assessment.

Regulatory alignment has firstly been used in the industrial workplace context and refers to the supportive attitudes, alignment and adherence to safety guidelines and policies to maintain an acceptable level of safety at the workplace (Bartel & Barclay, 2011; Chung, 2018). To assess regulatory alignment, two main approaches have been adopted. The first approach, reactive in nature, investigates the outcomes of the implemented regulations (i.e., the number of accidents and fatalities), and the second approach, which is proactive, considers the assessment of the unsafe behaviors of the drivers, for instance, unlicensed driving, poor driving practices, disregarding the traffic signals and signs, and deliberate deviations from the recommended safe behaviors (Dodoo & Al-Samarraie, 2019; TABLE et al.). The first approach has been criticized due to its reactive nature and the fact that it cannot provide early warning information to empower authorities to take action prior to accidents. Thus, there has been a shift towards using leading indicators, such as unsafe behaviors, to more effectively measure the regulatory alignment and secure traffic safety goals (Sacchi & Sayed, 2016; Tong et al., 2020).

Extensive studies have recognized the contribution of unsafe driving behaviors in traffic accidents and emphasized their overrepresentation in crashes, injuries and mortalities (Elliott et al., 2008). A review conducted to analyze 10 years of data (2005−2014) of fatal road crashes noted that unlicensed drivers were involved in 10% of fatal road crashes (Sagberg, 2018). Likewise, an epidemiological study conducted in Japan on risk factors of fatality in traffic accidents found that the risk of fatal traffic accidents was higher among the unlicensed drivers (Shibata & Fukuda, 1994). It is noteworthy that when addressing unsafe driving behaviors, many research studies tended to examine the influence of additional risk factors (e.g., individual factors) as a way to characterize the traffic accidents. For instance, a study analyzing the changes in driving behaviors (Soliman et al., 2018) found a significant relationship between the age and gender of the drivers and unsafe behaviors, i.e., violations, errors and lapses. Further, an analysis study of traffic accidents in China (Zhang et al., 2016)asserted that males are overconfident, risk takers and less likely to respect traffic laws, and concluded that these drivers are at high risk of causing fatigue-related crashes.

Although much valuable knowledge has been obtained from the afore mentioned studies, there is still little known about the relationship between unlicensed driving and other aberrant behaviors, on the one hand, and regulatory alignment and traffic accidents, on the other hand. To extend research beyond these trends, this paper conceptualizes the assessment of regulatory alignment of drivers considering the driving performance of unlicensed drivers.

There are good reasons to consider unlicensed driving an isolated risk behavior and to assess its moderating effect on the regulatory alignment. First, unlicensed driving negatively impacts the integrity of the driving management system (Watson, 1997). That is to say, due to its illegal nature, it is difficult to estimate the driving performance of unlicensed drivers and their qualifications. Second, even though driving without a valid driving license is said to play an indirect causative role in traffic accidents, it is noteworthy that for many countries, it is still a serious problem, and many researchers (Farris et al., 1997; Hanna et al., 2013; Watson et al., 2011) have suggested that there are behavioral differences between the aligned and the misaligned drivers that might be responsible for traffic accidents and their severe consequences. Finally, the purpose of the driving licensing system is identifying, monitoring and enforcing drivers’ behaviors using many programs and technologies (e.g., speed cameras) to facilitate the application of penalties and sanctions to traffic offenders. However, unlicensed driving is outside the licensing system, and it prevents authorities from tracking and managing unsafe behaviors (Watson, 2002).

This study investigates drivers’ unsafe behaviors and violations and the factors concerning traffic accidents considering driving license status and the influence of demographic variables (i.e., gender and age) as a way to better measure the regulatory alignment. Thus, it contributes to the literature in several ways. First, considering the growing concerns related to unlicensed driving and questions about the magnitude of traffic accidents involving unlicensed drivers, the present study examines their severity in depth. Second, whereas previous studies discussed unlicensed driving mainly as part of unsafe driving behaviors, this paper considers it as a separate risk behavior: it investigates the behaviors of the unlicensed drivers and elaborates the mechanism by which their behaviors are influenced by demographic factors so as to proactively measure the regulatory alignment and enable policymakers to set proper corrections. Finally, to overcome the shortcoming of the approaches used in road safety research and allow better estimation of the risk and uncertainties, the present paper uses the Bayesian network methodology to model the interplay between the driving license status and the behaviors of the drivers and therefore assess the impact of the influential factors, i.e., the demographics.

For conceptual clarity, in this paper, the term “traffic accident” is used to refer to the road accidents involving motor vehicles and occurring on roads open to public circulation. The traffic accidents are studied based on two factors: the type (i.e., collision, run over and other types), and the severity of the outcomes (none/mild or severe injuries/death).

5.3 MATERIALS AND METHODS

5.3.1 BAYESIAN NETWORK

Road safety has been approached by many disciplines, for instance, transportation engineering, economics, social sciences, psychology and safety research, and each discipline examines a particular facet. Most studies deploy frequentist approaches, which are ad-hoc and account only for the expected values and do not carry the force of deductive logic (Smid et al., 2020). As a response to the limitation of the frequentist methods, and to model the interplay between driving license status and drivers’ behaviors and to assess the impact of influential factors, the present study uses the Bayesian Network to derive posterior distributions from prior knowledge on the considered factors.

The deployment of the Bayesian methodology in recent decades has been developed for various subject areas for learning, modeling, forecasting and decision-making (García-Herrero et al., 2016; Novikova & Azofeifa, 2018). As regards the regulatory alignment and traffic safety research, Bayesian networks have been used to assess the safety impact of red-light cameras on the reduction of traffic signal violations (Lee et al., 2016), predict road safety hotspots [35], analyze the causation of road accidents (Cantillo et al., 2016; Zou & Yue, 2017), measure the influence the drivers’ behaviors and psychophysical factors on injury severity and distractions (Garcia-Herrero et al., 2020), measure the influence of the seat-belt use on the traffic accidents severity (Febres et al., 2020) and analyze the role of the journey purpose in road traffic injuries (Febres et al., 2019).

The Bayesian network is a formalism that combines graph and probability theory to provide a compact and natural representation offering effective inference and efficient learning (Friedman, 1997). The directed acyclic graph (DAG) represents the structure of the Bayesian network and qualifies the causal relationship between the variables of interest, while probability theory is responsible for the quantification of the network, that is, the quantification of the probabilistic causal relationships between the variables through the joint probability distribution (Equation (1)) based on the Bayes theorem (Equation (2)) (Valdes et al., 2019):

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \,|\text{Parents } (X_i)) \tag{1}$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2}$$

where P(X1, . . . , Xn) reflects the joint probability distribution, Parents (Xi) are parents of Xi, P(A|B) is the a posteriori probability, P(A) is the a priori probability and P(B|A) is the verisimilitude.

In this way, Bayesian networks consider the direct and conditional statistical dependencies between all of the study variables in one model. This flexibility allows the measurement of the influence of one or more variables on the target variable based on the a priori and a posteriori probabilities.

5.3.2 VALIDATION TECHNIQUES

5.3.2.1 CROSS -VALIDATION

The practicability of the obtained Bayesian network and its accuracy are assessed using the K-fold cross-validation approach, and the Bayes Net Toolbox (Murphy, 2001; "Toolbox, F.M.,") for Matlab (Matlab) is deployed to perform the cross-validation, generate the Bayesian Network and compute the sensitivity analysis.

In this study, a 10-fold cross-validation has been considered. Accordingly, the data were divided into 10 folds, each containing 10% of the sample, and 90% of the sample was used to predict the sample in each of the corresponding folds. This operation was repeated ten times, and the entire sample prediction was obtained by joining the 10 folds. The evaluation of model skills was therefore measured using the area under the receiver operating characteristic (ROC) curve, called AUC. This standard measure for probabilistic and binary classifiers ranges between 0 and 1, where less than 0.5 corresponds to opposite and wrong predictions, 0.5 implies random prediction and non-reliable model and 1 refers to a perfect prediction and denotes that the model is reliable.

5.3.2.2 Z-TEST

To validate the conclusions driven from the sensitivity analysis, the statistical Z-test was used to measure the significance of the differences between the initial and a posteriori probabilities through the following hypotheses (Guo & Drasgow, 2010; GutÚrrez Pulido et al., 2008)

$$\left\{ \begin{array}{l} H_0 : P_1 = P_2 \\ H_A : P_1 \neq P_2 \end{array} \right\} \quad (3)$$

where P1 is the initial probability and P2 is the a posteriori probability. Under the assumption of binomial distribution, the statistic test, Z0, is given by Equation (4):

$$Z_0 = \frac{P_1 - P_2}{\sqrt{\frac{P_1\,(1-P_1)}{n_1} + \frac{P_2\,(1-P_2)}{n_2}}} \quad (4)$$

where n1 and n2 are populations of the probabilities P1 and P2, respectively.

5.3.3 DATA ACQUISITION

The dataset for the study was prepared from three years of official data (2016, 2017 and 2018) of traffic accidents in Spain. The original data were provided by the Traffic National Department of Spain and are made up of three databases: accidents, drivers and vehicles databases ("Formulario de Accidentes de Tráfico.," 2020):

- The drivers database contained data about the drivers involved in the accidents, for instance, age, gender and unsafe driving behaviors.

- The accidents database contained data about the type of accidents and the severity of the injuries, zone, etc.

- The vehicles database contained data about the vehicles involved in the accidents, for instance, the type of the vehicle, vehicle inspection and insurance.

In general, the three databases contained a total of 169 statistical elements (variables) collected from the "Form of Traffic Accidents with Victims" and 306,894 registered traffic accidents in which 524,785 drivers and 539,772 vehicles were involved. Each traffic accident has been registered with a unique registration ID; however, one or more driver(s)/vehicle(s) could have been involved in any registered traffic accident. The traffic accidents involving stationary vehicles, i.e., without drivers, were considered too.

For the study purpose of the present study, the dataset used was obtained by filtering the original drivers' database to consider only car and motorcycle drivers and the study key variables, which were grouped into objective variables, i.e., the driving behaviors of the drivers and the traffic accident factors; the variables affecting the behaviors, i.e., the influential variables; and one evidence variable, i.e., the driving license (Figure 1). In doing so, the final dataset contains only a total of 467,431 drivers.

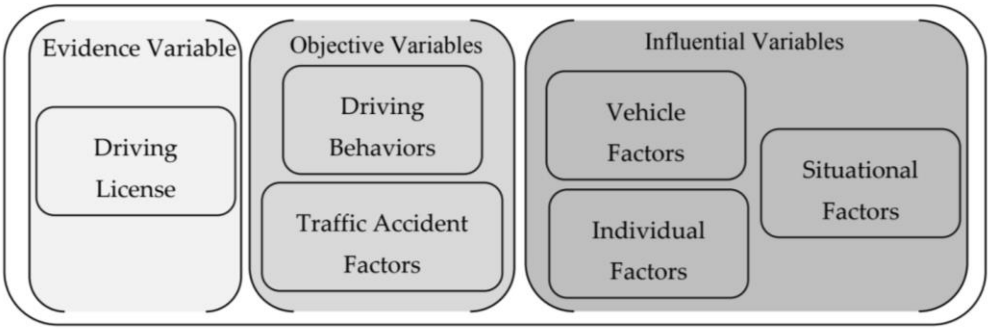
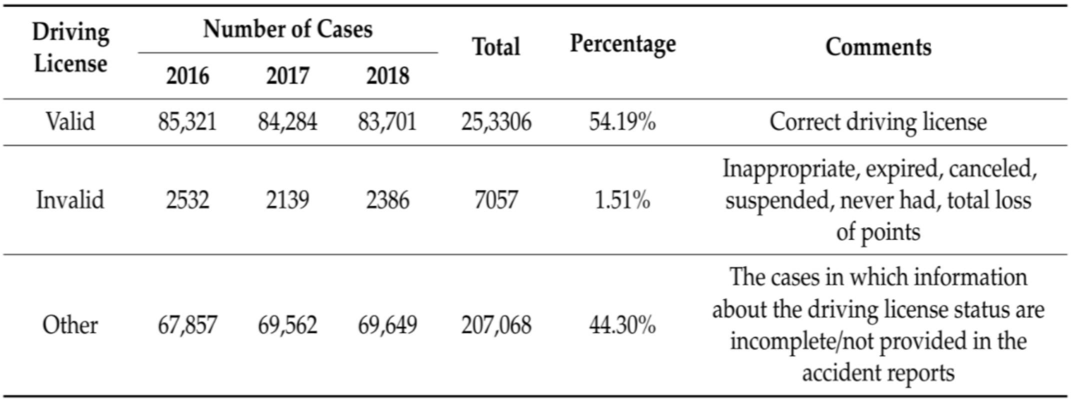


Figure 1. The variables of the sub-database used.

5.3.4 STUDY VARIABLES

In the present study, special attention is paid to the unsafe behaviors of drivers based on the driving license status (Table 1). Unlicensed driving is defined as operating illegally motor vehicles on the road, putting these drivers themselves and other legitimate drivers at great risk (Demmel et al., 2019). In the context of the present study, the target variable is the driving license, including valid driving license and invalid driving license, which entails not only driving prior to the eligible age for licensing but also those unlicensed due to license expiration, suspension and cancellation, or inappropriate class of the license.

Table 1. Frequencies of the driving license status.



Driving License	Number of Cases			Total	Percentage	Comments
	2016	2017	2018			
Valid	85,321	84,284	83,701	25,3306	54.19%	Correct driving license
Invalid	2532	2139	2386	7057	1.51%	Inappropriate, expired, canceled, suspended, never had, total loss of points
Other	67,857	69,562	69,649	207,068	44.30%	The cases in which information about the driving license status are incomplete/not provided in the accident reports

The objective variables are therefore the unsafe behaviors of drivers and traffic accident factors. In this study, unsafe behaviors were grouped into four main groups: distractive behaviors, speed infringement, other infringements and right-of-way violations (Table 2). As regards the traffic accident factors, two variables were considered, the type of the traffic accident—collision, run over and others—And the severity of the traffic accident, i.e., no-injury or mild injuries and serious injuries or death (Table 3).

Table 2. Frequencies of drivers' behaviors.

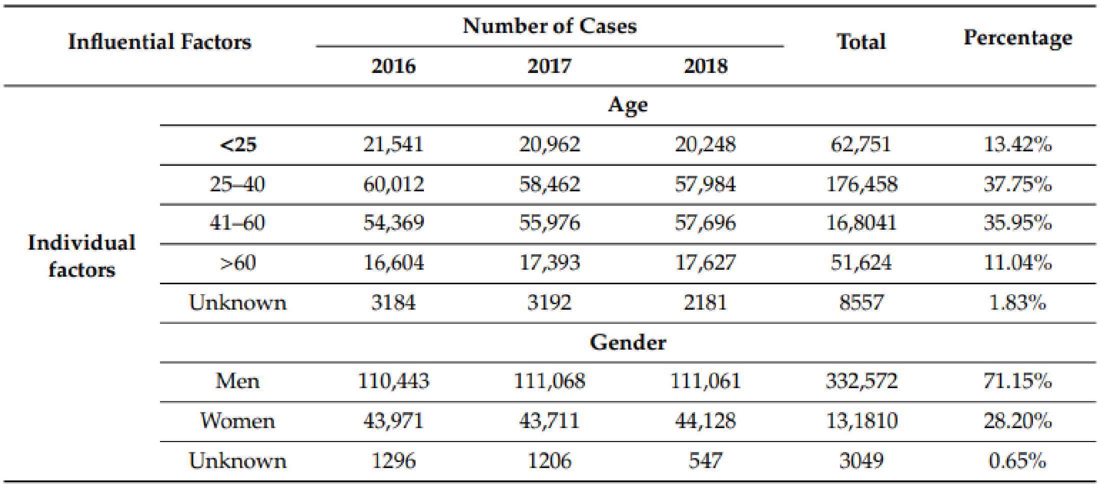
Unsafe Behaviors		Number of Cases			Total	Percentage	Comments
		2016	2017	2018			
Right-of-way violations	No	50,530	48,676	48,417	147,623	31.58%	/
	Yes	32,597	33,666	34,117	100,380	21.47%	Non-respect of traffic signals, indications of a traffic agent or crosswalk, or similar reckless maneuvers, and others
	Unknown	72,583	73,643	73,202	219,428	46.94%	/
Speed limit infringement	No	65,579	64,692	62,393	192,664	41.22%	/
	Yes	8423	7674	7880	23,977	5.13%	Inadequate and excessive speed for road conditions or the established legal speed
	Unknown	81,708	83,619	85,463	250,790	53.65%	/
Other infringements	No	59,762	60,196	60,133	180,091	38.53%	/
	Yes	578	572	562	1712	0.37%	Driving without lights, dazzling, overload in the vehicle, open doors, excess occupants and similar
	Unknown	95,370	95,217	95,041	285,628	61.11%	/
Distractions	No	38,804	38,884	38,857	116,545	24.93%	/
	Technology-based distractions	326	371	354	1051	0.22%	Use of mobile phone, GPS, hands-free, radio, DVD and similar
	Other distractions	8767	9673	10,042	28,482	6.09%	smoking, interactions with occupants, thoughtful or abstracted, sleepy and similar
	Unknown	107,813	107,057	106,483	321,353	68.75%	/

Table 3. Frequencies of traffic accident factors.

Traffic Accident Factors	Number of Cases			Total	Percentage	Comments
	2016	2017	2018			
Traffic accident severity						
None/mild	142,783	142,946	143,530	429,259	91.86%	/
Serious injury/death	12,890	12,967	12,163	38,020	8.14%	Serious or fatal traffic accident
Total	155,673	155,913	155,693	467,279	100%	/
Traffic accident type						
Collision	119,137	116,680	115,177	350,994	75.11%	Frontal, side, multiple collision, collision by range or against obstacle
Run over	13,169	12,576	12,302	38,047	8.14%	Running over a person or an animal
Other	23,367	26,657	28,214	78,238	16.74%	/
Total	155,673	155,913	155,693	467,279	/	/

The regulatory alignment in the context of road safety is a multidimensional construct and includes a wide range and multivariate combination of influencing factors, for instance, age, gender, decision-making behavior, personality, visibility, road type, zone, time and weather consideration and vehicle characteristics (Joewono & Susilo, 2017; Shangguan et al., 2020). In the present study, the influential factors were grouped into three categories considering the available data: individual factors, situational factors and vehicle factors. However, the interplay between unlicensed driving and unsafe behaviors was assessed considering only the influence of the first group of factors, i.e., the individual factors, which include two demographic variables: age and gender of the drivers (Table 4).

Table 4. Frequencies of the individual factors.



Influential Factors		Number of Cases			Total	Percentage
		2016	2017	2018		
Individual factors	Age					
	<25	21,541	20,962	20,248	62,751	13.42%
	25–40	60,012	58,462	57,984	176,458	37.75%
	41–60	54,369	55,976	57,696	16,8041	35.95%
	>60	16,604	17,393	17,627	51,624	11.04%
	Unknown	3184	3192	2181	8557	1.83%
	Gender					
	Men	110,443	111,068	111,061	332,572	71.15%
	Women	43,971	43,711	44,128	13,1810	28.20%
	Unknown	1296	1206	547	3049	0.65%

5.4. RESULTS

5.4.1 THE BAYESIAN NETWORK VALIDATION

As explained in the methodology section, the validation of the obtained model was performed with a 10-fold cross-validation method and the results are given in Table 5.

Table 5. The obtained AUC for the objective variables.

Objective Variables	Area Under the Curve (AUC)			
Right-of-way violations	No	Yes	Unknown	
	0.90	0.85	0.96	
Speed infringement	No	Yes	Unknown	
	0.94	0.82	0.95	
Other infringements	No	Yes	Unknown	
	0.94	0.53	0.94	
distractions	No	Technology-based distractions	Other distractions	Unknown
	0.91	0.69	0.85	0.91
Traffic accident type	Collision	Run-over	Other	
	0.69	0.75	0.77	
Traffic accident severity	None/mild	Serious injury/death		
	0.76	0.76		

All of the AUC scores range between 0.69 and 0.96 (with the exception of the affirmative status of the other infringements variable). These scores reflect the accuracy and high performance of the learned Bayesian network and confirm the practicability of the proposed approaches.

5.4.2 Z-TEST

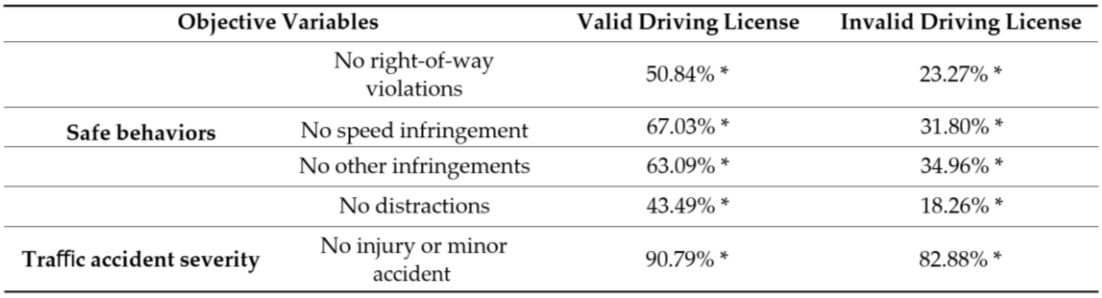
The differences between the probabilities used in the discussion of the sensitivity analysis results were examined using the statistical Z-test (results are given in Appendix A). The Z-test was conducted considering a confidence interval α of 95% (an admissible error of 5%) in a binomial distribution that proposes as limits +/−1.96 with Z0.0/2. To this end, all differences whose Z values are less than −1.96 or greater than 1.96 are acceptable statistical differences and significant.

5.4.3 Z-TEST

5.4.3.1 SENSITIVITY ANALYSIS OF THE OBJECTIVE VARIABLES CONSIDERING THE DRIVING LICENSE STATUS

The initial probabilities for each of the objective variables considering the driving license status were computed, and results are given in Tables 6 and 7. A confidence interval of 95% was considered to assess the statistical significance of the probabilities change.

Table 6. Probabilities of the safe behaviors of the drivers and traffic accident severity considering the driving license status.



Objective Variables		Valid Driving License	Invalid Driving License
Safe behaviors	No right-of-way violations	50.84% *	23.27% *
	No speed infringement	67.03% *	31.80% *
	No other infringements	63.09% *	34.96% *
	No distractions	43.49% *	18.26% *
Traffic accident severity	No injury or minor accident	90.79% *	82.88% *

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

The results in Table 6 show that the probabilities of the licensed drivers having safe driving behaviors are almost two times the probabilities of the unlicensed drivers.

For instance, the probability of committing no right-of-way violations when drivers are licensed is 50.84%, while the probability decreases to 23.27% when the drivers are unlicensed. Similarly, the probability of being involved in a minor traffic accident with no injuries is high at 90.79% when the drivers are licensed, and the probability decreases to 82.88% when the drivers have an invalid driving license.

However, according to Table 7, the probability of speeding is high when drivers are unlicensed, i.e., 12.38%, and decreases to 8.01% when the drivers have a valid driving license. In the case of right-of-way violations, the results show that licensed drivers have the highest probability, i.e., 35.08%, which decreases to 27.79% in the case of unlicensed drivers.

As regards the severity of traffic accidents, the probability of having a serious traffic accident leading to death is 9.21% when drivers are licensed and increases to 17.12% when the drivers have invalid driving licenses (a difference of 7.91%).

As far as the types of traffic accident, results show that the probability of having a collision is high in the case of licensed drivers, i.e., 77.65% and decreases to 73.56% in the case of unlicensed drivers; however, the probabilities of run-overs and other types of traffic accidents are high in the case of unlicensed drivers, i.e., 9.11% and 17.33% respectively.

According to these results, the status of the driving license is likely to have an important impact on the driving behaviors of drivers and the severity of traffic accidents.

5.4.3.2 SENSITIVITY ANALYSIS OF THE OBJECTIVE VARIABLES CONSIDERING THE DRIVING LICENSE STATUS AND THE INDIVIDUAL FACTORS

According to the objective of the present paper and considering the learned Bayesian network that includes the joint probability distribution of the study variables, a sensitivity analysis was conducted to measure (1) the influence of individual factors and driving license status on drivers' behaviors and (2) the influence of individual factors and driving license status on the type and severity of traffic accidents. A confidence interval of 95% has been considered to assess the statistical significance of probability change.

5.4.3.3 SENSITIVITY ANALYSIS OF THE PROBABILITIES OF THE DRIVERS' BEHAVIORS BASED ON THE DRIVING LICENSE STATUS AND THE INDIVIDUAL FACTORS

As regards the influence of individual factors, the sensitivity analysis results of Table 8 show that the probability of engaging in right-of-way violations increases from 27.79% (initial probability) in the case of the young unlicensed drivers (<25 years old) to 28.39% (a difference of 0.6%), and from 27.79% (initial probability) to 29.86% (a difference of 2.07%) in the case of older unlicensed drivers (>60 years old).

The probability of compliance with speed limits increases in the case of drivers older than 40 years old, regardless of the status of their driving licenses.

However, the probability decreases when drivers are younger than 25 years old from 67.03% (initial probability) to 60.34% (a difference of 6.69%) in case of valid driving licenses and from 31.80% (initial probability) to 26.98% (a difference of 4.82%) in the case of invalid driving licenses. Similarly, the results show that the probability of committing speed infringement increases in the case of the young licensed drivers by 6.47% and by 9.21% when they are unlicensed. However, in the case of the older drivers (>60 years old), the probability decreases regardless of the status of their driving licenses. The probability of not having other infringements increases in the case of the older licensed drivers (>60 years old) by 2.75% and decreases by 1.87% in the case of young, licensed drivers (<25 years old).

For distracted driving behaviors, the sensitivity analysis results show that the probability of having no distracted driving decreases in the case of the young, licensed drivers (<25 years old) by 2%. However, the probability increases by about 2% in the case of older licensed drivers (>60 years old).

Table 8. Probabilities for the behaviors of the drivers based on the driving license status and the age of the drivers.

Objective Variables		Initial Probabilities		Age	Driving License		
		Valid	Invalid		Valid	Invalid	Other
Right-of-way violations	No	50.84% *	23.27% *	<25	50.09% *	23.31% *	8.09% *
				$25\leq Y \leq 40$	50.44% *	23.35% *	8.10% *
				$40 < Y \leq 60$	51.31% *	23.73% *	8.62% *
				$Y > 60$	51.08% *	25.24% *	9.08% *
				Unknown	59.66% *	6.02% *	5.67% *
	Yes	35.08% *	27.79% *	<25	33.66% *	28.39% *	4.45% *
				$25 \leq Y \leq 40$	35.10% *	28.41% *	4.61% *
				$40 < Y \leq 60$	35.26% *	27.54% *	4.73% *
				$Y > 60$	36.47% *	29.86% *	5.29% *
				Unknown	28.49% *	8.45% *	2.31% *
Speed infringement	No	67.03% *	31.80% *	<25	60.34% *	26.98% *	8.99% *
				$25 \leq Y \leq 40$	65.71% *	31.16% *	9.64% *
				$40 < Y \leq 60$	69.26% *	34.02% *	10.59% *
				$Y > 60$	72.01% *	38.56%	11.69% *
				Unknown	66.50% *	8.15% *	5.94% *
	Yes	8.01% *	12.38% *	<25	14.48% *	21.59% *	2.36% *
				$25 \leq Y \leq 40$	8.69% *	13.43% *	1.44% *
				$40 < Y \leq 60$	5.99% *	9.42% *	1.09% *
				$Y > 60$	4.81% *	7.81% *	0.88% *
				Unknown	4.84%	3.54% *	0.25% *
Other infringements	No	63.09% *	34.96% *	$Y < 25$	61.22% *	35.34% *	8.70% *
				$25 \leq Y \leq 40$	62.56% *	35.08% *	8.81% *
				$40 < Y \leq 60$	63.84% *	35.43% *	9.39% *
				$Y > 60$	65.84% *	38.56%	10.47% *
				Unknown	39.20%	7.37% *	2.35% *
	Yes	0.60% *	0.39% *	$Y < 25$	0.61% *	0.44%	0.11% *
				$25 \leq Y \leq 40$	0.59% *	0.40%	0.11% *
				$40 < Y \leq 60$	0.60% *	0.39%	0.11% *
				$Y > 60$	0.58% *	0.39%	0.11% *
				Unknown	0.48%	0.17%	0.05% *
Distractions	No	43.49% *	18.26% *	$Y < 25$	41.54% *	18.04% *	2.57% *
				$25 \leq Y \leq 40$	43.11% *	18.36% *	2.45% *
				$40 < Y \leq 60$	43.81% *	18.49% *	2.49% *
				$Y > 60$	45.42% *	20.64% *	2.84% *
				Unknown	52.71% *	3.92% *	0.46% *
	Technology-based distractions	0.37% *	0.44% *	$Y < 25$	0.36% *	0.50%	0.03% *
				$25 \leq Y \leq 40$	0.37% *	0.45%	0.03% *
				$40 < Y \leq 60$	0.37% *	0.43%	0.03% *
				$Y > 60$	0.39% *	0.47%	0.04% *
				Unknown	0.24%	0.10%	0.01% *
	Other distractions	10.42% *	10.55% *	$Y < 25$	10.40% *	10.85% *	0.71% *
				$25 \leq Y \leq 40$	10.41% *	10.75% *	0.67% *
				$40 < Y \leq 60$	10.34% *	10.45% *	0.65% *
				$Y > 60$	10.91% *	11.57% *	0.72% *
				Unknown	6.35%	2.49% *	0.15% *

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

Results of the sensitivity analysis of the influence of the gender variable on the behaviors of the drivers, considering the status of the driving license, are given in Table 9. In general, these results propose that the variable gender does not have an important influence on the driving behaviors of the drivers, regardless of the driving license status. However, some slight changes in the probabilities can be noticed. For instance, the probability of not engaging in right-of-way violations in the case of licensed men drivers shows an increase of 0.63%. However, the probability of engaging in these aberrant behaviors increases by about 2% in the case of women drivers regardless of the driving license status. For speed limit infringement, the probability increases by 0.48% in the case of the unlicensed men drivers.

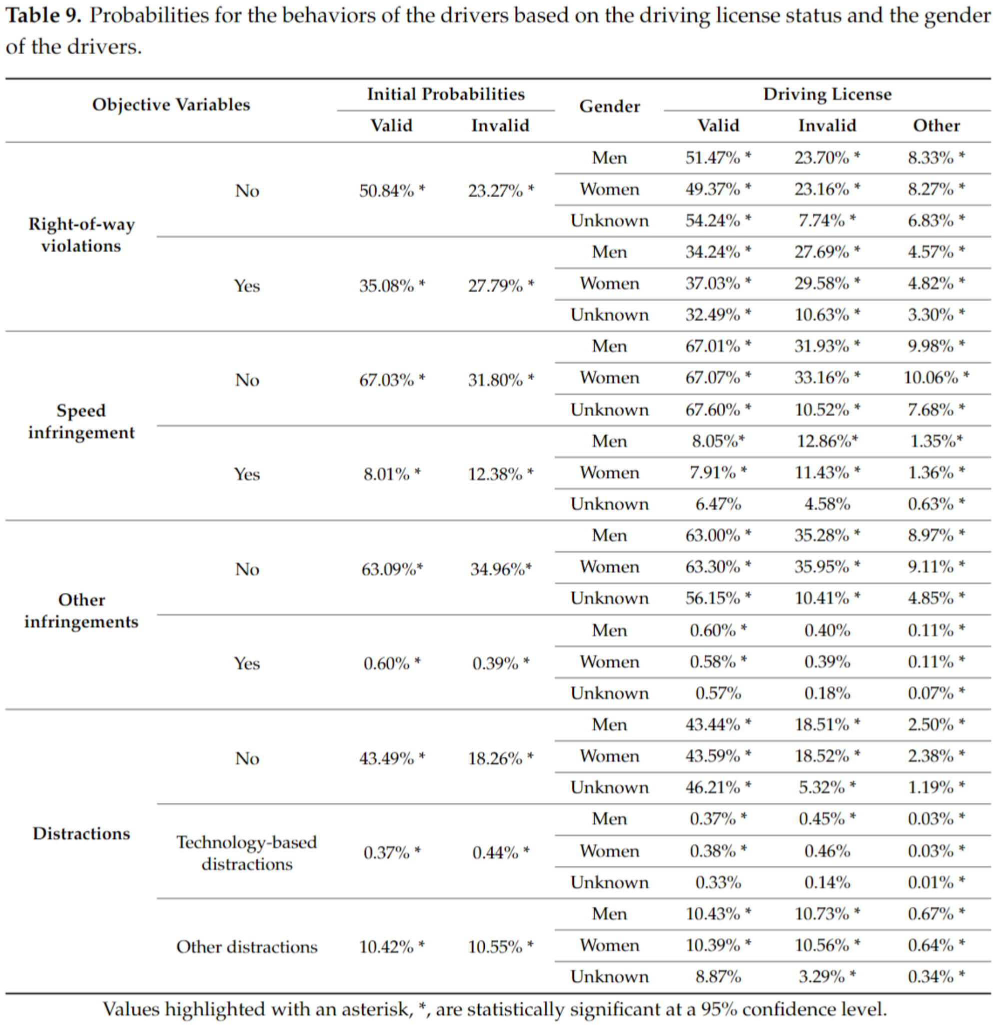


Table 9. Probabilities for the behaviors of the drivers based on the driving license status and the gender of the drivers.

Objective Variables		**Initial Probabilities**		**Gender**	**Driving License**		
		Valid	**Invalid**		**Valid**	**Invalid**	**Other**
Right-of-way violations	No	50.84% *	23.27% *	Men	51.47% *	23.70% *	8.33% *
				Women	49.37% *	23.16% *	8.27% *
				Unknown	54.24% *	7.74% *	6.83% *
	Yes	35.08% *	27.79% *	Men	34.24% *	27.69% *	4.57% *
				Women	37.03% *	29.58% *	4.82% *
				Unknown	32.49% *	10.63% *	3.30% *
Speed infringement	No	67.03% *	31.80% *	Men	67.01% *	31.93% *	9.98% *
				Women	67.07% *	33.16% *	10.06% *
				Unknown	67.60% *	10.52% *	7.68% *
	Yes	8.01% *	12.38% *	Men	8.05%*	12.86%*	1.35%*
				Women	7.91% *	11.43% *	1.36% *
				Unknown	6.47%	4.58%	0.63% *
Other infringements	No	63.09%*	34.96%*	Men	63.00% *	35.28% *	8.97% *
				Women	63.30% *	35.95% *	9.11% *
				Unknown	56.15% *	10.41% *	4.85% *
	Yes	0.60% *	0.39% *	Men	0.60% *	0.40%	0.11% *
				Women	0.58% *	0.39%	0.11% *
				Unknown	0.57%	0.18%	0.07% *
Distractions	No	43.49% *	18.26% *	Men	43.44% *	18.51% *	2.50% *
				Women	43.59% *	18.52% *	2.38% *
				Unknown	46.21% *	5.32% *	1.19% *
	Technology-based distractions	0.37% *	0.44% *	Men	0.37% *	0.45% *	0.03% *
				Women	0.38% *	0.46%	0.03% *
				Unknown	0.33%	0.14%	0.01% *
	Other distractions	10.42% *	10.55% *	Men	10.43% *	10.73% *	0.67% *
				Women	10.39% *	10.56% *	0.64% *
				Unknown	8.87%	3.29% *	0.34% *

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

5.4.3.3 SENSITIVITY ANALYSIS OF THE PROBABILITIES OF THE DRIVERS' BEHAVIORS BASED ON THE DRIVING LICENSE STATUS AND THE INDIVIDUAL FACTORS

Results of the sensitivity analysis of the influence of driving license status and individual factors on the traffic accidents are given in Tables 10–13.

Table 10. Probabilities of traffic accident types based on the driving license status and the age of the drivers.

Traffic Accident Type	Initial Probabilities		Age	Driving License		
	Valid	Invalid		Valid	Invalid	Other
Collision	77.65% *	73.56% *	Y < 25	75.26%	71.83% *	71.17% *
			25 ≤ Y ≤ 40	77.43% *	73.33% *	72.40% *
			40 < Y ≤ 60	78.01% *	73.87%	73.01% *
			Y > 60	79.90% *	75.70%	74.51% *
			Unknown	78.83% *	73.53%	74.37% *
Run Over	8.37% *	9.11% *	Y < 25	7.70% *	8.34%	6.80% *
			25 ≤ Y ≤ 40	8,32% *	8,97%	7,38% *
			40 < Y ≤ 60	8.58% *	9.31%	7.76% *
			Y > 60	8.57% *	9.66%	8.36%
			Unknown	10.60% *	10.78% *	9.64%*
Others	13.98% *	17.33%	Y < 25	17.04% *	19.83% *	22.03% *
			25 ≤ Y ≤ 40	14.25% *	17.70%	20.21% *
			40 < Y ≤ 60	13.41% *	16.82%	19.23% *
			Y > 60	11.53% *	14.65%	17.13% *
			Unknown	10.58% *	15.68%	15.99%

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

Table 11. Probabilities for the traffic accident severity based on the driving license status and the age of the drivers.

Traffic Accident Severity	Initial Probabilities		Age	Driving License		
	Valid	Invalid		Valid	Invalid	Other
None/mild	90.79% *	82.88% *	Y < 25	90.03% *	80.89% *	92.96% *
			25 ≤ Y ≤ 40	90.75% *	82.49% *	93.30% *
			40 < Y ≤ 60	90.90% *	83.23% *	93.52% *
			Y > 60	91.28% *	83.47% *	93.57% *
			Unknown	93.28%	93.62%	97.40% *
Serious injury/death	9.21% *	17.12% *	Y < 25	9.97% *	19.11% *	7.04% *
			25 ≤ Y ≤ 40	9.25% *	17.51% *	6.70% *
			40 < Y ≤ 60	9.10% *	16.77% *	6.48% *
			Y > 60	8.72% *	16.53% *	6.43% *
			Unknown	6.72%	6.38%	2.60% *

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

As regards the influence of the age variable and the driving license status on the type of the traffic accident, results of Table 10 show that the probability of being involved in a collision increases in the case of older drivers (>60 years old) by 2.25% in case of valid driving license and by 2.14% when their driving licenses are invalid. However, the probability of the younger drivers being involved in other types of traffic accidents increases by 3.06% when their driving licenses are valid and by 2.5% in the case of invalid driving licenses. As regards the severity of the traffic accidents, results in Table 11 show that in the case of older drivers (>60 years old), the probability of having a traffic accident with mild or no injuries increases regardless of the status of their driving licenses and it decreases in the case of serious traffic accidents.

Table 12. Probabilities of the traffic accident types based on the driving license status and the gender of drivers.

Traffic Accident Type	Initial Probabilities		Gender	Driving License		
	Valid	Invalid		Valid	Invalid	Other
Collision	77.65% *	73.56% *	Men	76.88% *	73.05% *	72.30% *
			Women	79.43% *	75.20%	73.88% *
			Unknown	78.00%	74.11%	74.10%
Run over	8.37% *	9.11% *	Men	8.20% *	9.01% *	7.47% *
			Women	8.78% *	9.33%	7.93%
			Unknown	8.42%	10.41%	9.40% *
Others	13.98% *	17.33%		14.92% *	17.93% *	20.23% *
			Women	11.79% *	15.47%	18.19% *
			Unknown	13.58%	15.48%	16.49%

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

Table 13. Probabilities of traffic accident severity based on the driving license status and the gender of the drivers.

Traffic Accident Severity	Initial Probabilities		Gender	Driving License		
	Valid	Invalid		Valid	Invalid	Other
None or mild	90.79% *	82.88% *	Men	89.57% *	80.50% *	92.86% *
			Women	93.58% *	89.80% *	95.17% *
			Unknown	96.33% *	95.45% *	96.03% *
Serious injury or death	9.21% *	17.12% *	Men	10.43% *	19.50% *	7.14% *
			Women	6.42% *	10.20% *	4.83% *
			Unknown	3.67% *	4.55% *	3.97% *

Values highlighted with an asterisk, *, are statistically significant at a 95% confidence level.

However, with younger drivers (<25 years old), the probability of having a severe traffic accident increases, and does so more importantly when they are driving unlicensed, by 2%.

Results of the influence of drivers' gender and driving license status on the probabilities of traffic accident types are summarized in Table 12.

These results reveal that the probability of having a collision increases by about 2% in the case of women drivers regardless of their driving licenses, while in the case of unlicensed men drivers, the probability increases in the case of other types of traffic accidents.

As regards the severity of the traffic accidents, results in Table 13 show that the probability of having a mild traffic accident with no injuries decreases in the case of men drivers regardless of their driving licenses; however, it increases in the case of women drivers by 2.79% when they have a valid driving license and, more importantly, when they hold an invalid driving license by about 7%. The same results show that the probability of having a serious traffic accident decreases in the case of women drivers regardless of their driving licenses. However, in the case of men drivers, the probability of having a serious traffic accident increases and, more importantly, when their driving licenses are invalid (an increase of 2.38%).

5.5. DISCUSSION

Despite the improvements in the legislation and enforcement of laws targeting many traffic risk factors (Notrica et al., 2020) and the fact that the drivers are aware of the adverse outcomes of engaging in unsafe driving behaviors, regulatory breaches continue to be witnessed and severe injuries, disabilities and deaths caused by traffic accidents continue to be recorded. Research studies have either shown the relationships between unsafe behaviors and traffic accidents or explained the contribution of unlicensed drivers to the frequency of traffic accidents. However, the relationship between these has not been investigated.

To assess the regulatory alignment, this study investigated the unsafe behaviors of unlicensed drivers. Such a focus first sheds light on the illegal driving of unlicensed drivers that escapes, in one way or another, follow-up strategies and road safety improvement projects. Second, such a focus proposes a proactive perspective for the assessment and monitoring of regulatory alignment, which is better than doing so reactively depending on traffic accident data, to help policymakers detect real deficiencies and make efficient and effective countermeasures.

In doing so, three years (2016, 2017 and 2018) of data were obtained from the Spanish National Traffic Department, and a Bayesian network has been deployed to provide predictions of changes in the probabilities and estimate how individual factors, i.e., demographic variables, impact the objective variables considering the statistical dependency relationships in the Bayesian network model.

This study demonstrated that licensed drivers are more likely to engage in safe driving behaviors such as respecting speed limits and less likely to be involved in run-over traffic accidents. In contrast, unlicensed drivers were found to engage in more unsafe behaviors like speeding and to have severe traffic accidents. This finding supports previous research studies (Blows et al., 2005; Hanna et al., 2013) that have reported similar observations on risky driving behaviors of unlicensed drivers such as speeding and non-use of seatbelts, showing that unlicensed drivers form an important part of the profile of regulatory misalignment and that better traffic safety results could be achieved if policymakers and road safety authorities tackle unlicensed driving. As regards the severity of traffic accidents, results of the present study show that the probability of being involved in a minor traffic accident with no injuries is high when the drivers are licensed. In contrast, the probability of having a serious traffic accident leading to death increases

when drivers have invalid driving licenses. This finding is in line with conclusions of many scholars (Hanna et al., 2010; Heck et al., 2008), confirming that unlicensed drivers are more likely to be involved in fatal traffic accidents than licensed drivers, and the severity of such accidents is therefore high.

However, the present study marked some exceptions and found that the probability of licensed drivers engaging in right-of-way violations is higher than that of unlicensed drivers. In our opinion, the explanation lies in the complexity of the phenomenon of driving behavior, which, in such a particular case, is not exclusively influenced by the status of the driving license. The high probability of licensed drivers engaging in right-of-way violations could be explained by the fact that unlicensed drivers become "prudent drivers" in the streets because, in many countries, if the driver is cited for driving without a valid driving license, they may be fined, barred from obtaining a valid driving license for a period of time or incarcerated. Indeed, as reported by (McDowell et al., 2009), drivers on roads or highways are more likely to be unlicensed than drivers on streets because on rural roads and highways, less public transport and taxi services are available and, considering the long distances, the likelihood of the unlicensed driver encountering the police is slim.

Another finding of notable interest is that both elder and younger drivers have unsafe driving behaviors. However, the results showed that each age group is likely to engage in some unsafe behavior more than others. For instance, young drivers are more likely to commit speed infringement, especially when their driving licenses are invalid. In contrast, older drivers (>60 years old) are more likely to engage in right-of-way violations. This finding supports the results of (Parlangeli et al., 2018; Shaaban & Hassan, 2017; Yahia & Ismail, 2014), confirming that young unlicensed drivers are the least committed to traffic instructions and violate traffic lights and use mobile phones the most. Adolescence is a critical developmental period that brings many important cognitive, social and emotional changes, affecting these young drivers' ways of dealing with hazard and their proneness to engage in unsafe driving behaviors. Furthermore, as in many studies (Romano et al., 2008; Scott-Parker et al., 2012), the present study found that young drivers, and particularly young unlicensed drivers, are overrepresented in traffic accidents resulting in most of the serious injuries and deaths.

As regards the influence of the gender variable, the sensitivity results showed that women are more likely to engage in right-of-way violations and to have collisions. It was also found that the probability of having mild traffic accidents increases in the case of women unlicensed drivers. For men drivers, the results suggested that they are more likely to be involved in other types of traffic accidents and that the probability of having a serious traffic accident generally increases when their driving licenses are invalid. In general, these results are significantly consistent with many previous studies (Cordellieri et al., 2016; Korn et al., 2017) that have agreed that women take fewer risks than men do when driving and are less involved in fatal traffic accidents.

To this end, it is clear that unlicensed driving is more than an unsafe behavior and that unlicensed driving motivates other disqualified driving performances. Thus, this study provides the most direct means for proactively estimating regulatory alignment and allows policymakers to better implement effective and efficient actions that might, first, buffer the impact of unlicensed driving unlicensed; second, reduce the likelihood of committing other unsafe behaviors; and finally, reduce the severity of traffic law violations and improve the alignment.

5.6 CONCLUSIONS

It is widely accepted that many people all around the world are killed or suffer disabilities due to traffic accidents. As a result, immense efforts are being made by road safety authorities all over the world to develop alternative ways to improve the behaviors of drivers at the wheel and therefore reduce the heavy costs of traffic accidents.

Relatively little previous research has investigated the mechanisms by which unlicensed driving affects driving performance and drivers' regulatory alignment. In this paper, the interrelations between the alignment and compliance with traffic enforcement regulations, unlicensed driving, unsafe behaviors and traffic accidents were investigated.

As expected, findings of the present study confirmed that unlicensed driving exerts a significant negative impact on drivers' behaviors and consequently their alignment with traffic regulations. Consequently, these findings provide evidence for promoting and improving traffic safety enforcements by targeting unlicensed driving in various safety education and enforcement programs.

5.6.1 PRACTICAL IMPLICATIONS

The present study provides a useful conceptualization of the regulatory alignment and the unsafe behaviors of unlicensed drivers that negatively affect traffic safety records. Accordingly, policymakers and practitioners could consider these results as the basis and empirical framework for interventions aimed at addressing unsafe behaviors and improving driving performance by paying more attention to the unlicensed driving problem. The interventions could fundamentally involve two important points: (i) the sanctions for the unlicensed driving should be reviewed, the laws tightened and special attention paid to unlicensed driving in prevention campaigns; and, (ii) since unlicensed driving is illegal and therefore goes underreported, moving towards using electronic driver licenses to deter unlicensed drivers from operating vehicles has become a necessity.

This study has also considered the use of big data techniques allowing, based on prior probabilities, the calculation of posterior probabilities, which is important to approach such public health problems and traffic safety studies.

5.6.2 LIMITATIONS AND FUTURE RESEARCH

The main limitation of the present study lies in the fact that the study variables were limited to those extracted from the database; however, there are many other unsafe driving behaviors and influential factors that could be of interest.

As regards the methodology, the machine-learning technique requires large amounts of data to train the data's behavior; consequently, the concept of unlicensed drivers, in this paper, has grouped all of the categories. Thus, it is recommended that future research considers the influence of each category separately. This is because not all unlicensed drivers are similar. For example, a driver whose license was suspended or canceled due to a past driving offense is not the same as a driver whose license was expired. In considering each category separately, the interventions targeting unlicensed driving could be more specified and the focus could be directed to the disqualified drivers only. Moreover, this study has investigated only the influence of individual factors, and follow-up studies could investigate the influence of other factors.

AUTHOR CONTRIBUTIONS

Conceptualization, W.B. and S.G.-H.; methodology, W.B. and R.C.; software, J.D.F.; validation, J.D.F., W.B. and S.G.-H.; resources, S.G.-H.; writing—original draft preparation, W.B.; writing—review and editing, W.B., S.G.-H., J.D.F., M.Á.M. and M.D.; project administration, S.G.-H. All authors have read and agreed to the published version of the manuscript.

FUNDING

This work started with funds from the Dirección General de Tráfico (DGT) for the Project “Modelo Cuantitativo de Red Bayesiana con capacidad predictiva de la gravedad del accidente en función de los comportamientos y actuaciones de las personas”, ref. SPIP2015-1852 and pursued with research project “Modelización mediante técnicas de machine learning de la influencia de las distracciones del conductor en la seguridad vial. Diseño de un sistema integrado: simulador de conducción, eye tracker y dispositivo de distracción. Ref. BU300P18” supported by funds from FEDER (Fondo Europeo de Desarrollo Regional - Junta de Castilla y León).

ACKNOWLEDGMENTS

As well as the funders, we would like to thank the Spanish General Directorate of Traffic (DGT) “Dirección General de Tráfico” for providing the data to undertake this study.

COMPETING INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication title “Influence of the seat-belt use on the severity of the injury in traffic accidents”. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

APPENDIX AND REFERENCES

(DOI: 10.3390/ijerph17186743)

6. ARTÍCULO 4: PEDESTRIANS' INJURY SEVERITY IN TRAFFIC ACCIDENTS IN SPAIN: A PEDESTRIAN ACTIONS APPROACH. A PEDESTRIAN ACTIONS APPROACH

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Journal: Sustainability

Published: 5 june 2021

Accesible at: https://doi.org/10.3390/su13116439

Keywords: road traffic injuries; pedestrian injury; Bayesian networks; human behaviour factors; infrastructure; and vehicle conditions

6.1 ABSTRACT

Road traffic accidents are currently between the seventh and tenth leading cause of death in the world, with approximately 1.35 million people killed per year. Despite extensive efforts by governments, according to the World Health Organization, road accidents still cause far too many deaths, especially among pedestrians, cyclists and two-wheel motor vehicle riders, who together account for almost 50% of road traffic fatalities. In particular, Spain had 410,974 traffic accidents between 2016 and 2019, involving 722,516 vehicles and 61,177 pedestrians with varying degrees of injury. This study uses the Bayesian network method to understand how the pedestrians' responsibility and actions at the time of the traffic accident affect the injury suffered by said pedestrian, also considering the variables of the road infrastructure and vehicles at the accident site. The results confirm that the variables linked to the unsafe behavior of pedestrians, and their responsibility in traffic accidents, increase the risk of suffering serious or fatal injuries during an accident; for example, if a pedestrian is distracted this increases his/her probability of suffering a severe injury (27.86%) with respect to not being distracted (20.73%). Conditions related to traffic in high-speed areas, areas with no or poor lighting, and areas lacking sidewalks, also record increases in pedestrian injury, as is the case in the age group of pedestrians over 60 years of age.

6.2 INTRODUCTION

Road traffic accidents and road safety have undoubtedly become the subject of public health studies worldwide, as they are currently the seventh to tenth leading cause of global deaths (WHO, 2020). Road traffic injuries rank sixth in the world in terms of years of life with disability, according to the World Health Organization (WHO, 2019). Road safety is studied through different risk factors, such as infrastructure factors (type of road, lighting, pavements), human and behavioural factors (age, gender, actions taken) and vehicle factors (type of vehicle, speed of vehicles), and their interactions allow for a better understanding of the causes of road accidents and their impact on the injury rate of those involved (Luo et al., 2020; Oviedo-Trespalacios & Scott-Parker, 2018).

In Spain, according to the “Dirección General de Tráfico” (DGT, General Directorate of Traffic), in 2019, 1755 people died (381 pedestrians), 130,475 were injured without hospitalization (13,016 pedestrians) and 8613 were hospitalized (2069 pedestrians), as a result of 104,080 traffic accidents, placing the rate at 37 deaths per million inhabitants. In the case of pedestrians, there are concurrent factors in road traffic accidents, which are those related to people, vehicles and infrastructure (Vial, 2019).

Other studies conducted regarding pedestrians in Spain show that they have a two to seven times higher risk of being injured than a car driver. The risk of being injured in a traffic accident is very high, in fact, approximately 18% of the fatalities resulting from a traffic accident are pedestrians (Montoro et al., 2002), a figure which, from the date of publication of the afore mentioned book (2000) to the present day, is far from decreasing, given that in 2019, pedestrian fatalities accounted for 21.70% of those killed in road accidents (Vial, 2019).

Within the study entitled “Las principales cifras de la Siniestralidad Vial España 2019” (The main figures of Road Accidents in Spain 2019) prepared by the Observatorio Nacional de Seguridad Vial (Vial, 2019) (the Spanish National Road Safety Observatory), the most recurrent variables in the statistics of traffic accidents involving pedestrians are grouped into factors related to human behavior, infrastructure and vehicles in the case of Spain. This study also highlights some important variables such as age, type of road where the accident occurs, distractions and light conditions at the time of the accident.

The study of pedestrian behavior and their possible responsibility in traffic accidents is essential in order to understand the impact they can have on the degree of injury of accident victims, as well as on causing the actual traffic accidents. For example, according to Twisk, et al. (Twisk et al., 2015), the use of certain electronic devices such as mobile phones and music players can impair pedestrian and cyclist behavior when cycling in cities, and while they are not prohibited by law, road safety could benefit from pedestrians and cyclists limiting their use.

In another example, a study conducted to understand the interaction between human behavioral and infrastructure factors that may affect cyclist safety (Useche et al., 2020) found that traffic accidents could be predicted by studying variables related to risk behavior and interactions with the user and infrastructure. Similarly, this research proposes the study of several of these variables and their possible impact on the safety of pedestrians, who, like cyclists, are more exposed to serious or fatal injuries than other road system users.

The interaction of pedestrians with their environment can also be studied to better understand the possibilities of preventing road accidents. Pedestrian behavior, given certain circumstances in the infrastructure, seems to directly influence the generation of traffic accidents, or the harmfulness of pedestrian injuries during these accidents. A study conducted in Italy, using data from 2005 to 2015, suggests that the risk of pedestrian accidents can increase approximately twice as much when on-street parking is available (Congiu et al., 2019).

As suggested by the study of (Dinh et al., 2020) on traffic in Vietnam, the responsibility of pedestrians through their actions could have a relevant impact on the degree of injuries during a traffic accident, as well as the possibility of generating one by means of these same actions. Risk behaviors and positive (proactive safe) behaviors are of relevant importance in studies and prevention of the causes of road accidents involving pedestrians and different road users, as mentioned in a validation study of a pedestrian behavior questionnaire conducted in Spain in 2019 (Useche et al., 2020). Some of these risk behaviors and positive behaviors were analyzed in this study within the behavioral factor variables, using data gathered between the years 2016 to 2019 to assess pedestrian distractions, violations, actions and errors, as well as their positive opposites, when the traffic accident took place.

Having demonstrated the importance of variables related to pedestrian behavior in traffic accidents, and the relevance of the study of these same accidents to protect the lives of road users, this study addresses the interaction of pedestrian behavior variables with the degree of pedestrian injuries, also considering situational variables of a demographic, infrastructure and vehicle nature. The objective is to understand how the actions of pedestrians can influence the degree of pedestrian injuries during a road accident, enabling road safety decision-makers to take action to protect the lives of road users.

6.3 MATERIALS AND METHODS

6.3.1 BAYESIAN NETWORKS AND VALIDATION

Following the approach of Aldred et al. (2019) (Aldred et al., 2020), in this study we consider Discrete Bayesian Networks (Castillo et al., 1997) to model the probabilistic direct and/or conditional (in)dependence relationships between variables. Bayesian Networks are part of the set of probabilistic graphical models (Koller & Friedman, 2009) whose associated graph is directed and acyclic (DAG). Such a graph reflects the probabilistic (in)dependencies between the different variables of the model resulting in a factorisation of the Joint Probability Distribution (JPD):

$$p(x_1, x_2, x_3, \dots, x_n) = \prod^{n} p(x_i \vee \pi_i) \tag{1}$$

where i=1, 2,. . .,n, X=[X1,X2, . . . ,Xn] are the variables included in the model and πi represents the set of parents of the variable xi given by the DAG. As a result, the learning process first seeks for these (in)dependencies obtaining the DAG (structural learning) and then, the parameters given by the factorization are estimated (parametric learning) by maximum likelihood as these are the ones that better explain the observed data. To learn the DAG, the score-based greedy learning algorithm proposed by Buntine, W. (1991) (Buntine, 1991) was applied. Note that the obtained DAG leads to a significant reduction of the JPD parameters, increasing the efficiency of the model learning process, and an easily interpretable representation of the relationships between the model variables included in the training sample.

Once the DAG and JPD, which together define the Bayesian Network, have been obtained from the sample (Neapolitan, 2004), we can assess how the probabilities of the model's variables are modified by introducing new evidence on one or more of its variables. That is, knowing that the variable x_1 takes the value v0 we can answer the question "how does the probability of the rest of the variables change?" through the conditional probabilities and the factorization shown above:

$$p(x_1, x_2, x_3, \ldots, x_n \vee x_i = v_i) \qquad (2)$$

In particular, through such expressions we can obtain a Bayesian classifier of our target variable, in this case degree of pedestrian injury (pedestrians at risk of minor or no injury): MNI Risk; and pedestrians at risk of serious or fatal injury: Killed/Seriously Injured Risk (KSI Risk), which we will assess through cross-validation (10-fold) and considering the Area Under the ROC Curve as an evaluation measure (Aldred et al., 2020; Fawcett, 2006), which is a standard measure of accuracy for binary probabilistic classifiers (Hanley & McNeil, 1982). This parameter takes values in the interval [1], with 0 corresponding to a perfect anti-predictive model (assigns one class the opposite in all cases), 0.5 to a random predictor and 1 to a perfect model. Thus, for each subsample of the 10-fold and the joint prediction, obtained by combining the predictions on the 10-folds, an AUC (Area Under the Curve) value will be obtained, resulting in 11 values that show both the predictive capacity of the model and the variability of this capacity.

Similarly, we can naturally set up different sensitivity experiments of the target variable, or any of the model, to changes in different subsets of variables, allowing us to isolate the effect of each factor on the target variable. That is, given a subset of the variables, changes in the probability of injury harmfulness are assessed based on the values taken by that subset of variables (Section 3.2.2).

For the learning of the Bayesian Network and the evaluation of probabilities, the Matlab toolbox (Matlab) Bayes Net (https://github.com/bayesnet/bnt, accessed on 1 June 2021) (Murphy, 2001).

6.3.2 GATHERING DATA

The dataset used for the study comes from the database gathered over four years (2016, 2017, 2018 and 2019) relating to traffic accidents occurring in Spain. Such data was originally gathered by the Dirección General de Tráfico de España and provided to the authors for analysis. The data was gathered through four forms obtained from traffic accidents which occurred during the years mentioned above, resulting in four databases: accident base, driver base, pedestrian base and vehicle base.

For this study, the authors have used three of these databases: the accident database, the vehicle database and the pedestrian database. Within the accident database, there are variables related to the type of accident, where the severity of the accident I analyzed through the injuries caused to the people affected in the accident, breaking down this information into minor injuries and no injuries, and serious and fatal injuries. The areas where the accidents occurred are also analyzed, dividing them into roads or highways (high-speed zones) and crossing or street (low-speed zone), as well as the type of road where the accident occurs, like ring roads and bypasses, residential street, pedestrian streets and streets with special regulation. In addition, the database contains variables such as the type of sidewalk or the lack of any sidewalk, and also adds the favorable or unfavorable lighting conditions. In addition, in this database are some meteorological conditions that occurred at the time of the accident, divided into states such as cloudy, clear, light rain, heavy rain, hail or snow, and it also breaks down fog and visibility conditions for the driver.

On the other hand, in the vehicle database, all the characteristics of the vehicles involved in the accident are described, such as the type of vehicle, the vehicle documents, the mechanical situation, etc. Finally, the pedestrian database contains demographic data of the pedestrian such as age and gender, the injury suffered during the traffic accident, disaggregated into minor injuries and no injuries, and serious and fatal injuries. There is also information on the actions carried out by the pedestrian at the time of the traffic accident, the responsibility of this pedestrian in the accident and other important information that is detailed in the study.

The databases contain a total of 410,974 records for traffic accidents which occurred during the years 2016, 2017, 2018 and 2019 as well as 722,516 vehicles involved and a total of 61,177 pedestrians involved in traffic accidents, data that was collected from the "Formulario de Accidentes de Tráfico con Víctimas" (Casualty Traffic Accident Form). These databases contain 156 coded statistical items (variables) from the above-mentioned form. It is worthy of note that each accident has a unique identification (ID) number, in which more than one vehicle and more than one pedestrian may be involved, also bearing in mind that it is possible to have a traffic accident where no pedestrian is involved. For this reason, the total number of cases considered is the result of filtering out only accidents involving pedestrians, resulting in 56,253 accidents, 59,651 vehicles involved and making each pedestrian involved in a traffic accident a case study, resulting in a total of 61,177 cases to be analyzed.

6.3.3 STUDY VARIABLES

The study model has been divided into three groups in order to properly organize the process of calculation and analysis of results. As can be seen in Figure 1, the first level of study refers to the first level factors comprising the demographic factor (pedestrian gender and age), the vehicle factor (vehicle type), the infrastructure factor (area where the accident occurs, road type, pavement condition and lighting) and the behavioural factor (pedestrian action, pedestrian violation, pedestrian attention factors and alleged pedestrian errors) which studies the actions of the pedestrian during the traffic accident.

The second level of study is made up by the pedestrian responsibility factor, comprising

a single variable (pedestrian responsibility), referring to the existence, or lack thereof, of pedestrian responsibility in traffic accidents. Finally, in the third part of the model seen in Figure 1, the target variable (pedestrian degree of injury) can be observed, which has been divided into two states: pedestrians at risk of minor or no injury (MNI Risk) and pedestrians at risk of serious or fatal injuries (KSI Risk).

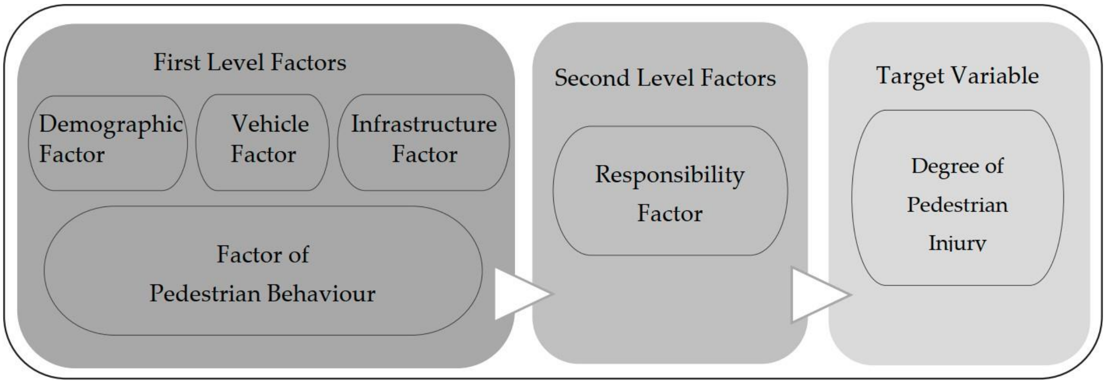
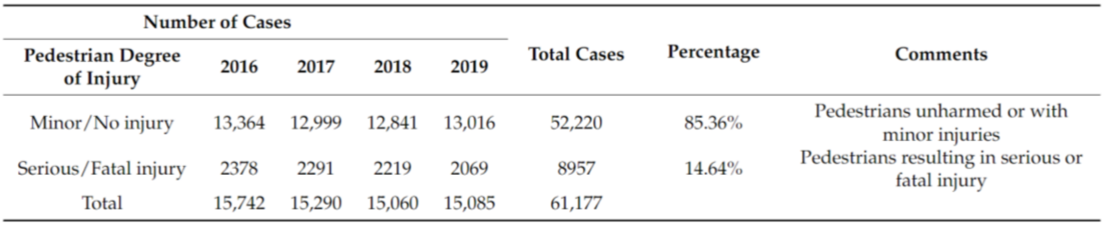


Figure 1. Study model.

This study places special focus on the pedestrians’ degree of injury during road accidents (Table 1), emphasizing the responsibility that the pedestrian may have through the actions he or she was taking at the time of the accident. As can be seen in Table 1, of the total number of cases analyzed (61,177) where at least one pedestrian was involved in the traffic accident, 14.64% (8957) involved pedestrians with serious or fatal injuries.

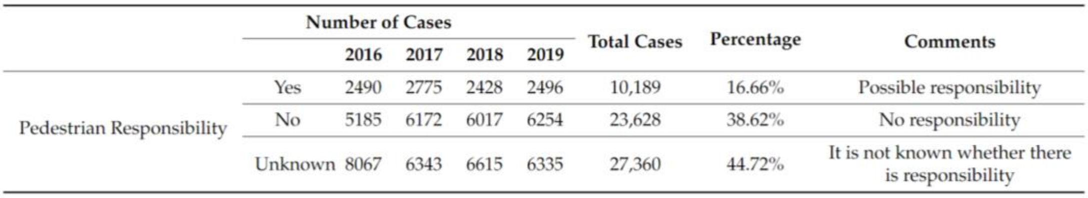
Table 1. Frequency of the target variable.



Number of Cases							
Pedestrian Degree of Injury	**2016**	**2017**	**2018**	**2019**	**Total Cases**	**Percentage**	**Comments**
Minor/No injury	13,364	12,999	12,841	13,016	52,220	85.36%	Pedestrians unharmed or with minor injuries
Serious/Fatal injury	2378	2291	2219	2069	8957	14.64%	Pedestrians resulting in serious or fatal injury
Total	15,742	15,290	15,060	15,085	61,177		

The responsibility factor variable, called “pedestrian responsibility”, has been discretized into two states (“yes” or “no”), to determine whether or not the pedestrian was responsible for causing the traffic accident (Table 2) and its direct influence on the degree of the injury. It can be seen that in 16.65% of the cases, the pedestrian was responsible for the accident, while in (38.62%) he/she was not. In the remaining cases it could not be determined whether or not the pedestrian was responsible for the accident. % start a new page without indent 4.6cm

Table 2. Frequency of responsibility factor variables.



		Number of Cases				Total Cases	Percentage	Comments
		2016	**2017**	**2018**	**2019**			
Pedestrian Responsibility	Yes	2490	2775	2428	2496	10,189	16.66%	Possible responsibility
	No	5185	6172	6017	6254	23,628	38.62%	No responsibility
	Unknown	8067	6343	6615	6335	27,360	44.72%	It is not known whether there is responsibility

The behavioural factor variables are, in relation to the target variable, those variables that, through the actions taken by the pedestrian, could modify the risk of degree of injury through the pedestrian’s responsibility and by themselves. Table 3 summarizes the four variables considered and the frequency of occurrence in each of their states.

Table 3. Frequency of behavioural factor variables.

		Number of Cases				Total Cases	Percentage	Comments
		2016	**2017**	**2018**	**2019**			
Pedestrian Action	Walking out	709	618	623	737	2687	4.39%	Between parked vehicles
	In front of a bus stop	39	41	41	35	156	0.26%	Standing on the road
	Crossing Properly	6333	6325	6193	6960	25,811	42.19%	
	Walking or standing	2003	1949	1918	2228	8098	13.24%	
	Road works	156	166	152	151	625	1.02%	
	Other	6502	6191	6133	4974	23,800	38.90%	
Pedestrian Violation		**2016**	**2017**	**2018**	**2019**			
	No violation	6098	6081	6071	7001	25,251	41.28%	
	Failure to respect traffic lights	340	336	341	498	1515	2.48%	Pedestrian traffic lights
	Does not cross properly	1279	1304	1311	1554	5448	8.91%	Crosses outside pedestrian crossings
	Unlawfully on road	529	461	437	502	1929	3.15%	Walks or is in
	Other	374	328	287	281	1270	2.07%	
	Unknown	7122	6780	6613	5249	25,764	42.11%	
Pedestrian Attention Factors		**2016**	**2017**	**2018**	**2019**			
	Distraction	425	395	386	457	1663	2.72%	
	Previous illness or accident	38	29	29	35	131	0.21%	
	No factors are discernible	3754	3559	3372	3156	13,841	22.63%	
	Unknown	11,525	11,307	11,273	11,437	45,542	74.44%	
Alleged Pedestrian Errors		**2016**	**2017**	**2018**	**2019**			
	No errors are noted	5445	5243	5187	5376	21,251	34.74%	
	Failure to see a sign	95	79	78	80	332	0.54%	
	Failure to see a danger	1259	1183	1155	1351	4948	8.09%	vehicle/obstacle
	Incorrect manoeuvre	559	590	574	762	2485	4.06%	delayed or wrong
	Not specified	8384	8195	8066	7516	32,161	52.57%	

Some variables, such as vehicle type, pedestrian age, pedestrian gender, accident location, pavement and road type, among others, are extensively studied to understand pedestrian degree of injury, as for example in the study by Seung-Hoon Park and Min-Kyung Bae (Park & Bae, 2020) to analyze the pedestrian degree of injury rates by age group. These variables have been considered in this study and distributed into three groups, referring to demographic, vehicle and infrastructure factors, with a total of seven variables(Table 4), according to the first study level reflected in the model represented in Figure 1.The percentage values of their occurrence in each case can be seen in Table 4, which shows a high participation of vehicles (cars, vans and off-road vehicles) in traffic accidents involving pedestrians (78.81%), as well as some significant values that are more repetitive and more frequent, such as people over 60 years of age (30.89%), the types of road (“urban crossing road” and “street”) (93.57%), raised pavements (46.85%) and lighting (92.21%). It is important to note that, when referring to raised pavements, we are referring to pavements that are not at the same level as the passing traffic, and not to overpasses over highways or streets within cities.

Table 4. Frequency of situational factor variables.

			Number of Cases				Total Cases	Percentage	Comments
			2016	**2017**	**2018**	**2019**			
Type of Vehicle		Bicycle	582	628	605	581	2396	4.02%	
		Car	12,179	11,795	11,633	11,401	47,008	78.81%	Passenger car, van, off-road
		Motorcycle	1375	1387	1358	1417	5537	9.28%	Motorcycles and Mopeds
		Lorry	410	384	377	350	1521	2.55%	Rigid lorries, tractor-trailers, and articulated lorries
		Bus	302	273	307	292	1174	1.97%	Minibus, bus, and articulated buses
		Other	151	125	170	358	804	1.35%	Other motorised and non-motorised vehicles
		Not specified	289	280	235	349	1153	2.05%	
Demographic Variables	Age		**2016**	**2017**	**2018**	**2019**			
		<25	3923	3747	3644	3577	14,891	24.34%	
		≥25 and ≤40	2736	2484	2591	2621	10,432	17.05%	
		>40 and ≤60	3765	3670	3672	3720	14,827	24.24%	
		>60	4815	4748	4632	4704	18,899	30.89%	
		Unknown	503	641	521	463	2128	3.48%	
	Gender		**2016**	**2017**	**2018**	**2019**			
		Male	7352	7123	6803	7033	28,311	46.28%	
		Female	8244	8002	8098	7894	32,238	52.70%	
		Unknown	146	165	159	158	628	1.03%	
Infrastructure Variables	Area		**2016**	**2017**	**2018**	**2019**			
		Road/Motorway	994	1011	969	962	3936	6.43%	
		Urban crossing road/Street	14,748	14,279	14,091	14,123	57,241	93.57%	
	Type of street		**2016**	**2017**	**2018**	**2019**			
		Peri-urban/ring road	1646	1534	1639	1949	6768	11.06%	
		Residential street	1944	1925	1831	2150	7850	12.83%	
		Pedestrian Zone	161	162	150	271	744	1.22%	

Table 4. *Cont.*

		Number of Cases				Total Cases	Percentage	Comments
		2016	**2017**	**2018**	**2019**			
	30 km/h limited area	557	556	618	756	2487	4.07%	
	Specially regulated	176	244	211	190	821	1.34%	
	Not specified	11,258	10,869	10,611	9769	42,507	69.48%	
Pavement		**2016**	**2017**	**2018**	**2019**			
	No	1538	1344	1314	1472	5668	9.26%	
	Not passable	25	31	22	21	99	0.16%	
	Yes, not raised	1194	1059	1078	1298	4629	7.57%	
	Raised	7025	6969	6689	7981	28,664	46.85%	
	Not specified	5960	5887	5957	4313	22,117	36.15%	
Lighting		**2016**	**2017**	**2018**	**2019**			
	Yes	14,651	14,135	13,844	13,780	56,410	92.21%	With natural or artificial light
	No/Deficient	1091	1155	1216	1305	4767	7.79%	No natural or artificial light

Figure 2 shows the interaction of the Bayesian Network variables for this study, where the primary and secondary dependencies and connections of the target variable (pedestrian degree of injury) can be observed. In relation to the first level situational factors (demographic, vehicle, infrastructure), the variables “lighting”, “pavement” and “zone” are closely related to the pedestrian degree of injury.

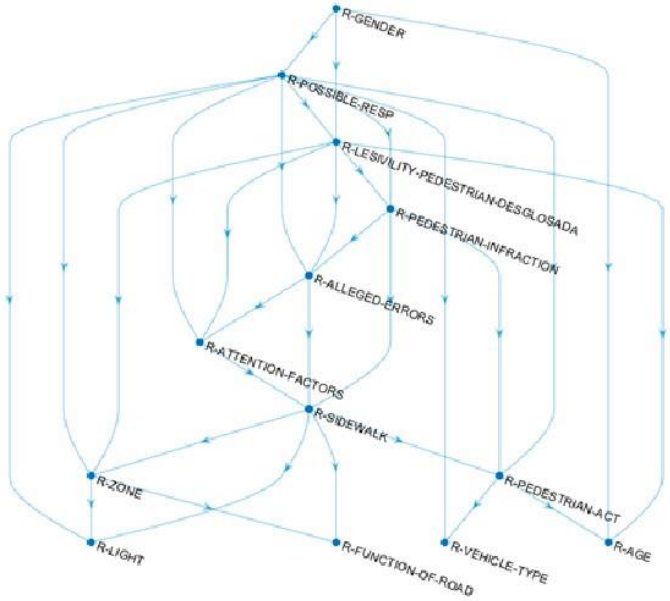


Figure 2. Bayesian Network. Processed by the authors and generated in MatLab.

It is also important to note the direct connection of the degree of injury variable with pedestrian behaviour variables, such as “attention factors”, “alleged errors”, “pedestrian violation” and “pedestrian action”, as well as its close relationship with the variable “pedestrian responsibility”. All these interactions generate important changes in the probability of a pedestrian’s degree of injury, which can be verified in the results section.

The shape of the network and the interaction of all variables with various dependency connections and direct and indirect relationships is an indication of how the Bayesian network considers the interaction of all variables in the model and thus of the data of which it is comprised.

6.4 RESULTS

6.4.1 BAYESIAN NETWORK STUDY MODEL

The methodology and validation section explains how the validation of the model was performed, as well as the data learning method used by the Bayesian networks to achieve a reliable approximation of the results obtained. In the case of the study model of this research, it can be seen in Figure 2 how the target variable interacts with the variables of the different factors used in the sensitivity analyses. The reliability of these interactions, and hence the results obtained, are supported by the calculation of the area under the curve (AUC), which is shown in Table 5.

The area under the curve (AUC) indicates the model’s ability to determine the probability of minor or no injury (MNI Risk) and fata or serious injury (KSI Risk) in the road traffic accident cases analysed. In the case of this study, the AUC values can be seen in Table 5, where AUC values correspond to the 10-fold (rows 1–10) and the joint series (row 11). The values vary from 0.71 to 0.75, demonstrating that there is no high variability present, which reflects the stability and accuracy of the Bayesian Network and its level of learning, confirming the viability of the proposed model and its “a priori” suitability for subsequent calculations.

Table 5. AUC for the objective variable.

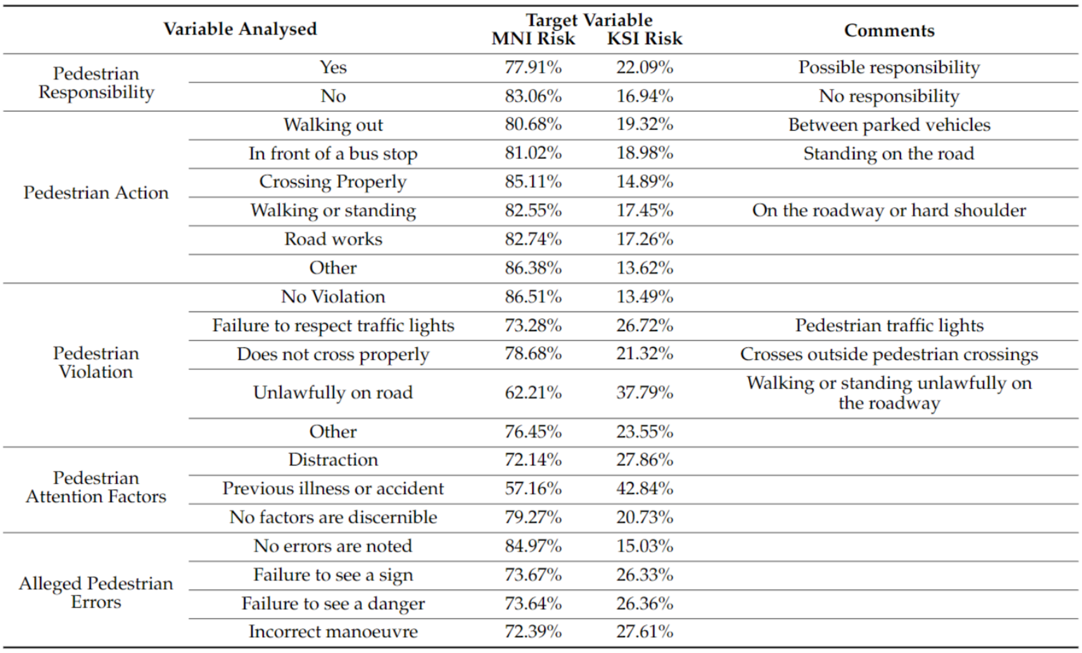
K-Folds	Target Variable	
	MNI Risk	**KSI Risk**
1	0.73	0.73
2	0.75	0.75
3	0.73	0.73
4	0.75	0.75
5	0.75	0.75
6	0.73	0.73
7	0.75	0.75
8	0.75	0.74
9	0.72	0.71
10	0.75	0.75
11	0.74	0.74

6.4.2 SENSITIVITY ANALYSIS

6.4.2.1 “A PRIORI” PROBABILITIES OF THE MODEL VARIABLES WITH RESPECT TO THE TARGET VARIABLE

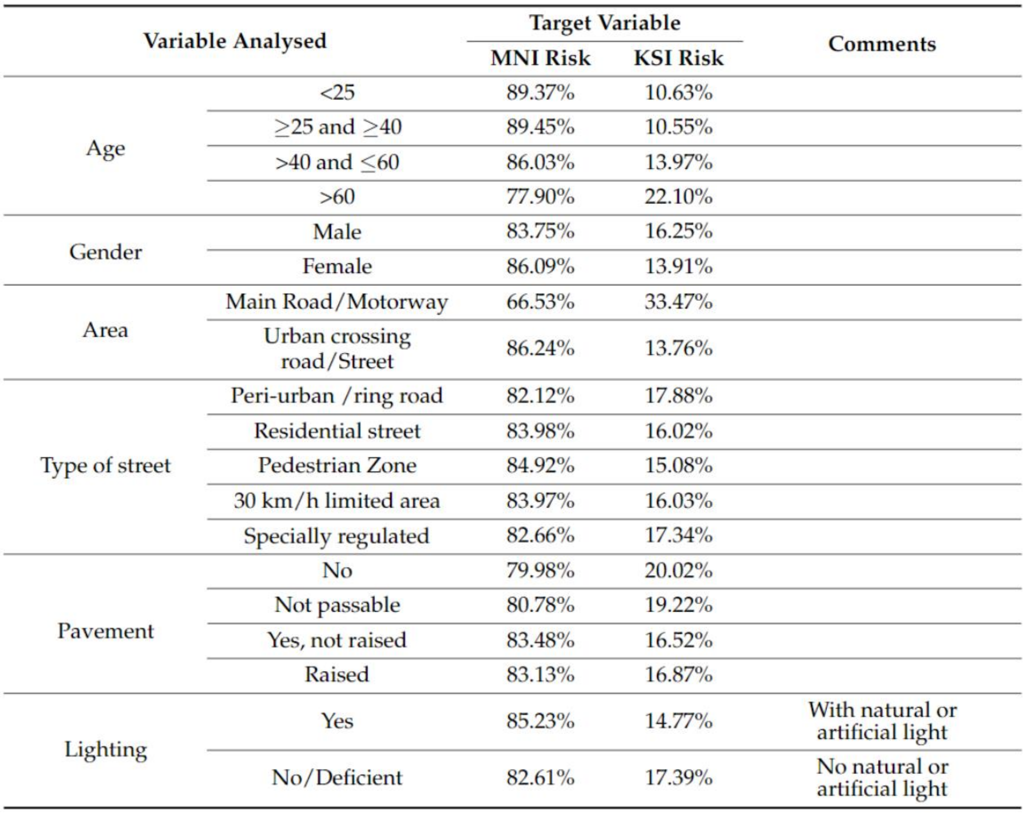
Initially, “a priori” probabilities are calculated for each of the variables of the first level factors (demographics, infrastructure and pedestrian behaviour) and for the liability factor located at the second level of the proposed model. These probabilities are based on the two states proposed for the target variable (minor or no injury; serious or fatal injury), results which can be seen in Tables 6 and 7. The “a priori” probabilities of the vehicle factor have not been studied, nor their possible combinations, since from the data provided by the DGT it is not possible to identify, for accidents with more than one vehicle, which vehicle has caused the pedestrian injury; however it is important to emphasise, as seen in Section 2.3 of this study, that cars (passenger cars, vans and off-road vehicles) are the type of vehicle most frequently involved in accidents involving pedestrians (78.74%).

Table 6. "a priori" probability of the target variable according to the pedestrian behaviour and responsibility factor variables.



Variable Analysed		Target Variable MNI Risk	KSI Risk	Comments
Pedestrian Responsibility	Yes	77.91%	22.09%	Possible responsibility
	No	83.06%	16.94%	No responsibility
Pedestrian Action	Walking out	80.68%	19.32%	Between parked vehicles
	In front of a bus stop	81.02%	18.98%	Standing on the road
	Crossing Properly	85.11%	14.89%	
	Walking or standing	82.55%	17.45%	On the roadway or hard shoulder
	Road works	82.74%	17.26%	
	Other	86.38%	13.62%	
Pedestrian Violation	No Violation	86.51%	13.49%	
	Failure to respect traffic lights	73.28%	26.72%	Pedestrian traffic lights
	Does not cross properly	78.68%	21.32%	Crosses outside pedestrian crossings
	Unlawfully on road	62.21%	37.79%	Walking or standing unlawfully on the roadway
	Other	76.45%	23.55%	
Pedestrian Attention Factors	Distraction	72.14%	27.86%	
	Previous illness or accident	57.16%	42.84%	
	No factors are discernible	79.27%	20.73%	
Alleged Pedestrian Errors	No errors are noted	84.97%	15.03%	
	Failure to see a sign	73.67%	26.33%	
	Failure to see a danger	73.64%	26.36%	
	Incorrect manoeuvre	72.39%	27.61%	

Table 7. "a priori" probability of the target variable according to the first-level factor variables.



Variable Analysed		Target Variable		Comments
		MNI Risk	KSI Risk	
Age	<25	89.37%	10.63%	
	≥25 and ≥40	89.45%	10.55%	
	>40 and ≤60	86.03%	13.97%	
	>60	77.90%	22.10%	
Gender	Male	83.75%	16.25%	
	Female	86.09%	13.91%	
Area	Main Road/Motorway	66.53%	33.47%	
	Urban crossing road/Street	86.24%	13.76%	
Type of street	Peri-urban /ring road	82.12%	17.88%	
	Residential street	83.98%	16.02%	
	Pedestrian Zone	84.92%	15.08%	
	30 km/h limited area	83.97%	16.03%	
	Specially regulated	82.66%	17.34%	
Pavement	No	79.98%	20.02%	
	Not passable	80.78%	19.22%	
	Yes, not raised	83.48%	16.52%	
	Raised	83.13%	16.87%	
Lighting	Yes	85.23%	14.77%	With natural or artificial light
	No/Deficient	82.61%	17.39%	No natural or artificial light

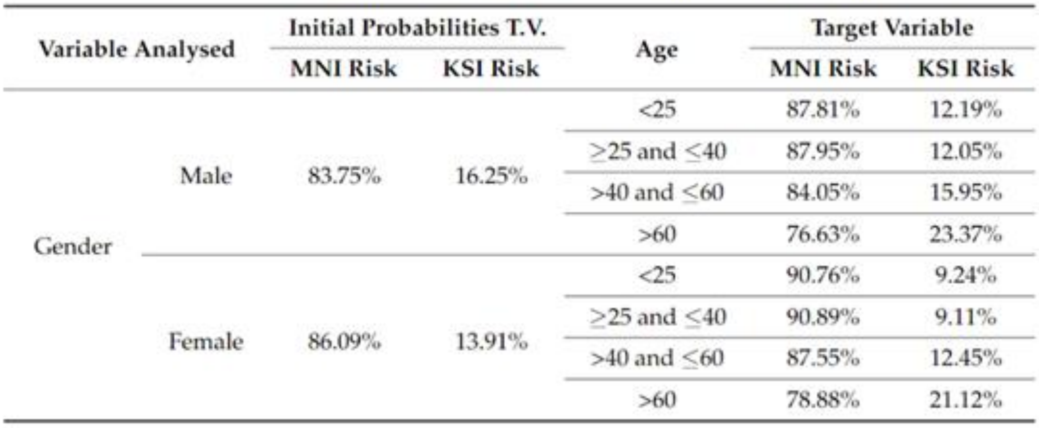
The results included in Table 6 show each of the pedestrian behaviours and responsibility factor variables and their "a priori" probabilities with respect to the target variable. As regards "pedestrian responsibility" it can be clearly observed that in a traffic accident the risk of serious or fatal injury decreases by (5.15%) if the pedestrian has no responsibility for the accident, with the states of this variable being "yes" (22.09%) and "no" (16.94%). In relation to the variables (pedestrian action, pedestrian violation, pedestrian attention factors and presumed pedestrian errors) that are grouped in the pedestrian behaviour factor according to the model represented in Figure 1, the “a priori” probabilities of these variables can be observed in Table 6, highlighting actions such as crossing correctly (14.89%), not committing violations (13.49%), not being distracted (20.73%) and not committing errors (15.03%), which represent the lowest values of the probability of enduring a serious or fatal injury for each of these variables, with differences of up to 24.30% with their opposite states, such as walking out between parked vehicles (19.32%) and walking unlawfully on a road (37.79%).

As for the rest of the first-level factors, the “a priori” probabilities of the states of the target variable with respect to the variables that are grouped in this factor are shown in Table 7. For example, in the case of the demographic factor in the variables “age” and “gender”, where people in the 25–40 age range have the lowest probability of suffering serious or fatal injury in a traffic accident (10.55%) and people over 60 years of age have the highest probability (22.10%); the division by gender denotes a slightly lower probability in the case of women (13.91%) and a higher probability in the case of men (16.25%).

On the other hand, in the infrastructure factor, several important values can be observed in the variables that make up this factor, such as that the “a priori” probability of suffering a serious or fatal injury for the pedestrian in traffic accidents is considerably lower if the area of the accident is “street or crossing” with (13.76%), while this probability rises to (33.47%) if the accident happens in the area “main road or motorway”, where the speed limits are higher. Similarly, the “a priori” probability of suffering serious or fatal injuries is higher when there are no pavements (20.02%) or no or poor lighting (17.39%), compared to the other states of the variables “pavement” and “lighting”, which fall to (16.87%) and (14.77%) if there are raised pavements or proper lighting, respectively.

According to the results observed in the ‘a priori’ probabilities of the target variable states in relation to the situational, behavioural and pedestrian responsibility factor variables, the correct actions of the pedestrian and the situational conditions in which the traffic accident occurs have a significant impact on the pedestrians’ degree of injury.

Table 8. Gender-based pedestrian degree of injury probabilities in relation to age groups.

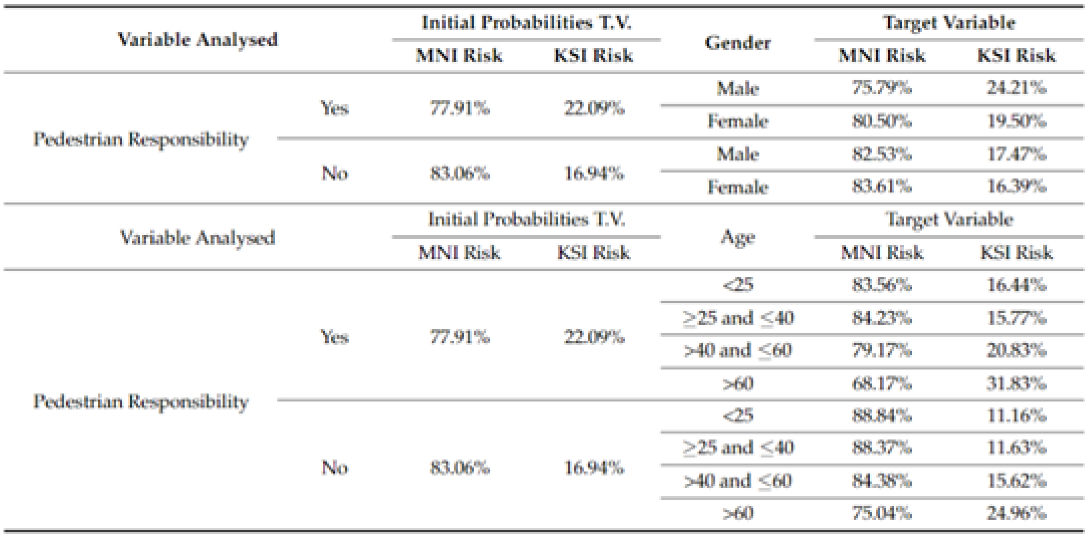


Variable Analysed		Initial Probabilities T.V.		Age	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Gender	Male	83.75%	16.25%	<25	87.81%	12.19%
				≥25 and ≤40	87.95%	12.05%
				>40 and ≤60	84.05%	15.95%
				>60	76.63%	23.37%
	Female	86.09%	13.91%	<25	90.76%	9.24%
				≥25 and ≤40	90.89%	9.11%
				>40 and ≤60	87.55%	12.45%
				>60	78.88%	21.12%

In terms of pedestrian degree of injury rates with respect to personal variables (Table 8), it can be seen for the group of people aged 25 to 40 years, both for the female gender (9.11%) and for the male gender (12.05%), that the probability values representing serious injuries are lower than those of the rest of their group. It is also important to note that with regard to the “a prior” probabilities of suffering a serious or fatal injury according to gender, male (16.25%) and female (13.91%), that age becomes an important factor, as the risk of suffering these types of injuries when the study group is over 60 years of age increases to (23.37%) in the case of the male gender (difference of 7.12%) and to (21.12%) in the case of the female gender (difference of 7.21%).

For the case of the same variables of the personal factor (gender and age), but in relation to the pedestrian’s responsibility in the traffic accident, the degree of injury prob- abilities is provided in Table 9. The “a priori” values of pedestrian responsibility for pedestrian degree of injury in fatal and serious injury accidents is 22.09% when there is responsibility and 16.94% when there is no responsibility. There is a significant shift in these values when there is pedestrian responsibility and also when the population is over 60 years old, reaching 31.83% in the probability of having serious or fatal injuries (difference of 9.74%); while when there is no responsibility in the group over 60 years old, the difference is a little less with respect to the ‘a priori’ probabilities (8.02%), evidencing that responsibility and age are important factors in pedestrian safety.

Table 9. Pedestrian degree of injury probabilities based on pedestrian responsibility in relation to gender and age groups.

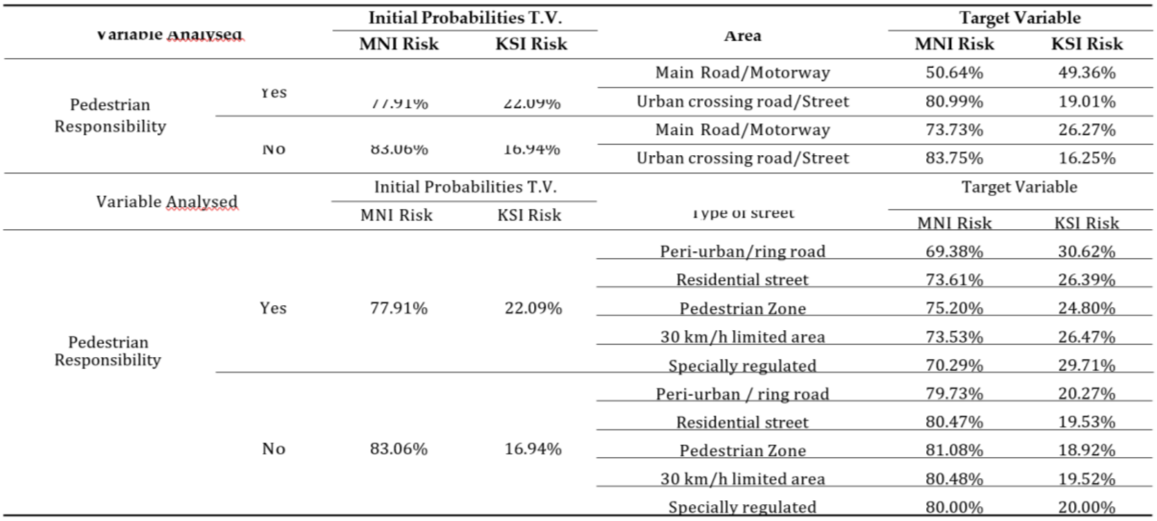


Variable Analysed		Initial Probabilities T.V.		Gender	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	Male	75.79%	24.21%
				Female	80.50%	19.50%
	No	83.06%	16.94%	Male	82.53%	17.47%
				Female	83.61%	16.39%
Variable Analysed		**Initial Probabilities T.V.**		**Age**	**Target Variable**	
		MNI Risk	**KSI Risk**		**MNI Risk**	**KSI Risk**
Pedestrian Responsibility	Yes	77.91%	22.09%	<25	83.56%	16.44%
				≥25 and ≤40	84.23%	15.77%
				>40 and ≤60	79.17%	20.83%
				>60	68.17%	31.83%
	No	83.06%	16.94%	<25	88.84%	11.16%
				≥25 and ≤40	88.37%	11.63%
				>40 and ≤60	84.38%	15.62%
				>60	75.04%	24.96%

On the other hand, it can be observed that in the interaction between pedestrian responsibility and gender, there is no major difference in any of their states with respect to the “a priori” probabilities of suffering a serious or fatal injury depending on the pedestrian’s responsibility for the accident.

(2) Results related to the pedestrian’s degree of injury due to responsibility in the road traffic accident with respect to the infrastructure variables (Tables 10 and 11).

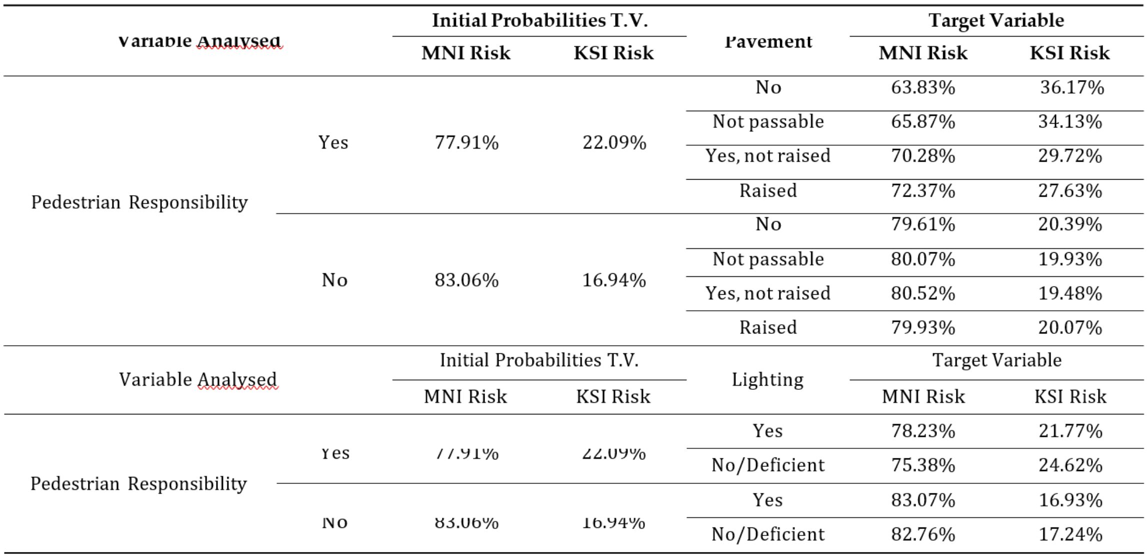
Table 10. Pedestrian degree of injury probability based on pedestrian responsibility and infrastructure factor location variables.



Variable Analysed		Initial Probabilities T.V.		Area	Target Variable	
		MNI Risk	**KSI Risk**		**MNI Risk**	**KSI Risk**
Pedestrian Responsibility	Yes	77.91%	22.09%	Main Road/Motorway	50.64%	49.36%
				Urban crossing road/Street	80.99%	19.01%
	No	83.06%	16.94%	Main Road/Motorway	73.73%	26.27%
				Urban crossing road/Street	83.75%	16.25%

Variable Analysed		Initial Probabilities T.V.		Type of street	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	Peri-urban/ring road	69.38%	30.62%
				Residential street	73.61%	26.39%
				Pedestrian Zone	75.20%	24.80%
				30 km/h limited area	73.53%	26.47%
				Specially regulated	70.29%	29.71%
	No	83.06%	16.94%	Peri-urban / ring road	79.73%	20.27%
				Residential street	80.47%	19.53%
				Pedestrian Zone	81.08%	18.92%
				30 km/h limited area	80.48%	19.52%
				Specially regulated	80.00%	20.00%

Table 11. Pedestrian degree of injury probability based on pedestrian responsibility and infrastructure factor situational variables.



Variable Analysed		Initial Probabilities T.V.		Pavement	Target Variable	
		MNI Risk	**KSI Risk**		**MNI Risk**	**KSI Risk**
Pedestrian Responsibility	Yes	77.91%	22.09%	No	63.83%	36.17%
				Not passable	65.87%	34.13%
				Yes, not raised	70.28%	29.72%
				Raised	72.37%	27.63%
	No	83.06%	16.94%	No	79.61%	20.39%
				Not passable	80.07%	19.93%
				Yes, not raised	80.52%	19.48%
				Raised	79.93%	20.07%

Variable Analysed		Initial Probabilities T.V.		Lighting	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	Yes	78.23%	21.77%
				No/Deficient	75.38%	24.62%
	No	83.06%	16.94%	Yes	83.07%	16.93%
				No/Deficient	82.76%	17.24%

In terms of pedestrian degree of injury severity based on pedestrian responsibility and the variables “zone” and “road type” which attempt to describe the location where the traffic accident occurred (Table 10), significant variations are found with respect to the ‘a priori’ probabilities of having a serious or fatal pedestrian injury, as these fall when the accident occurs in the state “urban crossing road/street” when there is no pedestrian responsibility (16.25%) as well as when there is responsibility (19.01%); the most notable variation occurs when there is pedestrian responsibility and the accident takes place in the “main road/motorway” state (49.36%), where the increase climbs to 27.27% in the described injury risk with respect to its “a priori” probability under the same conditions (22.09%).

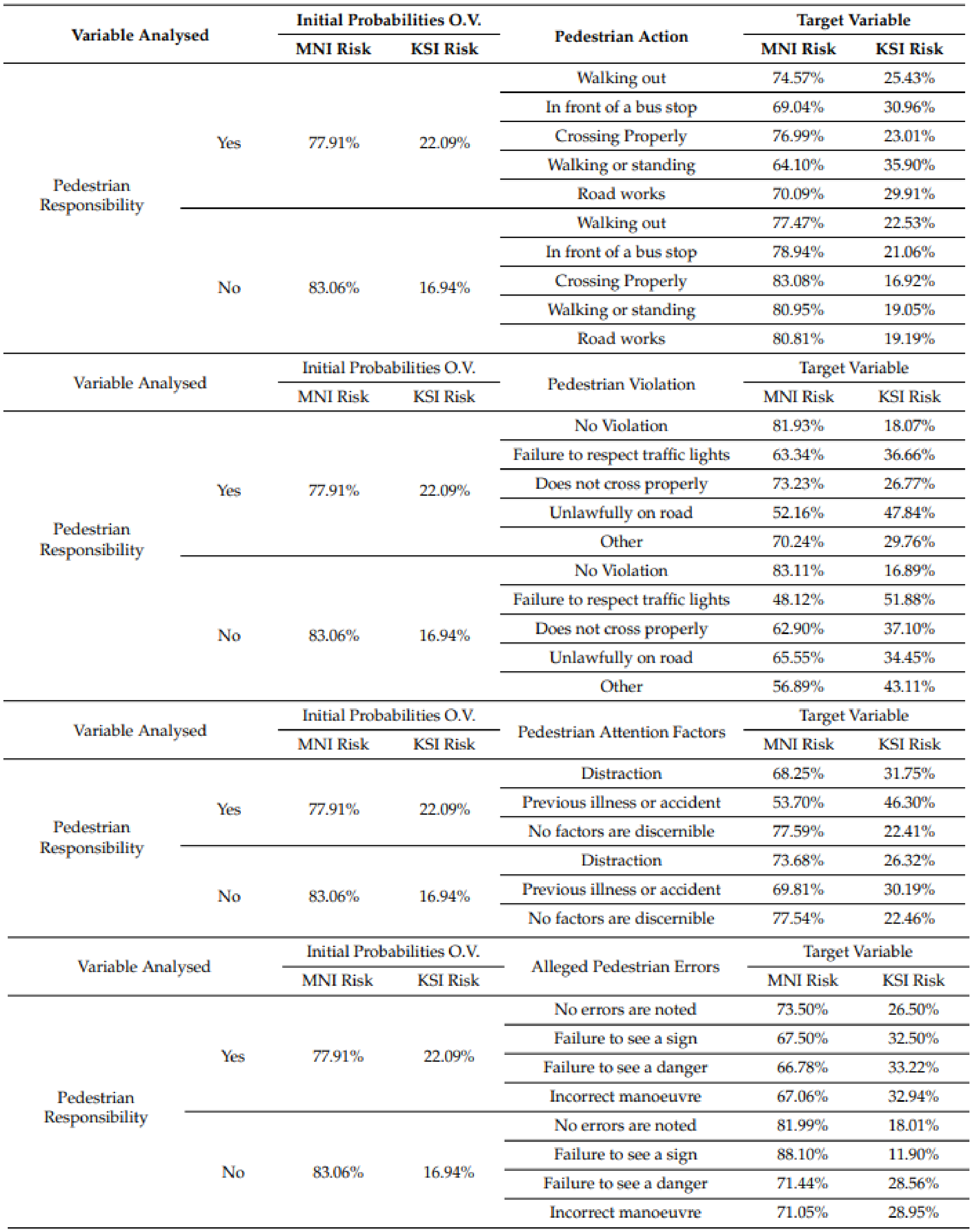
Similarly, in the case of the variable “type of road”, Table 10 reflects the differences in all the states of this variable, and that the responsibility of the pedestrian plays an important role in the traffic accident, since where there is no pedestrian responsibility, all the probabilities of suffering serious or fatal injuries during the traffic accident are seen to drop with respect to those where there is responsibility. However, the greatest increase in this risk is recorded in the peri-urban or ring roads (high speed), reaching a probability of 30.62% with respect to the ‘a prior’ probability of 22.09%, registering a difference of 8.53%, similar to the figures seen in the specially regulated zones (29.71%), with a difference of 7.62% with respect to their equal condition in the ‘a priori’ probabilities.

Under the same conditions, significant differences can be seen in the pedestrian’s degree of injury risk with respect to his or her responsibility and the situational variables of the infrastructure factor (Table 11), where it can be seen that the variable “pavement” seems to have a particular influence in the state in which it does not exist, i.e., when the traffic accident occurs in a place where there is no pavement for the pedestrian to walk on, increasing the risk of serious or fatal injury to 36.17% with respect to 22.09% of its “a priori” value (difference of 14.08%). Even if the pedestrian is not responsible for the accident, the risk of serious or fatal injury increases to 20.39% compared to the “a priori” probability of 16.94% if there are no pavements to walk on (an increase of 3.45%).

It is also important to note that in the case of the variable “lighting”, the behaviour is similar to that of pavements, since in both states of the variable “pedestrian responsibility” the probability of suffering serious or fatal injuries during the traffic accident decreases when there is adequate lighting (natural or artificial), which stands at 21.77% if there is pedestrian responsibility (a 0.32% decrease with respect to the “a priori” probabilities) and 16.93% if there is no pedestrian responsibility (a 0.01% decrease with respect to the ‘a prior’ probabilities). The same relationship can be observed in the opposite case, where lighting (natural or artificial) is poor or non-existent, the risk increases up to 24.62% when there is pedestrian responsibility (2.53% increase over the “a prior” probabilities) and to 17.24% when there is no pedestrian responsibility (0.30% increase over the “a priori” probabilities).

(3) Results related to the pedestrians' degree of injury rate due to the interaction of his/her actions and responsibility for the accident (Table 12).

Table 12. Probability of pedestrian injury according to pedestrian responsibility and variables with respect to pedestrian actions.



Variable Analysed		**Initial Probabilities O.V.**		**Pedestrian Action**	**Target Variable**	
		MNI Risk	**KSI Risk**		**MNI Risk**	**KSI Risk**
Pedestrian Responsibility	Yes	77.91%	22.09%	Walking out	74.57%	25.43%
				In front of a bus stop	69.04%	30.96%
				Crossing Properly	76.99%	23.01%
				Walking or standing	64.10%	35.90%
				Road works	70.09%	29.91%
	No	83.06%	16.94%	Walking out	77.47%	22.53%
				In front of a bus stop	78.94%	21.06%
				Crossing Properly	83.08%	16.92%
				Walking or standing	80.95%	19.05%
				Road works	80.81%	19.19%
Variable Analysed		Initial Probabilities O.V.		Pedestrian Violation	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	No Violation	81.93%	18.07%
				Failure to respect traffic lights	63.34%	36.66%
				Does not cross properly	73.23%	26.77%
				Unlawfully on road	52.16%	47.84%
				Other	70.24%	29.76%
	No	83.06%	16.94%	No Violation	83.11%	16.89%
				Failure to respect traffic lights	48.12%	51.88%
				Does not cross properly	62.90%	37.10%
				Unlawfully on road	65.55%	34.45%
				Other	56.89%	43.11%
Variable Analysed		Initial Probabilities O.V.		Pedestrian Attention Factors	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	Distraction	68.25%	31.75%
				Previous illness or accident	53.70%	46.30%
				No factors are discernible	77.59%	22.41%
	No	83.06%	16.94%	Distraction	73.68%	26.32%
				Previous illness or accident	69.81%	30.19%
				No factors are discernible	77.54%	22.46%
Variable Analysed		Initial Probabilities O.V.		Alleged Pedestrian Errors	Target Variable	
		MNI Risk	KSI Risk		MNI Risk	KSI Risk
Pedestrian Responsibility	Yes	77.91%	22.09%	No errors are noted	73.50%	26.50%
				Failure to see a sign	67.50%	32.50%
				Failure to see a danger	66.78%	33.22%
				Incorrect manoeuvre	67.06%	32.94%
	No	83.06%	16.94%	No errors are noted	81.99%	18.01%
				Failure to see a sign	88.10%	11.90%
				Failure to see a danger	71.44%	28.56%
				Incorrect manoeuvre	71.05%	28.95%

Table 12 shows the sensitivity analysis of pedestrians' degree of injury based on the pedestrian's responsibility and the different actions carried out by the pedestrian during the traffic accident. In the first section, it can be seen that in almost all states of the variable “pedestrian action”, the probability of suffering a serious or fatal accident increases with respect to the ‘a priori’ probabilities of pedestrian responsibility when the action committed is not correct, with the exception of the state called “crossing properly”, where the probability value remains remarkably similar. For example, the case in which the probability of degree of injury increases the most is in the “walking or standing” state (on the roadway or hard shoulder), reaching a value of 35.90% in the case of pedestrian responsibility for the accident (a 13.81% increase), and in the case of no responsibility. The greatest increase is found in the “walking out” state (between parked vehicles), with a value of 22.53%, a 5.59% increase with respect to the “a priori” probabilities.

When talking about pedestrian violations, we can observe that in all cases where a pedestrian commits a violation, regardless of his or her responsibility for the accident, the probability of suffering a serious or fatal accident increases, with the exception of when no violation is committed, in which case it decreases to 18.07% if there is responsibility (a 4.02% decrease) and 16.89% if there is no responsibility (a 0.05% decrease). The largest increase is registered when the pedestrian is walking or standing on the roadway in an unlawful manner (47.84%), resulting in a 25.75% increase in the probability of serious or fatal injury during the road traffic accident compared to the “a priori” probability of 22.09%. In the case of not being responsible for the traffic accident, the highest increase in the probability of having a serious or fatal injury during the traffic accident occurs when the pedestrian does not respect traffic lights (51.88%), compared to 16.94% of the ‘a priori’ probability (34.94% increase).

With respect to the variable “pedestrian care factors”, the greatest increase in the probability of suffering a serious or fatal injury during the traffic accident occurs when the pedestrian has just witnessed a previous accident or suffers from a sudden illness, which are represented in the state “previous illness or accident” with a probability of 46.30% if the pedestrian is responsible for the accident, and 30.19% if the pedestrian is not responsible, with an increase of 24.21% and 13.25%, respectively, in comparison to the ‘a priori’ probabilities (22.09%) and (16.94%).

Finally, with respect to Table 12, we have the sensitivity analysis relating to the alleged pedestrian errors, the cases where clear errors are recorded and there is responsibility for the traffic accident on the pedestrian’s part. The probabilities increase significantly in all states; for example, for the state “failure to see a sign” the probability of having a serious or fatal injury reaches 32.50%, as well as 32.94% in the state “incorrect manoeuvre”, with differences of 10.85% and 10.41% compared to its “a priori” probability of 22.09%.

6.5 RESULTS DISCUSSION

Pedestrian behaviours (actions, mistakes, violation, or distractions) and their responsibility for road accidents directly impact the likelihood of serious or fatal injuries during road accidents. The “a priori” probabilities show that a pedestrian has a 22.09% chance of serious or fatal injury if he/she is responsible for the accident, which decreases to 16.94% if the pedestrian is not responsible for the accident. These “a priori” probabilities are compared in this study with the interaction of behavioural and situational variables to understand the changes in pedestrian injury probabilities in different situations.

Some of the data initially worthy of note in this study (Table 6), are behaviours related to distractions with respect to other accidents or distractions in general (including distractions due to the use of technological equipment and mobile phones), where a difference in the probability of having a serious or fatal injury can be seen between the states “No factor is appreciated” with 20.73% and “Distraction” with 27.86%, values that are in accordance with what is expressed by Useche, Alonso and Montoro (2020) (Useche et al., 2020). The study also found, for example, that the use of mobile phones, as well as other social trends, could have implications for pedestrian safety.

As with the pedestrian behaviour factors, some other variables related to demographic and infrastructure factors (Table 7), show high probabilities of suffering a serious or fatal injury in a traffic accident compared to other states of their own variables; for example, people over 60 years old reach a probability of 22.10%, and an even higher value can be observed on main roads or motorways where speed limits are higher (33.47%); something similar can be understood from the study carried out by Rasouli, et al.(2017) (Rasouli et al., 2017), which studies the relationship between situational factors such as the speed of vehicles or the infrastructure of a pedestrian crossing on the behaviour of the pedestrian to perform certain actions, encountering findings of the possible interrelationship between these factors, as studied in this research.

Tables 8 and 11 show how pedestrian responsibility in traffic accidents, in interaction with demographic and infrastructure variables, show states with a higher risk of serious or fatal injury, especially when there are no pavements (36.17%), poor or no lighting (24.62%), high-speed roads that are not pedestrian-friendly (49.36%) and age groups over 60 years old (31.83%). Consistent with these data, a study published in 2020 using data from China (Hu et al., 2020),found that the higher severity of pedestrian casualties in traffic accidents is closely related to age (elderly), lighting conditions (occasional darkness), roads (high speed) and infrastructure (such as pavements), as well as pedestrian behaviour.

Overall, in Tables 8 and 12 of this study, it can be seen that in the interaction of all variables and pedestrian responsibility, there is at least one state where the probability of serious or fatal injury in a traffic accident increases significantly, even more so when the interaction is with the behavioural variables, which may be the elements leading to pedestrian responsibility in a traffic accident. For example, Table 12 shows that the pedestrian behaviours "not respecting a traffic light" and "unlawfully on road" increase this risk to 51.88% and 47.84%, respectively. These values, as well as the others shown in the tables above, are in line with the findings of the study conducted by (Poó et al., 2018), where it is said that the high level of pedestrian risk behaviour (pedestrian behaviour) reinforces the idea that in several cases pedestrians are the cause of certain traffic accidents, increasing their risk of being injured.

In particular, in Table 12, it can be evidenced that some actions of pedestrians such as standing and walking on inappropriate places, crossing inadequately or not seeing traffic signs, leading to an increase in the probability of suffering serious or fatal injuries during a traffic accident. Two studies conducted to understand traffic flow prediction and emergency traffic light control systems, indicate that prediction techniques using artificial neural networks and traffic light control systems dealing with accidents at intersections using deterministic and stochastic petri nets (Chen et al., 2020; Qi et al., 2015), can help improve accident management.

From the above, it is clear that pedestrian behaviours through their actions before and during road accidents are critical to reducing the number of road traffic fatalities and injuries. Therefore, this study provides important data on the interrelation of certain variables (demographic and infrastructure), pedestrian behavioural variables and pedestrian responsibility in road accidents with the probability of being seriously injured or killed as a result of a road accident. These data allow us to think about the implementation of preventive actions in programmes to reduce traffic accidents and the degree of pedestrian injury, as well as the possibility of new technological designs that consider the behavior of road users with a view to reducing the impact of possible traffic accidents.

6.6 CONCLUSIONS

As mentioned at the beginning of this study, road accidents continue to be a major cause of death or disability among road users. As a result, the efforts of road safety enforcement agencies worldwide are enormous, with multinational programmes such as the "Vision Zero" project or the World Health Organization's "Global Plan for the Decade of Action for Road Safety", which, among other topics, discusses the factors of responsibility and behavior of road users, with the fixed idea of reducing the rate of road accidents and road traffic injuries and fatalities.

Comparatively, there is not a large amount of previous research that can related pedestrian behavior and pedestrian responsibility in road accidents to the likelihood of serious or fatal injuries during road accidents. In this study, the relationships between demographic, infrastructure, behavioral and pedestrian responsibility factor variables were investigated to better understand how pedestrian actions (conditions that can be changed) and situational variables (conditions that cannot be changed) influence the degrees of pedestrian injury in traffic accidents.

As pointed out in some of the other articles studied and discussed in this research, this study confirms the close relationship between pedestrian behavior and the degree of pedestrian injury during road accidents. The findings indicate that unsafe pedestrian behaviors increase the likelihood of serious or fatal injuries during road accidents, and that safe behaviors help to reduce this likelihood, strengthening the lines along which road safety programs can be promoted and scaled up to reduce accident rates globally.

6.6.1. PRACTICAL IMPLICATIONS

This study provides general contextualization of the degree of pedestrian injury due to traffic accidents, and how their behaviour through their actions can influence the outcome of a pedestrian injury and in relation to causing accidents. Road safety regulators worldwide, and particularly in Spain, could consider the results obtained in this research for creating various road safety activities, focusing on raising awareness of the unsafe actions of pedestrians and other vulnerable road users when travelling in shared spaces or near vehicles. Activities designed to raise awareness could focus on three main points:

(1) the pedestrian's responsibility for the traffic accident, since in these cases there is a possibility of being the cause of injury to third parties, and furthermore, the probability of being seriously injured or even killed is very high; (2) traffic offences and errors on roads and pavements, which can focus on making pedestrians and vulnerable road users feel the need to pay attention to traffic signs; and, (3) pedestrian actions and attention factors, which are fundamental to ensuring order, safety and accident prevention in the world's road spaces.

6.6.2. LIMITATIONS AND FUTURE RESEARCH

Primarily, this study is limited by the amount of data (2016 to 2019) and variables in the global database. This was built from the four databases provided by the Spanish Directorate General of Traffic (DGT). There are several elements of study that have not been analyzed in the proposed network that may be of great interest in understanding the causes behind traffic accidents and the degree of pedestrian injury. Due to the naturalness of learning of the Bayesian networks, which gather a large amount of data for their operation, some peculiarities of each variable in its different states may go undetected, so a more extensive and separate research into the most relevant states found in this study would be advisable; for example, the incidence of the states of the variable "pedestrian violations", which generate the highest values for the probability of serious or fatal injury during a traffic accident, the states "not respecting a traffic light" and "standing unlawfully on the road", could be better analyzed separately and even disaggregated for further study. Likewise, important situational factors occurred during the accident should also be analyzed, such as the meteorological conditions that are included in the questionnaire filled out during traffic accidents in Spain, which could influence the actions of pedestrians and drivers in traffic accidents. However, this study is based on individual pedestrian behavior, but it is also possible to analyze group behavioral factors.

AUTHOR CONTRIBUTIONS

Conceptualization, J.D.F. and S.G.-H.; methodology, S.H. and J.D.F.; software,

J.D.F. and S.H.; validation, J.D.F., S.H. and S.G.-H.; resources, S.G.-H.; writing-original draft preparation, J.D.F.; writing-review and editing, J.D.F., S.G.-H., M.Á.M. and S.H.; project administration, S.G.-H. All authors have read and agreed to the published version of the manuscript.

ACKNOWLEDGMENTS

We would like to thank the Dirección General de Tráfico de España for providing the data for this study, as well as the people who collaborated in the research.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest

REFERENCES

(DOI: 10.3390/ su13116439)

7. ARTÍCULO 5: ASSESSMENT OF THE INFLUENCE OF TECHNOLOGY BASED DISTRACTED DRIVING ON DRIVERS' INFRACTIONS AND TH SUBSEQUENT IMPACT ON TRAFFIC ACCIDENTS SEVERITY

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Journal: International Journal of Environmental Research and Public Health

Published: 4 july 2021

Accesible at: https://doi.org/10.3390/ijerph18137155

Keywords: road traffic accidents; technology-based distractions; aberrant infractions; speed infractions; bayesian network; traffic accidents severity.

7.1 ABSTRACT

Multitasking while driving negatively affects driving performance and threatens people's lives every day. Moreover, technology-based distractions are among the top driving distractions that are proven to divert the driver's attention away from the road and compromise their safety. This study employs recent data on road traffic accidents that occurred in Spain and uses a machine- learning algorithm to analyze, in the first place, the influence of technology-based distracted driving on drivers' infractions considering the gender and age of the drivers and the zone and the type of vehicle. It assesses, in the second place, the impact of drivers' infractions on the severity of traffic accidents. Findings show that (i) technology-based distractions are likely to increase the probability of committing aberrant infractions and speed infractions; (ii) technology-based distracted young drivers are more likely to speed and commit aberrant infractions; (iii) distracted motorcycles and squad riders are found more likely to speed; (iv) the probability of committing infractions by distracted drivers increases on streets and highways; and, finally, (v) drivers' infractions lead to serious injuries.

7.2 INTRODUCTION

The road transportation system presents a high-risk system that threatens people's lives every day (Le et al., 2020). The severity of traffic accidents raises many social direct and indirect problems, physical and mental health disorders, economic expenses, and massive damage to the surroundings and properties (Jin et al., 2020). The World Health Organization estimates that approximately 1.35 million people die in road traffic accidents each year (on average, 3700 people lose their lives per day), and 20 to 50 million more people suffer non-fatal injuries, which often lead to long- term disabilities (WHO) In this regard, studies on the features of road safety concluded that traffic accidents occur mainly due to human factors, road infrastructure, environmental aspects, and their interactions (Soehodho, 2017) (Cai, 2020). Nevertheless, a growing body of research suggests that human factors, e.g., speeding, drink-driving, distracted driving, have the strongest influence and are responsible for 80–90% of road traffic acci- dents (Alavi et al., 2017; Ledesma et al., 2010; Petridou & Moustaki, 2000) (Boulagouas et al., 2020). Indeed, past research reported that distracted driving contributes to over half of inattention traffic accidents (Stutts et al., 2001). This is supported by an explosion of studies. For in- stance, in the USA, the National Highway Safety Administration estimated that distracted driving is responsible for approximately 10% of all fatal traffic accidents (Xiong et al., 2014). Similarly, in Spain, the General Traffic Department, reported that distracted driving contributed to approximately 28% of police-reported fatal traffic accidents (Vial, 2019).

Placing greater importance on the fact that secondary tasks that compete for the driver's attention and potentially degrade their perception and their ability to interpret the information they receive continually from a changing roadway (Ngueutsa & Kouabenan, 2017; Vial, 2019), in the recent past, many researchers and traffic transportation experts have deeply studied aspects of distracted driving and concluded that a majority of distracted driving is related to new technologies. Furthermore, a review of the current literature on distracted driving found a specific focus on mobile phone-related distractions. For instance, a survey study reported that 42% of drivers confirmed that they answer their mobile phones when driving, and 56% admitted to continuing to drive while completing the conversation (Schroeder et al., 2018). An observational study of 6578 drivers on randomly selected urban roads in Spain found that 20% of the observed drivers engaged in secondary tasks including talking on handheld mobile phones (i.e., 1.3%) (Prat et al., 2015).

A simulator study investigating the relationship between performing a secondary task (e.g., mobile phone use) and driving performance reported that engaging in a secondary task influences longitudinal and lateral control of the vehicle and leads to higher speeds (Oviedo-Trespalacios et al., 2016). Moreover, an examination of the chance of drivers colliding increases twelvefold when they handled their mobile phones (Dingus et al., 2016). Furthermore, it has been found that the effects of the use of mobile phones on drivers' reactions are worse than driving under a 0.08% blood alcohol level (Strayer et al., 2006).

Another experimental study analyzed the effects of the use of mobile phones on the reaction time of drivers in dangerous situations (pedestrian crossing and road crossing by parked vehicles, in particular) found that the use of mobile phones leads up to 204% increments in reaction times, proving that distractions decrease the driving performance (Choudhary & Velaga, 2017).

However, an estimation of the contribution of distracted driving in traffic accidents causality and its impact on other unsafe driving behaviors is complex. Indeed, there are the following three major challenges (Beanland et al., 2013; Wundersitz, 2019):

(i) obtaining reliable data about pre-accident conditions is difficult, (ii) there is a lack of systemic reporting, and (iii) there are inconsistencies in the definitions, classifications, and approaches used. Dealing with these challenges, many scholars have reviewed traffic accident assessment tools and advanced techniques and algorithms to increase the efficiency and effectiveness of road safety protective measures (Gutierrez-Osorio & Pedraza, 2020; Lord & Mannering, 2010; Yannis et al., 2017). Recently, many researchers have moved toward correlating the analysis methods with prediction techniques to model interactions between risk factors and predict potential impacts on causalities, frequencies, and the severity of traffic accidents. Such a combination considers several parameters to analyze the current conditions that are, therefore, assessed using the mean of the prediction models that contribute to mitigate the magnitude of traffic accidents and enhance the transportation system and safety strategies (Akgüngör & Doğan, 2009). Among the emergent techniques, there are the Grey System Theory and Markov Model (Jin et al., 2020), Data Mining Techniques (Gupta et al., 2017), Structural Time Series (Yousefzadeh-Chabok et al., 2016), Logistic Regression Analysis (Hu et al., 2020), and Bayesian Networks (Hongguo et al., 2010).

Building on these attempts, this paper focuses particularly on analyzing the influence of technology-based distracted driving on drivers' infractions and assesses their subsequent impact on the severity of traffic accidents employing recent data on road traffic accidents in Spain.

The present study is designed to provide relevant pieces of evidence on the relationship between technology-based distracted driving and other infractions. The assessment is therefore extended to evaluate the relationships between the infractions of the distracted drivers and the severity of traffic accidents and investigate the impact of a set of factors grouped into demographics, type of vehicle, and zone.

An assessment of the influence of technology-based distractions on drivers' infractions allows the accident risk to be estimated. In other words, it allows for, first, an appreciation of the proportion by which the probability of committing aberrant infractions and speeding would be expected to increase, provided that the driver is distracted. Second, it captures the infractions that lead to serious traffic accidents resulting in fatalities, while incorporating relevant parameters.

The remainder of this paper is arranged as follows: Section 2 reviews distracted driving; Section 3 sums up the data and methodology of the study; Section 4 provides the results of the study; Section 5 discusses the results and puts forward main findings, limitations, and future research guideline, while Section 6 concludes the paper.

7.3 BACKGROUND

Distracted driving has emerged as a major phenomenon that compromises traffic safety. It adversely impacts driving performance, increases reaction time, and reduces control over the vehicle; thus, it accounts for 25% of severe motor vehicle accidents, leading to significant morbidity and mortality (Lee, 2014). In terms of definition, distracted driving refers to the inattention of drivers and their focus on other competing activities while operating a motor vehicle, for instance, talking, smoking, texting, putting on make-up, reading, eating, using mobile phones, etc. (Donmez et al., 2006).

In light of the past research, distracted driving could be either intentional and voluntary, which occurs when drivers divert their attention from the driving tasks, or in- voluntary due to a failure to ignore non-related stimuli that motivates drivers to become distracted (Chen et al., 2018; Feng et al., 2014; Marulanda et al., 2015).

Distractors have been grouped into the following four main categories (Le et al., 2020; Sundfor et al., 2019)]: (i) visual, which implies taking the eyes off the road; (ii) auditory, which prevents making the best use of hearing; (iii) manual, which considers taking the hands off the wheel; and, finally, (iv) cognitive, when losing concentration on driving.

Moreover, distractions have been classified into (Hudák & Madleňák, 2017; Ito et al., 2001; Shaaban et al., 2020) (i) in-vehicle distractions, such as using mobile phones, interacting with an entertainment system, an iPod, radio, DVD player, operating navigation system, etc., and (ii) on-road distractions, such as roadside advertisements, crash scenes, digital billboards, etc.

Although other potential distractions are still of interest, technology-based distractions have attracted the focus of researchers who thoroughly investigated the risks associated with the use of technology devices (e.g., smartphones, wearable devices, portable devices, and in-vehicle information systems) while driving and used many approaches for risk estimation, for instance (Hill et al., 2015), surveys, simulators, phone records, on-road testing, and naturalistic studies.

A study analyzing the contribution of distracted driving to traffic accidents in the United States reported that 16% of motor vehicle crashes in which people were killed and 20% of those that caused injuries were a result of distracted driving (Overton et al., 2015). Furthermore, a synthesis of previous studies on mobile phone use and its effects on traffic safety has identified mobile phones as leading sources of distraction that reduce driving performance as they decrease the reaction time of the drivers (Oviedo-Trespalacios et al., 2016) (Llerena et al., 2015; Stavrinos et al., 2013; Zatezalo et al., 2018). After investigating the driving performance of distracted drivers, many studies have concluded that distracted drivers are more likely to engage in unsafe driving behaviors and several errors and violations increase, for instance, speeding violations, right-of-way violations, and failure to stop at stop signs and red lights (Garcia-Herrero et al., 2020; Huisingh et al., 2015; S. A. Useche et al., 2018). For a better understanding of the characteristics of distracted drivers and the frequency of being engaged in distractions, many researchers have investigated the demographics of distracted drivers. Indeed, in terms of gender, a study conducted in the UK reported that no differences have been found for many types of distractions (e.g., mobile phone conversations) (Sullman et al., 2015). Furthermore, the results of this study considered the age of the driver as a crucial predictor for most of the studied distractions (including technology-based distractions), concluding that older drivers are less likely to be distracted, unlike younger drivers. Similarly, a roadside observational survey in Melbourne (Young et al., 2010) has found that gender does not influence distracted driving, in contrast to age, where it has been suggested that young or middle-aged drivers are the predominant group in distracted driving.

Second, despite the increasing body of research on the effects of distracted driving on traffic accidents, a large part of the literature relies mostly on survey, observational, and simulator studies, which suffer a set of limitations. First, survey studies, most of the time, target one particular group of drivers (e.g., young, male, female, etc.) or analyze distracted driving by accumulating all the groups together. Furthermore, the data collected in such survey and/or interview studies are likely to be biased (Qi et al., 2020). Even though observational studies are typically conducted at particular places, allowing sufficient time for the observer to capture the behaviors of the drivers, they, in turn, limit the data to one location along the roadway (Wenners & Knodler Jr, 2014). Finally, driving simulator experiments are safe assessment procedures and provide a more realistic environment; however, traffic situations are unpredictable and uncontrollable and, therefore, simulators have limited fidelity (Karthaus et al., 2021).

The present study is designed to adequately remove, first, the bias of underreporting and after that deploys a machine learning technique to adequately investigate the influence of distracted driving on drivers' infractions considering the drivers' characteristics, the type of vehicle, and the zone, and assess the impact on the severity of traffic accidents.

7.4 MATERIALS AND METHODS

7.4.1 DATA DESCRIPTION

For this study, a dataset has been prepared using official data of traffic accidents that occurred in Spain in a period of four years (2016–2019) provided by the Spanish National Transportation Department. The data have been gathered by the Civil Guard General Directorate or local police officers and include information related to the traffic accident, for instance, the date, location, type of vehicles involved in the traffic accidents, demographics of the drivers, number of fatalities, trip purpose, violations, and errors, etc.

The current sample of this analysis includes 410,974 traffic accidents involving 666,504 drivers. Details of the study sample are given in Table 1.

Table 1. Frequencies of the study sample.

Variables		Number of Cases				
	Vehicle Type	**2016**	**2017**	**2018**	**2019**	**Total**
Traffic Accident	Car, van, all-terrain vehicles	120,831	120,261	119,755	118,491	479,338
	Motorcycles, quads, quadricycles	35,222	36,051	36,319	37,467	145,059
	Heavy vehicles	8906	8901	9176	8873	35,856
	Other vehicles	922	759	1039	3531	6251
	Total	165,881	165,972	166,289	168,362	666,504
Drivers Demographics	**Age**					
	Y < 25	21,983	21,350	20,707	21,432	85,472
	25 ≤ Y ≤ 40	63,188	61,476	61,191	60,538	246,393
	40 ≤ Y ≤ 60	59,857	61,660	63,696	65,369	250,582
	Y > 60	17,399	18,102	18,333	19,010	72,844
	Unspecified	3454	3384	2362	2013	11,213
	Total	165,881	165,972	166,289	168,362	666,504
	Gender					
	Male	119,878	120,447	120,920	122,407	483,652
	Female	445,44	44,225	44,772	45,407	178,948
	Unspecified	1459	1300	597	548	3904
	Total	165,881	165,972	166,289	168,362	666,504

The dataset contains information about the severity of traffic accidents presented in (Table 2). This information is aggregated into the following two groups: (i) Fatal accidents (FA) resulting in serious injuries (SI) or fatalities to the drivers involved in serious accidents (55545), and (ii) Minor accidents (MA) causing no injuries (NI) or resulting in slight injuries to the drivers involved in these minor accidents.

Table 2. Traffic accident severity distribution.

	Severity Level	**Number of Cases**				**Total**
		2016	**2017**	**2018**	**2019**	
Traffic Accident Severity	M/NI	151,446	151,595	152,757	155,161	610,959
	SI/F	14,435	14,377	13,532	13,201	55,545
	Total	165,881	165,972	166,289	168,362	666,504

SI/F: Serious Injuries and/or Fatalities M/NI: Minor and/or No Injuries.

The collected information from the dataset about technology-based distractions and drivers' infractions is given in Table 3.

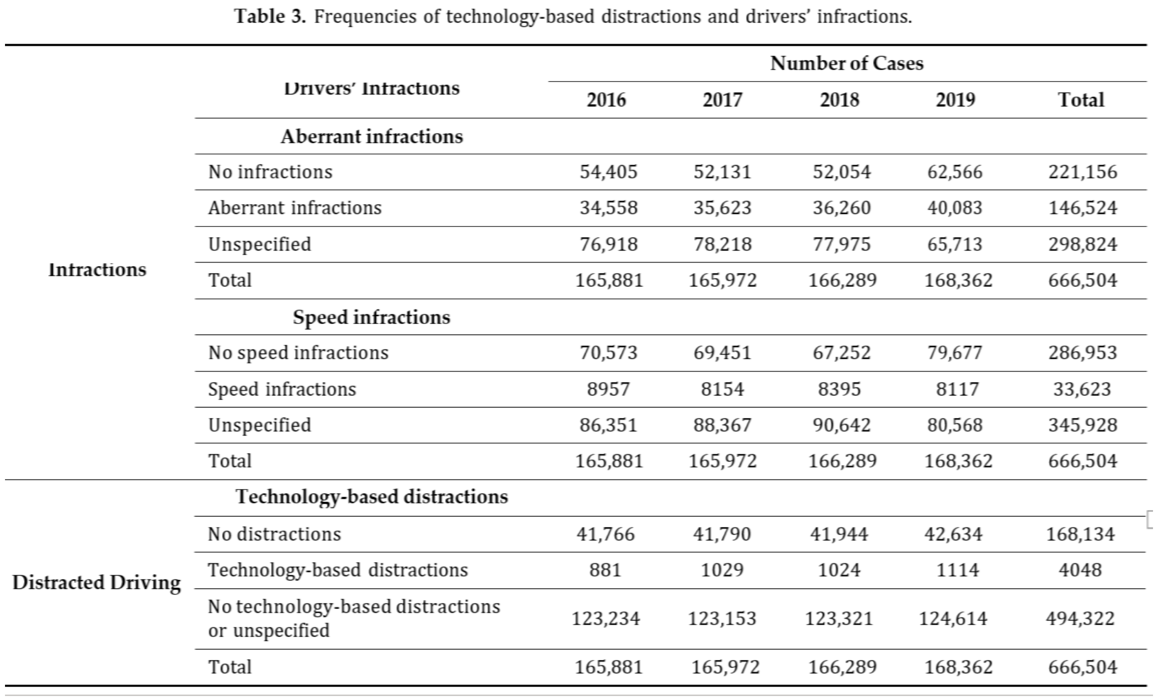


Table 3. Frequencies of technology-based distractions and drivers' infractions.

	Drivers' Infractions	Number of Cases				
		2016	2017	2018	2019	Total
Infractions	**Aberrant infractions**					
	No infractions	54,405	52,131	52,054	62,566	221,156
	Aberrant infractions	34,558	35,623	36,260	40,083	146,524
	Unspecified	76,918	78,218	77,975	65,713	298,824
	Total	165,881	165,972	166,289	168,362	666,504
	Speed infractions					
	No speed infractions	70,573	69,451	67,252	79,677	286,953
	Speed infractions	8957	8154	8395	8117	33,623
	Unspecified	86,351	88,367	90,642	80,568	345,928
	Total	165,881	165,972	166,289	168,362	666,504
Distracted Driving	**Technology-based distractions**					
	No distractions	41,766	41,790	41,944	42,634	168,134
	Technology-based distractions	881	1029	1024	1114	4048
	No technology-based distractions or unspecified	123,234	123,153	123,321	124,614	494,322
	Total	165,881	165,972	166,289	168,362	666,504

7.4.2 BIAS IDENTIFICATION

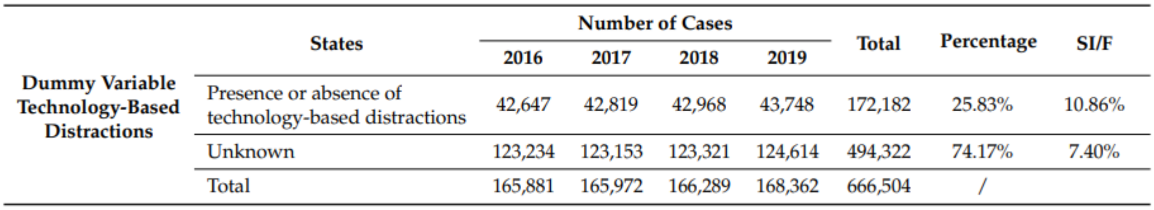
The dataset used to conduct this study was gathered by the Civil Guard General Directorate and local police officers who register information on traffic accidents, which is always incomplete. Indeed, many researchers have confirmed that as data on traffic accidents involving distracted drivers are collected from traffic accident reports, the real influence of this later on driving behaviors goes underestimated (Farmer et al., 2010).(Bucsuházy et al., 2020) Furthermore, distractions are hard to prove using statistics from the police (Wegman, 2017), because, in general, police officers only look for distractions when the consequences of traffic accidents are serious and, therefore, many distracted driving cases may not be recorded. Thus, scientific studies lead to unreliable conclusions.

To address the reporting biases, a methodology proposed in recent research (S. A. Useche et al., 2018)has been adopted. It is based on the introduction of a "dummy variable" into the model to isolate homogeneous subsamples and generate valid model and unbiased parameter

estimations. Accordingly, the frequencies of "technology-based distractions" have been thoroughly analyzed. Particularly, differences between the percentage of drivers involved in severe accidents knowing the states (i.e., being or not distracted) and the percentage of drivers involved in severe accidents having unknown states (i.e., unspecified) are computed (10.86% versus 7.40%, respectively) (Table 4). The differences are found to be significant;

therefore, the variable "technology-based distractions" is biased, and a dummy variable is introduced to differentiate homogeneous cases. In the rest of the paper, the sensitivity analysis results will only show the probabilities of drivers' infractions in traffic accident severity in a case of the state, "presence or absence of technology-based distractions" of dummy variable technology-based distractions. In this way, the subsamples containing unknown cases about the technology-based distractions are eliminated.

Table 4. Dummy Variable Frequencies.



	States	Number of Cases				Total	Percentage	SI/F
		2016	2017	2018	2019			
Dummy Variable Technology-Based Distractions	Presence or absence of technology-based distractions	42,647	42,819	42,968	43,748	172,182	25.83%	10.86%
	Unknown	123,234	123,153	123,321	124,614	494,322	74.17%	7.40%
	Total	165,881	165,972	166,289	168,362	666,504	/	

7.4.3 BAYESIAN NETWORKS

In the present study, Bayesian Networks have been deployed to model the influence of distracted driving on the severity of traffic accidents and unsafe driving behaviors. Over the last few decades, the Bayesian approach has been extensively applied to traffic safety studies, for instance, an assessment of road safety (Febres et al., 2020; Grande et al., 2017; Mora et al., 2017), an assessment of the influence of seatbelt use on the severity of traffic accidents (Febres et al., 2020), an estimation of committing an infraction due to mobile use [59], music distraction among young drivers (Catalina et al., 2020), a prediction of traffic accidents (Alizadeh et al., 2014), etc.

The Bayesian Networks model is a graphical inference methodology capable of predicting the future behavior of a particular variable based on past experience learned from the historical data source. Furthermore, they consist mainly of the following:

The qualitative aspect of the Bayesian Networks given by a directed acyclic network generally denoted as DAG (V, E), consisting of nodes (V) representing the variables related with directed edges (E), denoting the dependencies between the variables; The quantitative aspect consists of the conditional probability of each node, where every node has parents and has a conditional probability table expressing the depen- dencies of the father nodes. Therefore, the joint probability distribution is expressed as follows:

$$P(X_1,\ldots,X_n) = \prod_{i=1}^{n} P(X_1|X_{i-1},\ldots,X_n) \qquad (1)$$

$$P(X) = \prod_{i=1}^{n} P(X_i|pa_i) \qquad (2)$$

Where i=1, 2,. . .,n, X= [X1,X2, . . . ,Xn] is a set of variables of the Bayesian Network, *P* is a set of local probability distributions associated with each variable, X_1 refers to the variable node and, pa_i the father node of Xi. Many types of software could be used to build the Bayesian network, among them we cite the following (Zou & Yue, 2017): Bayes Builder, Java Bayes, and Bayes Net Toolbox, which were used in the present study.

7.4.3 BAYESIAN NETWORKS

To measure the performance of the obtained Bayesian Network, a ten-fold cross-validation has been conducted. K-fold cross-validation is a powerful means of testing the success rate, accuracy, and robustness of models used for classification (Marcot & Hanea, 2021). It consists of randomly partitioning the dataset into ten subsets of equal size; then each subset, in turn, is used to validate the model fitted on the remaining k-1 subsets. The evaluation of the obtained models is performed using the Area Under the ROC (Receiver Operating Characteristic) Curve—named AUC—that plots the following two parameters: True Positive Rate and False Positive Rate that yield the performance of a classification model. The standard scores range from 0 (opposite and wrong prediction) to 0.5 (random prediction) and 1 (perfect prediction).

7.5 RESULTS

7.5.1 VALIDATION OF BAYESIAN NETWORK

The results of the performance evaluation of the learned Bayesian Network (Figure 1) are given in Table 5.

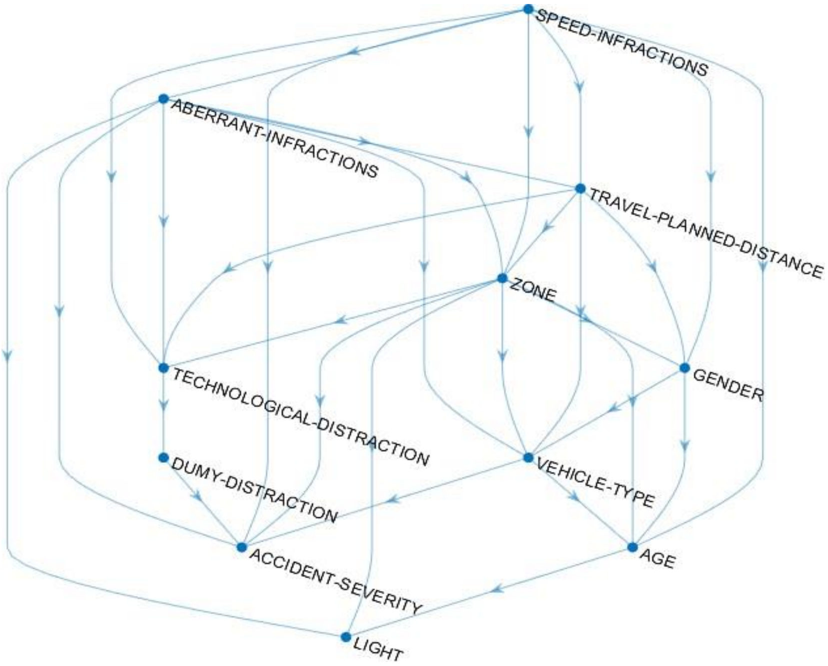


Figure 1. Obtained directed acyclic graph corresponding to the study variables.

Table 5. Validation results of the 10-fold cross-validation.

Variables	Accident Severity		Aberrant Infractions		Speed Infractions		Technology-Based Distraction	
States	SI/F	M/NI	No	Yes	No	Yes	No	Yes
AUC scores	0.62	0.62	0.88	0.77	0.90	0.77	0.99	0.93

The AUC score metrics obtained a range from 0.62 to 0.99 for the variables, which confirms the high robustness of the Bayesian Network.

The directed acyclic graph of Figure 1 specifies the joint distribution and represents the dependences/independences between the study variables. Indeed, in the lower right part of the graph, the largest number of study variables such as the zone, gender, vehicle type, and age can be observed in a grouped way. These variables have direct relationships with the infractions' variables before relating, directly or indirectly, to the severity of the accident.

At the top of the graph, the infractions' variables are directly related to the technology-based distraction variable. Furthermore, aberrant and speed infractions are related to the dummy variable, which is directly related to the severity of the traffic accidents.

7.5.2. SENSITIVITY ANALYSIS

7.5.2.1. ASSESSMENT OF THE INFLUENCE OF TECHNOLOGY-BASED DISTRACTIONS ON DRIVERS' INFRACTIONS

Estimation of the "a priori" probabilities of drivers' infractions considering the technology-based distractions is given by the sensitivity analysis results in Table 6.

Table 6. *Sensitivity analysis for the influence of technology-based distractions on drivers' infractions.*

Technology-Based Distractions	*Aberrant Infractions*		*Speed Infractions*	
States	***No***	***Yes***	***No***	***Yes***
No	*76.43%*	*23.57%*	*92.22%*	*7.78%*
Yes	*33.25%*	*66.75%*	*85.55%*	*14.45%*

The results in Table 6 show that the probability of committing aberrant infractions increases significantly (from 23.57 to 66.75%) given the fact that the drivers are distracted. Interestingly, these results show that the probability of not committing aberrant infractions increased notably (from 33.25 to 76.43%) when the drivers are not distracted.

Similarly, the sensitivity analysis results in Table 6 show that drivers are more likely to speed when they are distracted. Indeed, the probability increases from 7.78 to 14.45%. Moreover, the probability of respecting the speed limit increases from 85.55% to 92.22% when drivers are not distracted.

The results also show that technology-based distractions are more likely to affect aberrant infractions than speed infractions.

7.5.2.2. ASSESSMENT OF THE INFLUENCE OF TECHNOLOGY-BASED DISTRACTIONS ON DRIVERS’ INFRACTIONS CONSIDERING THE AGE AND GENDER OF THE DRIVERS

The influence of distracted driving on drivers’ infractions considering the effect of demographics is given by the sensitivity analysis results in Table 7.

According to these results, the probability of not committing aberrant infractions, considering the fact that the drivers are not distracted, increases for drivers younger than 60 years old. Similarly, it has been found that the probability of not speeding, considering the fact that the drivers are not distracted, increases for drivers older than 40 years old and more significantly in the case of elderly drivers (from 92.22 to 95.39%).

With regard to the gender, the results in Table 8 show that the probability of not speeding, considering the fact that the drivers are not distracted, increases notably in the case of females (from 92.22 to 94.08%).

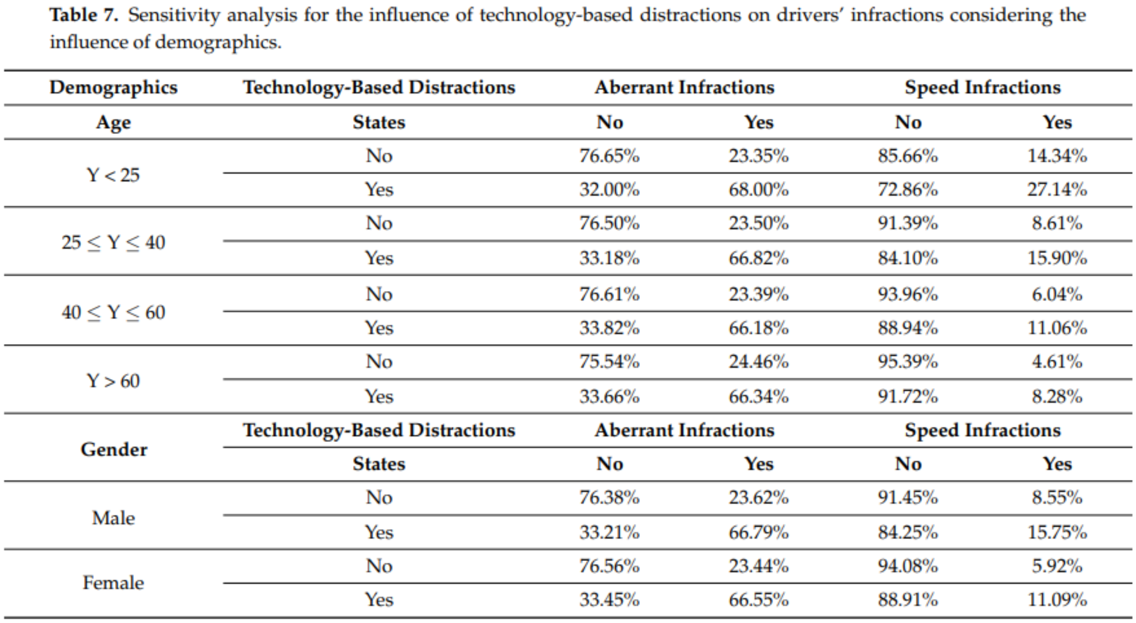


Table 7. Sensitivity analysis for the influence of technology-based distractions on drivers’ infractions considering the influence of demographics.

Demographics	Technology-Based Distractions	Aberrant Infractions		Speed Infractions	
Age	**States**	**No**	**Yes**	**No**	**Yes**
Y < 25	No	76.65%	23.35%	85.66%	14.34%
	Yes	32.00%	68.00%	72.86%	27.14%
25 ≤ Y ≤ 40	No	76.50%	23.50%	91.39%	8.61%
	Yes	33.18%	66.82%	84.10%	15.90%
40 ≤ Y ≤ 60	No	76.61%	23.39%	93.96%	6.04%
	Yes	33.82%	66.18%	88.94%	11.06%
Y > 60	No	75.54%	24.46%	95.39%	4.61%
	Yes	33.66%	66.34%	91.72%	8.28%
Gender	**Technology-Based Distractions**	**Aberrant Infractions**		**Speed Infractions**	
	States	**No**	**Yes**	**No**	**Yes**
Male	No	76.38%	23.62%	91.45%	8.55%
	Yes	33.21%	66.79%	84.25%	15.75%
Female	No	76.56%	23.44%	94.08%	5.92%
	Yes	33.45%	66.55%	88.91%	11.09%

Table 8. Sensitivity analysis for the influence of technology-based distractions on drivers' infractions considering the influence of the zone and vehicle type.

Variables	Technology-Based Distractions	Aberrant Infractions		Speed Infraction	
Vehicle Type	**States**	**No**	**Yes**	**No**	**Yes**
Car/Van/All Terrain	No	73.73%	26.27%	92.02%	7.98%
	Yes	31.09%	68.91%	85.80%	14.20%
Motorcycles/quads/quadricycles	No	86.58%	13.42%	93.46%	6.54%
	Yes	43.83%	56.17%	84.56%	15.44%
Heavy vehicles	No	78.28%	21.72%	90.44%	9.56%
	Yes	39.70%	60.30%	84.73%	15.27%
Other vehicles	No	85.48%	14.52%	95.67%	4.33%
	Yes	34.90%	65.10%	85.37%	14.63%
Zone	**Technology-Based Distractions**	**Aberrant Infractions**		**Speed Infraction**	
	States	**No**	**Yes**	**No**	**Yes**
Road	No	76.19%	23.81%	89.03%	10.97%
	Yes	41.06%	58.94%	85.64%	14.36%
Street or similar	No	76.74%	23.26%	96.97%	3.03%
	Yes	18.89%	81.11%	85.50%	14.50%
Highway	No	83.82%	16.18%	94.19%	5.81%
	Yes	20.20%	79.80%	60.41%	39.59%

In terms of aberrant infractions, the sensitivity analysis results show that the probabilities increase given the fact that the drivers are distracted (from 66.75 to 68%) in the case of younger drivers (<25 years old). Similarly, it has been found that the probability of speeding for distracted drivers increases, interestingly, in the case of younger drivers (<25 years old) (from 14.45 to 27.14%) and decreases significantly in the case of older drivers (from 14.45 to 8.28%).

7.5.2.3. ASSESSMENT OF THE INFLUENCE OF TECHNOLOGY-BASED DISTRACTIONS ON DRIVERS' INFRACTIONS CONSIDERING THE ZONE AND TYPE OF THE VEHICLE

The results of the estimation of the influence of technology-based distractions on drivers' infractions considering the zone and type of the vehicle are given in Table 8. The results show that the probability that drivers do not commit aberrant infractions increases in the case of motorcycles, quads, and quadricycles (from 76.43 to 86.58%) and other types of vehicles (from 76.43 to 85.48%), considering the fact that the drivers are not distracted. In contrast, the results show that the probability of committing aberrant infractions increases more significantly in the case of distracted drivers of cars, vans, and all-terrain vehicles (from 66.75 to 68.91%).

With regard to speed, similarly, the results of the sensitivity analysis show that the probability of respecting the speed limits increases significantly in the case of non-distracted motorcycle riders and drivers of other vehicles (from 92.22 to 93.46%, and from 92.22 to 95.67%, respectively). Moreover, the probability of speeding increases, logically, in the case of distracted motorcycle riders.

The results of the effect of the zone on the behaviors of distracted drivers confirm that distracted drivers commit aberrant infractions on highways and streets (the probabilities increase from 66.75 to 79.80% and from 66.75 to 81.11%, respectively). Nevertheless, distracted drivers are more likely to not respect the speed limit on highways (the probability increases significantly from 14.45 to 39.59%).

7.5.2.4. ASSESSMENT OF THE INFLUENCE OF DRIVERS' INFRACTIONS ON TRAFFIC ACCIDENT SEVERITY

The severity of traffic accidents due to aberrant infractions or speeding is not always reported in the case of minor traffic accidents. In other words, in such accidents, the police officers are not used to thoroughly fill in the traffic accident report and, most of the time, they do not provide details on whether the drivers involved in minor accidents had committed aberrant infractions or speed infractions.

The influence of drivers' infractions on the severity of traffic accidents is given by the sensitivity analysis results in Table 9.

Table 9. Sensitivity analysis for the influence of the drivers' infractions on the severity of traffic accidents.

Drivers' Infractions	**Severity of Traffic Accidents**	
Aberrant infractions	*M/NI*	*SI/F*
No	90.62%	9.38%
Yes	90.31%	9.69%
Speed infractions		
No	90.97%	9.03%
Yes	82.11%	17.89%

The results in Table 9 show that the probability that the severity of injuries is serious, resulting in fatalities, increases, given the fact that the drivers committed aberrant infractions (from 9.38 to 9.69%) and more significantly in the case of speeding (the probability increases from 9.03 to 17.89%).

7.6 DISCUSSION

Traffic accidents have become a major health public issue and preservation of the lives of drivers, passengers and users is among the main concerns of communities around the world. The literature revealed the fact that numerous factors contribute to and influence the occurrence of these accidents and the severity of injuries (Sanyang et al., 2017) (Hosseinian et al., 2021; Xie et al., 2020). Although the continuous efforts of governments and numerous traffic safety policies being issued to control traffic accidents, the rates of disabilities, fatalities, and injuries continue to increase dramatically. Therefore, it has been extensively recommended to analyze the different risk factors influencing traffic accident severity to yield more patterns and polish knowledge to effectively and efficiently prevent road accidents and ameliorate traffic safety.

In this study, we focused, particularly, on the assessment of the influence of technology-based distractions on the performance of drivers behind the wheel. The contribution of this research is twofold. First, it deployed machine learning technique algorithms that, taking advantage of advancements in information technology, allow traffic accidents to be predicted and detect the role of different risk factors in traffic accident scenarios. Second, it overviewed the relationships between the technology-based distractions and the infractions of drivers with full consideration of the impact of gender, age, zone, and the type of vehicle.

Given the crucial aspect of traffic safety, i.e., the prediction of the most important risk factors impacting the occurrence of traffic accidents and influencing the severity of the outcomes, in the present study, a predictive model has been developed to assess the influence of technology-based distractions on the traffic accidents' severity and unsafe driving behaviors considering the effect of a set of selected risk factors using

Bayesian Networks methodology. Indeed, the obtained Bayesian model presented the knowledge in the form of joint probabilities distributions of the study variables, which is vital to make effective and efficient decisions that avoid the drivers' infractions resulting from technology- based distractions and reduce the severity of injuries to the drivers and passengers.

To conduct this investigation, a recent database over four years (from 2016–2019) on traffic accidents that occurred in Spain was used. According to the sensitivity analyses, the findings indicated that technology-based distracted driving has a significant effect on both the aberrant infractions and speeding. Indeed, the study found that the presence of distractions notably increases the probability of committing aberrant infractions and speeding. This is in line with the literature (Eid & Abu-Zidan, 2017; Foss & Goodwin, 2014) that overviewed the characteristics of distracted driving, which has agreed that new technologies can absorb drivers' attention and reduce their abilities to judge driving demands and disrespect driving safety requirements that lead, most of the time, to aberrant infractions and unsafe behaviors.

With regard to the risk factors related to the demographics of the drivers involved in traffic accidents, vehicle, and zone, the findings of the present study reported increased probabilities as regards the infractions of distracted young drivers (under 25 years old). These findings coincide with many conclusions of existing studies (Ali et al., 2014; Hı́jar et al., 2000; Tanveer et al., 2020)which had reported similar observations on risky driving behaviors and violations of young drivers who are more susceptible to be involved in fatal crashes due to distraction activities (e.g., mobile phone use, radio, DVD, etc.). In this context, young drivers are inexperienced and easily distracted by interactions with music devices, texting and conversations on mobile phones resulting in slower reaction times (Buckley et al., 2014).

The sensitivity analysis results of the present study also showed that there are no significant differences in the probabilities of the impact of the gender of drivers on the driving behaviors of distracted drivers.

Furthermore, it has been found that speeding will lead to severe traffic accidents, leading to serious injuries and/or fatalities. These results are tightly associated with the findings of many previous researchers (Lee et al., 2018; Ratanavaraha & Suangka, 2014) that confirmed that speed increases the chance of traffic accidents that result in greater severity.

With regard to the influence of the zone and type of the vehicle factors, the sensitivity analysis showed that distracted drivers are more likely to speed on highways, whereas on streets, distracted drivers are more susceptible to commit aberrant infractions. Moreover, it has been found that the probability of motorcycle riders speeding increases because they are distracted, while car drivers are more likely to commit aberrant infractions. Similar findings reported that mortalities on highways and outside the urban center are mainly due to speed-related crashes (Cooper, 1997; Valent et al., 2002). Furthermore, an investigation into drivers’ violations found that speeding infractions represent 80% of registered traffic violations on highways (Shawky et al., 2017).

For future research, it is recommended to extend the current study by considering other risk factors. Such consideration would give wider context and more shreds of evidence on the influence of distracted driving that would help improve and enhance traffic safety more effectively and efficiently.

7.7 CONCLUSIONS

Distracted driving is a growing threat to road safety and accounts for a significant number of serious injuries and deaths in traffic accidents. In this paper, the distracting effects of various technologies on driving performance have been assessed using Bayesian Networks. Unlike other studies, the assessment was then extended to analyze the influence of the driver’s infractions on the severity of traffic accidents. The design of this study considered the driver’s characteristics, the type of vehicle, and zone.

The results of this study documented a strong link between technology-based dis- tracted driving and aberrant and speed infractions. Moreover, the findings showed that these infractions have a direct impact on the severity of traffic accidents. Furthermore, this study specifically found that young drivers are more likely to be distracted.

The deployment of Bayesian Networks yielded a representative graphical structure of the relationships among the technology-based distractions, drivers' infractions, and traffic accidents' severity. It contributed to overcoming the observed limitations of most research that has used regression models. Thus, machine learning techniques proved to be more suitable for prediction models in traffic safety problems.

AUTHOR CONTRIBUTIONS

Conceptualization, S.G.-H., J.D.F. and W.B.; methodology, J.M.G.; software, J.D.F.; validation, J.D.F. and S.G.-H.; formal analysis, J.D.F. and W.B.; investigation, W.B. and J.D.F.; resources, S.G.-H.; data curation, J.D.F.; writing—original draft preparation, W.B., J.D.F. and S.G.-H.; writing—review and editing, W.B., J.D.F., S.G.-H., M.Á.M.S. and J.M.G.; supervision, S.G.-H. and J.M.G.; project administration, S.G.-H.; funding acquisition, S.G.-H. All authors have read and agreed to the published version of the manuscript.

FUNDING

This research was funded by the project "Modelización mediante técnicas de machine learn- ing de la influencia de las distracciones del conductor en la seguridad vial", grant number BU300P18, and was funded by FEDER (Fondo Europeo de Desarrollo Regional—Junta de Castilla y León).

ACKNOWLEDGMENTS

We would like to thank the Dirección General de Tráfico from España (DGT) for providing the data for this study.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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(DOI: 10.3390/ ijerph18137155)

CONCLUSIONES

8. CONCLUSIONES GENERALES

La tesis se orientó desde un inicio al estudio de la lesividad de los accidentes de tráfico en España, con el objetivo de modelizar los factores que influyen e intervienen en estos accidentes, clasificándolos en factores técnicos y humanos. Cada uno de estos dos grupos de factores incluyen una serie de variables relevantes que intervienen en el estudio de la lesividad de los usuarios de las vías. El aporte científico de esta Tesis Doctoral se basa en el análisis y la modelización de cinco estudios científicos concretos que determinan la lesividad de los accidentes de tráfico en España. Dichos modelos analizan y cuantifican la probabilidad de lesividad de los conductores, de los peatones, y de los usuarios en general de las vías en función de las variables o factores relevantes.

Los objetivos planteados fueron resueltos satisfactoriamente con la búsqueda y análisis previo de la literatura, y con la posterior aplicación de la metodología seleccionada y la investigación plasmada en las contribuciones científicas. A continuación, se resumen las conclusiones derivadas de esta Tesis Doctoral en 3 secciones diferentes: (i) conclusiones generales y relacionadas con el apartado de metodología, (ii) conclusiones generales relacionadas con las contribuciones científicas, ya que las específicas de cada artículo científico se encuentran en el apartado de contribuciones científicas, (iii) áreas o temas de interés para dar continuidad al presente trabajo y que sugieren las líneas futuras de investigación.

8.1 CONCLUSIONES RELACIONADAS A LA METODOLOGÍA

- El marco metodológico que se ha utilizado en esta tesis responde a la necesidad de modelización del clasificador "lesividad" en los accidentes de tráfico, el cual ha sido estudiado a través del modelado de los factores técnicos y humanos con los datos proporcionados por la Dirección General de Tráfico de España (DGT).
- El conjunto de datos obtenidos por los agentes de tráfico y gestionados por la DGT, contienen, como es natural, algunos sesgos y erratas ocurridas en el momento de registrar la información en campo o transcribir los datos a la base de datos general; sin embargo, cada modelo generado ha demostrado que los datos son consistentes para modelizar los mismos y obtener valores de predicción acertados. En concreto, el caso en el que se detectó mayor sesgo fue en la contribución científica que estudia las distracciones de base tecnológica; la solución aportada fue la creación de variables ficticias para corregir el sesgo de perdida de información en el momento de la obtención de datos.

- Los modelos generados para el estudio de cada contribución científica demostraron que, el análisis de datos en materia de accidentabilidad de tráfico tiene un alto índice de eficiencia predictiva si se utiliza algoritmos de aprendizaje autónomo con redes bayesianas, especialmente si existe una gran cantidad de datos y variables que alimentan el modelo. Esta técnica permite desagregar los estados de cada variable en el modelo, utilizando cualquiera de ellos como el clasificador para el aprendizaje de la red, y convirtiéndolo en el objeto de estudio frente al resto del modelo, siendo en este caso la lesividad el clasificador seleccionado.
- Se puede aseverar que la técnica de validación de datos por área bajo la curva ROC (AUC) permite evaluar adecuadamente cada modelo teórico que se genere, para luego calcular los resultados buscados a través del algoritmo de aprendizaje autónomo de redes bayesianas. En el caso de esta tesis, los cinco modelos de las contribuciones científicas fueron evaluadas con esta técnica, dando siempre valores superiores a 0.7 para el clasificador de la lesividad, incluso en algunos casos superiores a 0.90.
- Finalmente, en dos contribuciones científicas se utilizó también la regresión logística lineal para el análisis de datos, y la prueba "z" como método de validación, y en ambos casos, la validación mediante AUC y las predicciones mediante algoritmos de aprendizaje autónomo por redes bayesianas, tuvieron igual o mejores resultados.

8.1 CONCLUSIONES GENERALES DE LAS CONTRIBUCIONES CIENTÍFICAS

- Los conductores están peligrosamente expuestos a las lesiones de tráfico, por lo que estar atentos durante la conducción es un factor importante en el grado de lesividad que pueden sufrir los conductores. Si bien es cierto, que factores como la edad, especialmente en personas jóvenes inexpertas o personas muy adultas sujetas a súbitas enfermedades o pocos reflejos resultan influyentes, son los factores relacionados al comportamiento durante el manejo los más importantes. Concretamente, acciones como, utilizar el equipo de seguridad adecuado, no infringir la normativa de velocidad, conducir concentrado, respetar normas de tránsito, colaboran a reducir los índices de lesividad. Es importante decir también que, los conductores de motocicletas y bicicletas son los más expuestos a lesiones graves o mortales, por lo cual las medidas de seguridad y el diseño de infraestructuras especiales son una prioridad en estos casos, al igual que el control normativo en vías de alta velocidad.
- En general, los conductores que se encuentran fuera de la ley con sus permisos de conducir, o sanciones similares, generan un impacto negativo de eficiencia en

la conducción, incrementando el número de infracciones de tránsito y por ende los accidentes, convirtiéndose en un factor importante en la generación de accidentes de tráfico y en el grado de lesividad general de los usuarios de las vías. Es por ello que, la promoción e implementación de mejoras en la seguridad vial, tanto a nivel regulatorio, como de programas de educación vial, son una necesidad para reducir el número de accidentes de tráfico y reducir los índices de lesividad grave o mortal en las personas.

- El avance de la tecnología ha traído consigo grandes avances también en la automatización de los vehículos, mejorando sus condiciones de seguridad constante para sus usuarios. Sin embargo, el uso de equipos con base tecnológica durante la conducción es un factor relevante en el comportamiento de los conductores y la conducción distraída, demostrando un vínculo fuerte con las infracciones aberrantes y de velocidad, las mismas que generan un aumento en el número de accidentes de tráfico y en la lesividad de los usuarios de las vías que se ven afectados por estos accidentes. Es importante recalcar que, los conductores jóvenes, como era de esperarse por ser nativos tecnológicos, tienen una mayor probabilidad de distraerse por el uso de equipos tecnológicos, es por ello que, el trabajo de concienciación se vuelve prioritario para quienes se dedican a esta área de la enseñanza.
- Los peatones, ciclistas y usuarios de vehículos similares son sin duda los más vulnerables si se ven envueltos en un accidente de tráfico, porque los elementos de protección que pueden utilizar no son comparables con los utilizados en los vehículos de motor, considerando que el mismo vehículo se convierte en un elemento protector del conductor. Sin embargo, el comportamiento de estos usuarios tiene un papel preponderante en los accidentes de tráfico y el grado de lesividad, pues también pueden ser responsables de la generación de accidentes de tráfico debido a sus errores, distracciones o comportamientos inadecuados cuando circulan en los diferentes tipos de vías. Es por ello que, los programas de seguridad vial también deben centrar su mirada en estos usuarios, no únicamente como potenciales víctimas, sino también como posibles generadores de accidentes de tráfico, con el fin de impartir programas de educación dirigidos exclusivamente a estos grupos para mejorar el uso del espacio vial.
- En general, los factores técnicos y humanos son predeterminantes en el grado de lesividad de un accidente de tráfico, y por ello, las condiciones que de aquí se derivan, tanto las que no pueden ser cambiadas en el corto o largo plazo por distintos motivos (especialmente algunos factores técnicos), así como aquellas condiciones que se pueden cambiar, como por ejemplo los comportamiento de todos los usuarios de la vías (conductores, acompañantes, ciclistas, peatones, etc), deben ser tratadas como condiciones de riesgo en materia de seguridad vial, estructurando normativa específica y programas dirigidos para cada situación.

Además, se debe prestar especial atención al registro de datos de accidentabilidad, siendo este la principal fuente de conocimiento para determinar qué factores son los que deben regularse y estudiarse permanentemente, porque el continuo cambio de las condiciones del tráfico obliga a mantener los estudios actualizados.

8.3 ÁREAS DE FUTUROS ESTUDIOS

- El estudio de los datos relacionados con los factores ambientales y de diseño de las infraestructuras viales es muy importante para analizar las variables que influyen en el aumento de la lesividad de los accidentes de tráfico. Por ello, se sugiere mejorar el registro de estos datos, se propone la utilización de herramientas tecnológicas que aporten datos climatológicos precisos en el momento del accidente, y se recomienda analizar las infraestructuras en relación a la normativa vigente de construcción. Todo este conocimiento será necesario para proponer cambios tanto en la normativa como en la formación práctica de la conducción bajo condiciones climatológicas de riesgo.
- El comportamiento de todos los usuarios de las vías debe ser estudiado constantemente. Se recomienda como futura línea de trabajo analizar los datos de los accidentes de tráfico registrados por la Dirección General de Tráfico de España, y contrastarlos o compararlos con estudios de simulación en laboratorios. Los laboratorios de simulación permiten generar condiciones cercanas a la realidad, dejando en evidencia las certezas que aporta el análisis de datos de lo ya sucedido. Así, la simulación permitiría estimar lo que sucedería bajo ciertas condiciones, y por lo tanto determinaría con más precisión la predicción de futuros accidentes de tráfico. Esta línea mixta de aprendizaje autónomo de datos, que combina aquello que sucedió y la simulación en tiempo real de lo que podría suceder, es un campo prometedor en materia de accidentabilidad de tráfico.
- Un factor adicional que requiere un cuidadoso estudio es el uso de sustancias y la ingesta de alcohol en todos los usuarios de las vías, y principalmente en los conductores. Sin embargo, los datos que se proporcionan sobre estas situaciones suelen tener varios sesgos, por lo que el uso de la tecnología en la detección de estos casos durante la conducción es un factor que podría reducir ampliamente la accidentabilidad. Siendo así, nuevamente, la unión de la simulación y el posible uso de la tecnología en el control de esta situación, una prometedora línea de estudio en el campo de la seguridad vial.

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lucha contra las enfermedades no transmisibles y los traumatismos causados por
el tránsito <p class="MsoBodyText" style="margin-top:6.0pt;margin-right:0in;margin-bottom:
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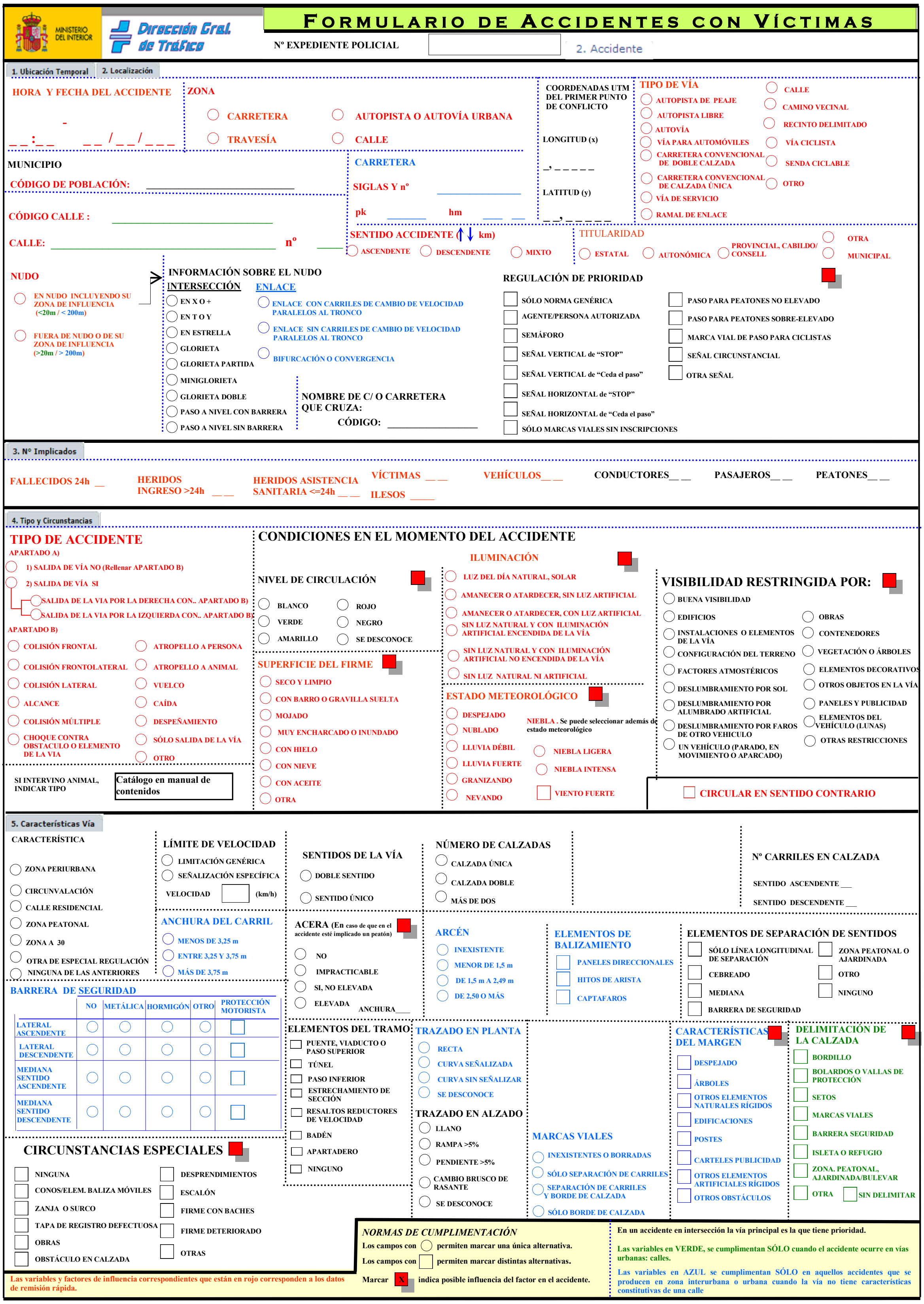
ANEXO A

ANEXO I

Formulario de accidentes de tráfico con víctimas



MINISTERIO DEL INTERIOR
Dirección Gral. de Tráfico

FORMULARIO DE ACCIDENTES CON VÍCTIMAS

Nº EXPEDIENTE POLICIAL ________

1. Ubicación Temporal | 2. Localización | 2. Accidente

HORA Y FECHA DEL ACCIDENTE

_ _:_ _ - _ _ / _ _ / _ _ _

ZONA
○ CARRETERA
○ AUTOPISTA O AUTOVÍA URBANA
○ TRAVESÍA
○ CALLE

COORDENADAS UTM DEL PRIMER PUNTO DE CONFLICTO

LONGITUD (x) _’ _ _ _ _ _

LATITUD (y) _ _’ _ _ _ _ _ _

TIPO DE VÍA
○ AUTOPISTA DE PEAJE
○ AUTOPISTA LIBRE
○ AUTOVÍA
○ VÍA PARA AUTOMÓVILES
○ CARRETERA CONVENCIONAL DE DOBLE CALZADA
○ CARRETERA CONVENCIONAL DE CALZADA ÚNICA
○ VÍA DE SERVICIO
○ RAMAL DE ENLACE
○ CALLE
○ CAMINO VECINAL
○ RECINTO DELIMITADO
○ VÍA CICLISTA
○ SENDA CICLABLE
○ OTRO

MUNICIPIO

CÓDIGO DE POBLACIÓN: ____________________

CÓDIGO CALLE : ____________________

CALLE: ______________________________ nº ____

CARRETERA

SIGLAS Y nº ____________

pk ______ hm ___ ___

SENTIDO ACCIDENTE (↑↓ km)
○ ASCENDENTE ○ DESCENDENTE ○ MIXTO

TITULARIDAD
○ ESTATAL ○ AUTONÓMICA ○ PROVINCIAL, CABILDO/ CONSELL ○ OTRA ○ MUNICIPAL

NUDO
○ EN NUDO INCLUYENDO SU ZONA DE INFLUENCIA (<20m / < 200m)
○ FUERA DE NUDO O DE SU ZONA DE INFLUENCIA (>20m / > 200m)

INFORMACIÓN SOBRE EL NUDO

INTERSECCIÓN
○ EN X O +
○ EN T O Y
○ EN ESTRELLA
○ GLORIETA
○ GLORIETA PARTIDA
○ MINIGLORIETA
○ GLORIETA DOBLE
○ PASO A NIVEL CON BARRERA
○ PASO A NIVEL SIN BARRERA

ENLACE
○ ENLACE CON CARRILES DE CAMBIO DE VELOCIDAD PARALELOS AL TRONCO
○ ENLACE SIN CARRILES DE CAMBIO DE VELOCIDAD PARALELOS AL TRONCO
○ BIFURCACIÓN O CONVERGENCIA

NOMBRE DE C/ O CARRETERA QUE CRUZA:
CÓDIGO: ____________

REGULACIÓN DE PRIORIDAD 🟥
☐ SÓLO NORMA GENÉRICA
☐ AGENTE/PERSONA AUTORIZADA
☐ SEMÁFORO
☐ SEÑAL VERTICAL de “STOP”
☐ SEÑAL VERTICAL de “Ceda el paso”
☐ SEÑAL HORIZONTAL de “STOP”
☐ SEÑAL HORIZONTAL de “Ceda el paso”
☐ SÓLO MARCAS VIALES SIN INSCRIPCIONES
☐ PASO PARA PEATONES NO ELEVADO
☐ PASO PARA PEATONES SOBRE-ELEVADO
☐ MARCA VIAL DE PASO PARA CICLISTAS
☐ SEÑAL CIRCUNSTANCIAL
☐ OTRA SEÑAL

3. Nº Implicados

FALLECIDOS 24h __
HERIDOS INGRESO >24h __ __
HERIDOS ASISTENCIA SANITARIA <=24h __ __
VÍCTIMAS __ __
ILESOS ____
VEHÍCULOS__ __
CONDUCTORES__ __
PASAJEROS__ __
PEATONES__ __

4. Tipo y Circunstancias

TIPO DE ACCIDENTE

APARTADO A)
○ 1) SALIDA DE VÍA NO (Rellenar APARTADO B)
○ 2) SALIDA DE VÍA SI
  - ○ SALIDA DE LA VIA POR LA DERECHA CON.. APARTADO B)
  - ○ SALIDA DE LA VIA POR LA IZQUIERDA CON.. APARTADO B)

APARTADO B)
○ COLISIÓN FRONTAL
○ COLISIÓN FRONTOLATERAL
○ COLISIÓN LATERAL
○ ALCANCE
○ COLISIÓN MÚLTIPLE
○ CHOQUE CONTRA OBSTACULO O ELEMENTO DE LA VIA
○ ATROPELLO A PERSONA
○ ATROPELLO A ANIMAL
○ VUELCO
○ CAÍDA
○ DESPEÑAMIENTO
○ SÓLO SALIDA DE LA VÍA
○ OTRO

SI INTERVINO ANIMAL, INDICAR TIPO: Catálogo en manual de contenidos

CONDICIONES EN EL MOMENTO DEL ACCIDENTE

NIVEL DE CIRCULACIÓN 🟥
○ BLANCO ○ ROJO
○ VERDE ○ NEGRO
○ AMARILLO ○ SE DESCONOCE

SUPERFICIE DEL FIRME 🟥
○ SECO Y LIMPIO
○ CON BARRO O GRAVILLA SUELTA
○ MOJADO
○ MUY ENCHARCADO O INUNDADO
○ CON HIELO
○ CON NIEVE
○ CON ACEITE
○ OTRA

ILUMINACIÓN 🟥
○ LUZ DEL DÍA NATURAL, SOLAR
○ AMANECER O ATARDECER, SIN LUZ ARTIFICIAL
○ AMANECER O ATARDECER, CON LUZ ARTIFICIAL
○ SIN LUZ NATURAL Y CON ILUMINACIÓN ARTIFICIAL ENCENDIDA DE LA VÍA
○ SIN LUZ NATURAL Y CON ILUMINACIÓN ARTIFICIAL NO ENCENDIDA DE LA VÍA
○ SIN LUZ NATURAL NI ARTIFICIAL

ESTADO METEOROLÓGICO 🟥
○ DESPEJADO
○ NUBLADO
○ LLUVIA DÉBIL
○ LLUVIA FUERTE
○ GRANIZANDO
○ NEVANDO

NIEBLA . Se puede seleccionar además de estado meteorológico
○ NIEBLA LIGERA
○ NIEBLA INTENSA
☐ VIENTO FUERTE

VISIBILIDAD RESTRINGIDA POR: 🟥
○ BUENA VISIBILIDAD
○ EDIFICIOS
○ INSTALACIONES O ELEMENTOS DE LA VÍA
○ CONFIGURACIÓN DEL TERRENO
○ FACTORES ATMOSTÉRICOS
○ DESLUMBRAMIENTO POR SOL
○ DESLUMBRAMIENTO POR ALUMBRADO ARTIFICIAL
○ DESLUMBRAMIENTO POR FAROS DE OTRO VEHICULO
○ UN VEHÍCULO (PARADO, EN MOVIMIENTO O APARCADO)
○ OBRAS
○ CONTENEDORES
○ VEGETACIÓN O ÁRBOLES
○ ELEMENTOS DECORATIVOS
○ OTROS OBJETOS EN LA VÍA
○ PANELES Y PUBLICIDAD
○ ELEMENTOS DEL VEHÍCULO (LUNAS)
○ OTRAS RESTRICCIONES

☐ CIRCULAR EN SENTIDO CONTRARIO

5. Características Vía

CARACTERÍSTICA
○ ZONA PERIURBANA
○ CIRCUNVALACIÓN
○ CALLE RESIDENCIAL
○ ZONA PEATONAL
○ ZONA A 30
○ OTRA DE ESPECIAL REGULACIÓN
○ NINGUNA DE LAS ANTERIORES

LÍMITE DE VELOCIDAD
○ LIMITACIÓN GENÉRICA
○ SEÑALIZACIÓN ESPECÍFICA
VELOCIDAD ☐ (km/h)

SENTIDOS DE LA VÍA
○ DOBLE SENTIDO
○ SENTIDO ÚNICO

NÚMERO DE CALZADAS
○ CALZADA ÚNICA
○ CALZADA DOBLE
○ MÁS DE DOS

Nº CARRILES EN CALZADA
SENTIDO ASCENDENTE ___
SENTIDO DESCENDENTE ___

ANCHURA DEL CARRIL
○ MENOS DE 3,25 m
○ ENTRE 3,25 Y 3,75 m
○ MÁS DE 3,75 m

ACERA (En caso de que en el accidente esté implicado un peatón) 🟥
○ NO
○ IMPRACTICABLE
○ SI, NO ELEVADA
○ ELEVADA ANCHURA____

ARCÉN
○ INEXISTENTE
○ MENOR DE 1,5 m
○ DE 1,5 m A 2,49 m
○ DE 2,50 O MÁS

ELEMENTOS DE BALIZAMIENTO
☐ PANELES DIRECCIONALES
☐ HITOS DE ARISTA
☐ CAPTAFAROS

ELEMENTOS DE SEPARACIÓN DE SENTIDOS
☐ SÓLO LÍNEA LONGITUDINAL DE SEPARACIÓN
☐ CEBREADO
☐ MEDIANA
☐ BARRERA DE SEGURIDAD
☐ ZONA PEATONAL O AJARDINADA
☐ OTRO
☐ NINGUNO

BARRERA DE SEGURIDAD

	NO	METÁLICA	HORMIGÓN	OTRO	PROTECCIÓN MOTORISTA
LATERAL ASCENDENTE	○	○	○	○	☐
LATERAL DESCENDENTE	○	○	○	○	☐
MEDIANA SENTIDO ASCENDENTE	○	○	○	○	☐
MEDIANA SENTIDO DESCENDENTE	○	○	○	○	☐

ELEMENTOS DEL TRAMO
☐ PUENTE, VIADUCTO O PASO SUPERIOR
☐ TÚNEL
☐ PASO INFERIOR
☐ ESTRECHAMIENTO DE SECCIÓN
☐ RESALTOS REDUCTORES DE VELOCIDAD
☐ BADÉN
☐ APARTADERO
☐ NINGUNO

TRAZADO EN PLANTA
○ RECTA
○ CURVA SEÑALIZADA
○ CURVA SIN SEÑALIZAR
○ SE DESCONOCE

TRAZADO EN ALZADO
○ LLANO
○ RAMPA >5%
○ PENDIENTE >5%
○ CAMBIO BRUSCO DE RASANTE
○ SE DESCONOCE

MARCAS VIALES
○ INEXISTENTES O BORRADAS
○ SÓLO SEPARACIÓN DE CARRILES
○ SEPARACIÓN DE CARRILES Y BORDE DE CALZADA
○ SÓLO BORDE DE CALZADA

CARACTERÍSTICAS DEL MARGEN 🟥
☐ DESPEJADO
☐ ÁRBOLES
☐ OTROS ELEMENTOS NATURALES RÍGIDOS
☐ EDIFICACIONES
☐ POSTES
☐ CARTELES PUBLICIDAD
☐ OTROS ELEMENTOS ARTIFICIALES RÍGIDOS
☐ OTROS OBSTÁCULOS

DELIMITACIÓN DE LA CALZADA 🟥
☐ BORDILLO
☐ BOLARDOS O VALLAS DE PROTECCIÓN
☐ SETOS
☐ MARCAS VIALES
☐ BARRERA SEGURIDAD
☐ ISLETA O REFUGIO
☐ ZONA. PEATONAL, AJARDINADA/BULEVAR
☐ OTRA ☐ SIN DELIMITAR

CIRCUNSTANCIAS ESPECIALES 🟥
☐ NINGUNA
☐ CONOS/ELEM. BALIZA MÓVILES
☐ ZANJA O SURCO
☐ TAPA DE REGISTRO DEFECTUOSA
☐ OBRAS
☐ OBSTÁCULO EN CALZADA
☐ DESPRENDIMIENTOS
☐ ESCALÓN
☐ FIRME CON BACHES
☐ FIRME DETERIORADO
☐ OTRAS

NORMAS DE CUMPLIMENTACIÓN

Los campos con ○ permiten marcar una única alternativa.

Los campos con ☐ permiten marcar distintas alternativas.

Marcar ☒ indica posible influencia del factor en el accidente.

En un accidente en intersección la vía principal es la que tiene prioridad.

Las variables en VERDE, se cumplimentan SÓLO cuando el accidente ocurre en vías urbanas: calles.

Las variables en AZUL se cumplimentan SÓLO en aquellos accidentes que se producen en zona interurbana o urbana cuando la vía no tiene características constitutivas de una calle

Las variables y factores de influencia correspondientes que están en rojo corresponden a los datos de remisión rápida.

1. Descripción del vehículo — **3. Vehículo**

INFORMACIÓN DEL VEHÍCULO ☐ ☐ SIN CONDUCTOR

VEHÍCULO MOTOR

MATRÍCULA

FECHA 1ª MATRÍCULA __ / __ / ____

CÓDIGO NACIONALIDAD

MARCA

MODELO

SEGURO
- ○ SI
- ○ NO
- ○ SE DESCONOCE

ITV
- ○ CORRECTA
- ○ CADUCADA
- ○ SE DESCONOCE

INFORMACIÓN DEL VEHÍCULO ☐ ☐ SIN CONDUCTOR

VEHÍCULO MOTOR

MATRÍCULA

FECHA 1ª MATRÍCULA __ / __ / ____

CÓDIGO NACIONALIDAD

MARCA

MODELO

SEGURO
- ○ SI
- ○ NO
- ○ SE DESCONOCE

ITV
- ○ CORRECTA
- ○ CADUCADA
- ○ SE DESCONOCE

TIPO DE VEHÍCULO

- ○ ○ TURISMO
- ○ ○ FURGONETA
- ○ ○ TODO TERRENO
- ○ ○ CICLO
- ○ ○ BICICLETA
- ○ ○ CICLOMOTOR
- ○ ○ MOTOCICLETA ≤125
- ○ ○ MOTOCICLETA >125
- ○ ○ QUAD LIGERO
- ○ ○ QUAD NO LIGERO

- ○ ○ CUADRICICLO LIGERO
- ○ ○ CUADRICICLO NO LIGERO
- ○ ○ AUTOCARAVANA
- ○ ○ MAQUINARIA OBRAS/ SERVICIOS
- ○ ○ MAQUINARIA
- ○ ○ MICROBÚS<=17 OCUP.
- ○ ○ AUTOBÚS
- ○ ○ AUTOBÚS ARTICULADO
- ○ ○ TRANVÍA

CAMIÓN
- ○ ○ CAMIÓN RÍGIDO
- ○ ○ TRACTOCAMIÓN (CABEZA TRACTORA)
- ○ ○ VEHÍCULO ARTICULADO
- ○ ○ TREN/METRO
- ○ ○ OTROS VEH. SIN MOTOR
- ○ ○ OTROS VEH. CON MOTOR
- ○ ○ VEHÍCULO SIN ESPECIFICAR

MMA →
- ○ ○ MENOR DE 3,5 T
- ○ ○ DE 3,5 A 10 T
- ○ ○ DE 10T A 20 T
- ○ ○ MÁS DE 20 T

↓
- ○ ○ TRANSPORTE ESPECIAL
- ○ ○ MERCANCÍAS PELIGROSAS

Nº DE LA ONU __ __ __ __ | Nº DE LA ONU __ __ __ __

REMOLQUE
- ☐ ☐ REMOLQUE
- ☐ ☐ CARAVANA
- ☐ ☐ SEMIRREMOLQUE
- ☐ ☐ OTRO TIPO
- ☐ ☐ VEHÍCULO ADAPTADO

MATRÍCULA DEL REMOLQUE

ANOMALÍAS PREVIAS ☐ ☐
- ☐ ☐ APARENTEMENTE NINGUNA
- ☐ ☐ NEUMÁTICOS MUY DESGASTADOS/DEFECTUOSOS
- ☐ ☐ REVENTÓN
- ☐ ☐ DIRECCIÓN
- ☐ ☐ FRENOS
- ☐ ☐ OTRAS

2. Circunstancias del vehículo

☐ Nº OCUPANTES

☐ Nº OCUPANTES

USO ALUMBRADO REGLAMENTARIO
- ○ ○ SI
- ○ ○ NO
- ○ ○ SE DESCONOCE

☐ ☐ FUGADO ☐ ☐ INCENDIADO

CUANDO EL ACCIDENTE OCURRA EN NUDO:

POSICIÓN RESPECTO A LA VÍA
- ○ ○ CIRCULABA POR LA VÍA PRINCIPAL (LA QUE TIENE PRIORIDAD)
- ○ ○ CIRCULABA POR LA VÍA SECUNDARIA
- ○ ○ SE DESCONOCE

APROXIMACIÓN AL NUDO
- ○ ○ APROXIMÁNDOSE
- ○ ○ ALEJÁNDOSE
- ○ ○ EN EL NUDO
- ○ ○ SE DESCONOCE

SENTIDO DE CIRCULACIÓN (⇅Km o nº en la calle)
- ○ ○ ASCENDENTE
- ○ ○ DESCENDENTE
- ○ ○ SE DESCONOCE

SI HAY MÁS DE UN VEHICULO IMPLICADO Y CIRCULABAN POR LA MISMA VÍA
- ○ CIRCULABAN POR CALZADAS DIFERENTES
- ○ POR LA MISMA CALZADA
  - ○ CIRCULABAN POR EL MISMO CARRIL
  - ○ CIRCULABAN POR CARRILES DISTINTOS
  - ○ SE DESCONOCE
- ○ SE DESCONOCE

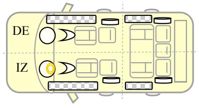
Si más de dos vehículos la posición será respecto a V1.

DISCO TACÓGRAFO (SI ES OBLIGATORIO)
- ○ ○ FUNCIONA CORRECTAMENTE
- ☐ ☐ LEÍDO — VELOCIDAD FINAL (km/h) ☐ ☐
- ○ ○ MANIPULADO
- ○ ○ FUNCIONAMIENTO INCORRECTO
- ○ ○ NO LLEVA Y DEBERÍA LLEVARLO
- ○ ○ SE DESCONOCE

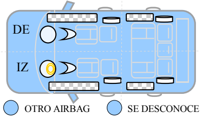
TIEMPOS DE DESCANSO
- ☐ ☐ HA RESPETADO EL DESCANSO DIARIO
- ☐ ☐ HA SUPERADO LAS HORAS DE CONDUCCIÓN CONTINUADA
- ☐ ☐ HA SUPERADO LAS HORAS DE CONDUCCIÓN DIARIA

HORAS CONDUCCIÓN CONTINUADA ☐ ☐

AIRBAG



- ○ OTRO AIRBAG
- ○ SE DESCONOCE



- ○ OTRO AIRBAG
- ○ SE DESCONOCE

ÁREA MÁS DAÑADA DEL VEHÍCULO ○ ○ SIN DAÑOS
- ○ ○ FRONTAL IZQUIERDO
- ○ ○ FRONTAL CENTRO
- ○ ○ FRONTAL DERECHO
- ○ ○ DELANTE NO ESPECIFICADO
- ○ ○ POSTERIOR DERECHO
- ○ ○ POSTERIOR CENTRO
- ○ ○ POSTERIOR IZQUIERDO
- ○ ○ DETRÁS NO ESPECIFICADO
- ○ ○ LADO DERECHO
- ○ ○ LADO IZQUIERDO
- ○ ○ PARTE SUPERIOR
- ○ ○ SE DESCONOCE

MANIOBRA DEL VEHÍCULO PREVIA AL ACCIDENTE

- ○ ○ SIGUIENDO TRAYECTORIA RECTA
- ○ ○ TOMANDO CURVA A LA DERECHA
- ○ ○ TOMANDO CURVA A LA IZQUIERDA
- ○ ○ ADELANTANDO POR LA DERECHA
- ○ ○ ADELANTANDO POR LA IZQUIERDA
- ○ ○ CAMBIANDO AL CARRIL DE LA DERECHA
- ○ ○ CAMBIANDO AL CARRIL DE LA IZQUIERDA
- ○ ○ CIRCULANDO MARCHA ATRÁS ___ m
- ○ ○ GIRANDO EN U, 180º O CAMBIO DE SENTIDO
- ○ ○ CIRCULANDO EN PARALELO
- ○ ○ CRUZANDO LA CALZADA
- ○ ○ INCORPORÁNDOSE A LA CIRCULACIÓN

- ○ ○ INCORPORÁNDOSE A UNA VÍA DE MAYOR NIVEL QUE QUEDA A LA DERECHA
- ○ ○ INCORPORÁNDOSE A UNA VÍA DE MAYOR NIVEL QUE QUEDA A LA IZQUIERDA
- ○ ○ ESPERANDO EN UNA SEÑALIZACIÓN DE PRIORIDAD/SEMÁFORO
- ○ ○ ATRAVESANDO INTERSECCIÓN, NO GIRANDO
- ○ ○ SIGUIENDO TRAYECTORIA EN GLORIETA
- ○ ○ GIRANDO O SALIENDO HACIA OTRA VÍA QUE QUEDA A LA DERECHA
- ○ ○ GIRANDO O SALIENDO HACIA OTRA VÍA QUE QUEDA A LA IZQUIERDA
- ○ ○ RETENCIÓN POR IMPERATIVO DE LA CIRCULACIÓN
- ○ ○ MANIOBRA RÁPIDA PARA SALVAR OBSTÁCULO/VEHÍCULO
- ○ ○ MANIOBRA RÁPIDA PARA SALVAR A PEATÓN
- ○ ○ MANIOBRA RÁPIDA PARA SALVAR ANIMAL

- ○ ○ ACCIÓN DE FRENADO
- ○ ○ PARADO A LA DERECHA
- ○ ○ PARADO A LA IZQUIERDA
- ○ ○ PARADO EN DOBLE FILA
- ○ ○ ESTACIONANDO O SALIENDO DEL ESTACIONAMIENTO
- ○ ○ ESTACIONADO A LA DERECHA
- ○ ○ ESTACIONADO A LA IZQUIERDA
- ○ ○ SE DESCONOCE

LUGAR POR EL QUE CIRCULABA EL VEHÍCULO ☐ ☐

- ○ ○ CARRIL DERECHO
- ○ ○ CARRIL IZQUIERDO
- ○ ○ CARRIL CENTRAL
- ○ ○ CARRIL REVERSIBLE
- ○ ○ ARCÉN HABILITADO

- ○ ○ CARRIL DE ACELERACIÓN
- ○ ○ CARRIL DE DECELERACIÓN
- ○ ○ CARRIL DE TRENZADO
- ○ ○ CARRIL ADICIONAL PARA CIRCULACIÓN RÁPIDA
- ○ ○ CARRIL ADICIONAL PARA CIRCULACIÓN LENTA

- ○ ○ CARRIL HABILITADO EN SENTIDO CONTRARIO
- ○ ○ CARRIL PARA CAMBIO DE SENTIDO/DIRECCIÓN
- ○ ○ CARRIL BUS
- ○ ○ CARRIL VAO
- ○ ○ CARRIL TRANVÍA

- ○ ○ MEDIANA
- ○ ○ CUNETA
- ○ ○ ACERA-BICI
- ○ ○ CARRIL BICI
- ○ ○ CARRIL BICI PROTEGIDO

- ○ ○ PISTA-BICI
- ○ ○ ARCÉN
- ○ ○ ACERA-REFUGIO
- ○ ○ OTRO
- ○ ○ SE DESCONOCE

1. Datos Personales — **4. Conductor**

DATOS DEL CONDUCTOR

NOMBRE Y APELLIDOS
- ○ NIF
- ○ PASAPORTE
- ○ TARJETA DE RESIDENCIA
- ○ OTRO _ _ _ _ _ _ _ _ _ _

FECHA DE NACIMIENTO __ / __ / ____

SEXO
- ○ H
- ○ M
- ○ D

NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ ○ SE DESCONOCE

POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ ○ SE DESCONOCE

DATOS DEL CONDUCTOR

NOMBRE Y APELLIDOS
- ○ NIF
- ○ PASAPORTE
- ○ TARJETA DE RESIDENCIA _ _ _ _ _ _ _ _ _ _
- ○ OTRO

FECHA DE NACIMIENTO __ / __ / ____

SEXO:
- ○ H
- ○ M
- ○ D

NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ ○ SE DESCONOCE

POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ ○ SE DESCONOCE

LESIVIDAD
- ○ ○ FALLECIDO 24 HORAS
- ○ ○ INGRESO SUPERIOR A 24 HORAS
- ○ ○ INGRESO INFERIOR O IGUAL A 24 HORAS
- ○ ○ ATENCIÓN EN URGENCIAS SIN POSTERIOR INGRESO
- ○ ○ ASISTENCIA SANITARIA AMBULATORIA CON POSTERIORIDAD
- ○ ○ ASISTENCIA SANITARIA INMEDIATA EN CENTRO DE SALUD O MUTUA
- ○ ○ ASISTENCIA SANITARIA SOLO EN EL LUGAR DEL ACCIDENTE
- ○ ○ SIN ASISTENCIA SANITARIA
- ○ ○ SE DESCONOCE

HOSPITAL AL QUE SE TRASLADA (Nombre del hospital) ○ ○ SE DESCONOCE

NO CONTABILIZABLE POR
- ○ ○ MUERTE NATURAL
- ○ ○ SUICIDIO
- ○ ○ INTENTO DE SUICIDIO
- ○ ○ HOMICIDIO
- ○ ○ INTENTO DE HOMICIDIO

NORMAS DE CUMPLIMENTACIÓN

Los selectores de color amarillo ☐ corresponden al vehículo 1. Igual sucede con el conductor y los pasajeros

Los selectores de color azul ☐ corresponden al vehículo 2. Igual sucede con el conductor y los pasajeros

2. Datos Permiso

4. Conductor

PERMÍSO O LICENCIA DE CONDUCCIÓN (VEHÍCULOS A MOTOR)

FECHA EXPEDICIÓN __ / __ / ____ CLASE ☐ ○ SE DESCONOCE

FECHA EXPEDICIÓN __ / __ / ____ CLASE ☐ ○ SE DESCONOCE

CARACTERÍSTICAS DEL PERMISO

- ○ ○ EN VIGOR
- ○ ○ CANJEADO
- ○ ○ INAPROPIADO
- ○ ○ CADUCADO
- ○ ○ (SI ES MOTORISTA) B AUTORIZADO 125CC, SIN A1-A
- ○ ○ ANULADO O SUSPENDIDO
- ○ ○ NO LO PRESENTA
- ○ ○ NO HA TENIDO NUNCA
- ○ ○ PÉRDIDA TOTAL DE PUNTOS DECLARADA

3. Circunstancias

ACCESORIOS DE SEGURIDAD

- ○ ○ CINTURÓN UTILIZADO
- ○ ○ CINTURÓN NO UTILIZADO
- ○ ○ SE DESCONOCE
- ○ ○ CASCO UTILIZADO
- ○ ○ CASCO NO UTILIZADO
- ○ ○ CASCO SUPUESTAMENTE EXPULSADO

OTROS ACCESORIOS DE SEGURIDAD

EQUIPAMIENTO DE PROTECCIÓN EN

- ☐ ☐ BRAZOS
- ☐ ☐ ESPALDA
- ☐ ☐ TORSO
- ☐ ☐ MANOS
- ☐ ☐ PIERNAS
- ☐ ☐ PIES
- ☐ ☐ PRENDA REFLECTANTE

PRUEBA DE ALCOHOL

- ○ ○ NO SE REALIZA PRUEBA
- ○ ○ NO, PORQUE SE NIEGA
- ○ ○ NO ,PORQUE NO PUEDE
- ○ ○ PRUEBA EN AIRE

mg/l ________ mg/l ________

mg/l ________ mg/l ________

- ○ ○ PRUEBA EN SANGRE

g/l ________ g/l ________

SIGNOS DE INFLUENCIA

- ○ ○ SIN SIGNOS
- ○ ○ CON SIGNOS

PRUEBA DE DROGAS

- ○ ○ NO SE REALIZA PRUEBA
- ○ ○ EN SALIVA
- ○ ○ EN SANGRE
- ○ ○ OTRAS

SIGNOS DE INFLUENCIA

- ○ ○ SIN SIGNOS
- ○ ○ CON SIGNOS

RESULTADO +/- → CONFIRMADO SI/NO (SI EL RESULTADO ES +)

AMP	☐	☐	Si No	Si No
BDZ	☐	☐	Si No	Si No
COC	☐	☐	Si No	Si No
THC	☐	☐	Si No	Si No
OPI	☐	☐	Si No	Si No
METH	☐	☐	Si No	Si No
OTRAS	☐	☐	Si No	Si No

▼ ☐ ___________

MOTIVO DE DESPLAZAMIENTO

- ○ ○ TRANSPORTE PROFESIONAL DE MERCANCÍAS
- ○ ○ TAXI
- ○ ○ BUS URBANO
- ○ ○ BUS ESCOLAR
- ○ ○ SERVICIO DE LIMPIEZA, RECOGIDA DE BASURA
- ○ ○ SERVICIO DE MANTENIMIENTO VIARIO
- ○ ○ BOMBEROS, POLICÍA, AMBULANCIA
- ○ ○ IN ITINERE (TRANSP. NO PROFESIONAL)
- ○ ○ EN PRÁCTICAS DE AUTOESCUELA
- ○ ○ SERVICIO AUXILIO EN CARRETERA
- ○ ○ BUS EN TRANSPORTE DE MENORES
- ○ ○ BUS DE LÍNEA REGULAR
- ○ ○ BUS DE LÍNEA DISCRECIONAL
- ○ ○ EN MISIÓN (TRANSP. NO PROFESIONAL)
- ○ ○ OTRAS ACTIVIDADES PARTICULARES
- ○ ○ OCIO Y ENTRETENIMIENTO
- ○ ○ ACTIVIDAD DEPORTIVA PARTICULAR
- ○ ○ ESTUDIANTE HACIA CENTRO DE ESTUDIOS
- ○ ○ TRANSPORTE DE MENORES AL COLEGIO
- ○ ○ IDA/REGRESO DE PUENTES/FESTIVOS VACACIONES
- ○ ○ SE DESCONOCE

DESPLAZAMIENTO PREVISTO

- ○ ○ LOCAL (<50KM)
- ○ ○ MEDIO (50-200KM)
- ○ ○ LARGO (MÁS DE 200KM)
- ○ ○ SE DESCONOCE

ACCIÓN ESPECIAL DEL CONDUCTOR

- ○ ○ BAJANDO O SUBIENDO DEL VEHÍCULO
- ○ ○ CAÍDA EN LA VÍA DESDE EL VEHÍCULO

PRESUNTAS INFRACCIONES DEL CONDUCTOR

- ○ ○ PRESUNTAMENTE NO EXISTE INFRACCIÓN
- ○ ○ NO RESPETAR EL STOP
- ○ ○ NO RESPETAR "CEDA EL PASO"
- ○ ○ NO RESPETAR EL SEMÁFORO
- ○ ○ NO RESPETAR LA NORMA GENÉRICA DE PRIORIDAD
- ○ ○ NO RESPETAR EL PASO DE PEATONES
- ○ ○ NO RESPETAR LAS INDICACIONES DE UN AGENTE
- ○ ○ NO RESPETAR OTRAS SEÑALES DE PRIORIDAD DE PASO
- ○ ○ INVADIR PARCIALMENTE EL SENTIDO CONTRARIO
- ○ ○ CIRCULAR EN ZIG ZAG
- ○ ○ GIRAR O CAMBIAR DE SENTIDO INCORRECTAMENTE
- ○ ○ CIRCULAR MARCHA ATRÁS DE MANERA INCORRECTA
- ○ ○ ADELANTAR ANTIRREGLAMENTARIAMENTE
- ○ ○ FRENAR SIN CAUSA JUSTIFICADA
- ○ ○ NO MANTENER EL INTERVALO DE SEGURIDAD
- ○ ○ PARADO O EN ESTACIONAMIENTO PROHIBIDO O PELIGROSO
  - ☐ ☐ SIN LUCES DE EMERGENCIA
  - ☐ ☐ EN SU CASO, SIN TRIÁNGULO DE PRESEÑALIZACIÓN
- ○ ○ NO INDICAR O INDICAR MAL UNA MANIOBRA
- ○ ○ CIRCULAR EN SENTIDO CONTRARIO

  Nº kms ☐ Nº kms ☐
- ○ ○ CIRCULAR POR LUGAR PROHIBIDO
- ○ ○ COMPETICIONES O CARRERAS
- ○ ○ SE DESCONOCE

PRESUNTAS INFRACCIONES DE VELOCIDAD

- ○ ○ NINGUNA
- ○ ○ VELOCIDAD INADECUADA PARA LAS CONDICIONES DE LA VÍA
- ○ ○ SOBREPASAR LA VELOCIDAD ESTABLECIDA
- ○ ○ MARCHA LENTA ENTORPECIENDO LA CIRCULACIÓN
- ○ ○ SE DESCONOCE

OTRA INFRACCIÓN

- ○ ○ NINGUNA
- ○ ○ CIRCULAR SIN LUZ
- ○ ○ CIRCULAR DESLUMBRANDO
- ○ ○ CARGA MAL ACONDICIONADA
- ○ ○ EXCESO DE CARGA
- ○ ○ DESPRENDIMIENTO DE CARGA
- ○ ○ APERTURA DE PUERTAS SIN PRECAUCIÓN
- ○ ○ EXCESO DE OCUPANTES
- ○ ○ OTRA INFRACCIÓN Texto especificando infracción
- ○ ○ SE DESCONOCE

POSIBLE RESPONSABLE DEL ACCIDENTE

○ ○ SI ○ ○ NO ○ ○ SE DESCONOCE

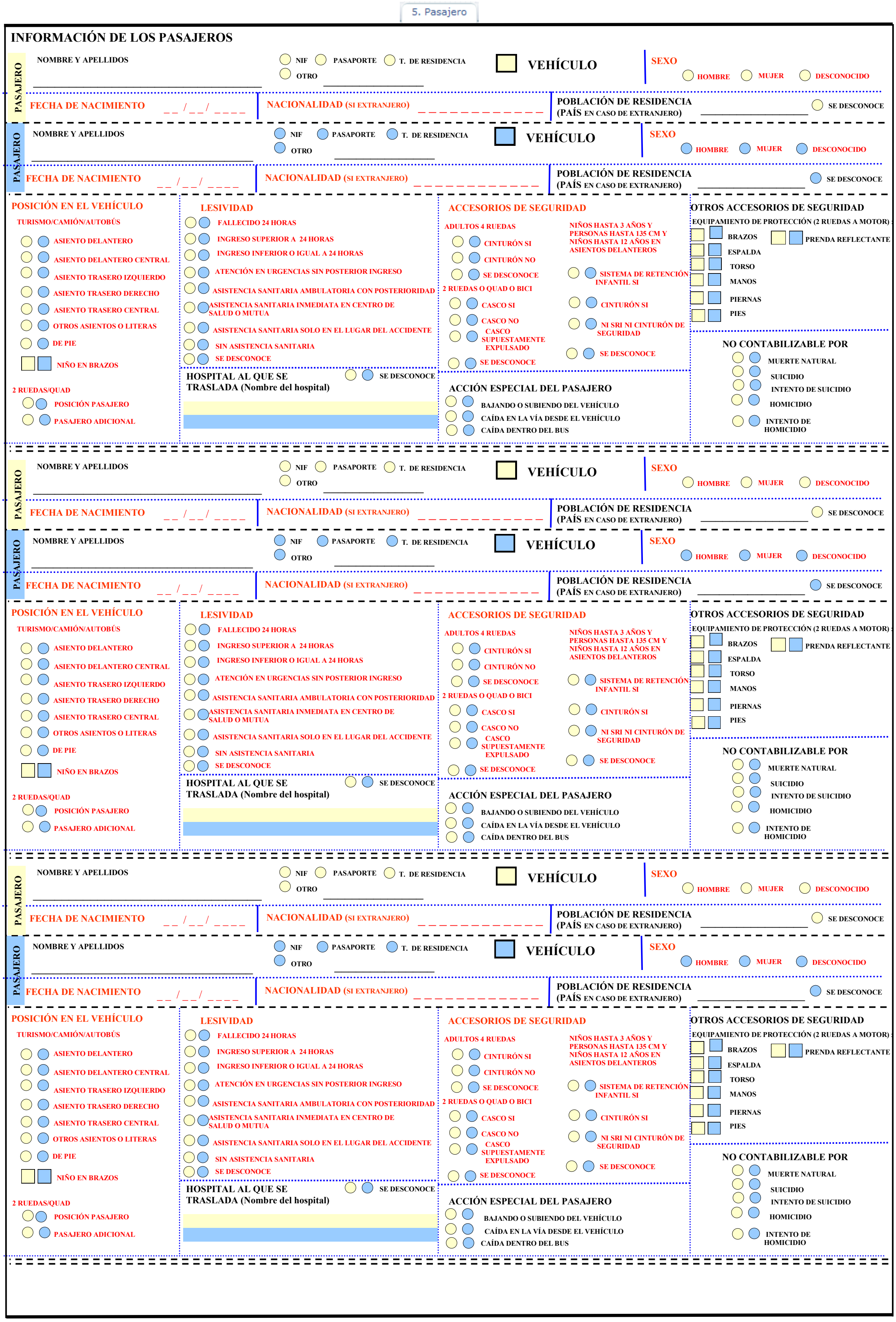
FACTORES QUE PUEDEN AFECTAR LA ATENCIÓN Y PRESUNTOS ERRORES

FACTORES QUE PUEDEN AFECTAR A LA ATENCIÓN

- ○ ○ USO DE TELÉFONO MÓVIL
- ○ ○ USO DE MANOS LIBRES
- ○ ○ USO DE GPS
- ○ ○ USO DE RADIO, DVD, VIDEO, AURICULARES...
- ○ ○ FUMAR
- ○ ○ ACTIVIDADES SIMULTÁNEAS A LA CONDUCCIÓN (COMER, BEBER, BUSCAR OBJETOS...)
- ○ ○ INTERACCIÓN CON LOS OCUPANTES
- ○ ○ PRESENCIA ACCIDENTE ANTERIOR
- ○ ○ MIRAR EL ENTORNO (PAISAJE, PUBLICIDAD, SEÑALES...)
- ○ ○ ESTAR PENSATIVO O ABSTRAIDO
- ○ ○ SUEÑO, CANSANCIO/FATIGA
- ○ ○ ENFERMEDAD SÚBITA/INDISPOSICIÓN
- ○ ○ NO SE APRECIA NINGÚN FACTOR

PRESUNTOS ERRORES DEL CONDUCTOR

- ○ ○ NO SE APRECIAN ERRORES
- ○ ○ NO VER UNA SEÑAL
- ○ ○ NO VER UN VEHÍCULO/PEATÓN/OBSTÁCULO...
- ○ ○ NO ENTENDER UNA SEÑAL DE TRÁFICO O CONFUNDIRLA
- ○ ○ INDECISIÓN, DEMORA O RETRASO EN TOMAR UNA DECISIÓN
- ○ ○ EJECUCIÓN INCORRECTA DE MANIOBRA/MANIOBRA INADECUADA
- ○ ○ OLVIDOS (INTERMITENTES, LUCES...)



5. Pasajero

INFORMACIÓN DE LOS PASAJEROS

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

POSICIÓN EN EL VEHÍCULO
TURISMO/CAMIÓN/AUTOBÚS
○ ○ ASIENTO DELANTERO
○ ○ ASIENTO DELANTERO CENTRAL
○ ○ ASIENTO TRASERO IZQUIERDO
○ ○ ASIENTO TRASERO DERECHO
○ ○ ASIENTO TRASERO CENTRAL
○ ○ OTROS ASIENTOS O LITERAS
○ ○ DE PIE
☐ ☐ NIÑO EN BRAZOS
2 RUEDAS/QUAD
○ ○ POSICIÓN PASAJERO
○ ○ PASAJERO ADICIONAL

LESIVIDAD
○ ○ FALLECIDO 24 HORAS
○ ○ INGRESO SUPERIOR A 24 HORAS
○ ○ INGRESO INFERIOR O IGUAL A 24 HORAS
○ ○ ATENCIÓN EN URGENCIAS SIN POSTERIOR INGRESO
○ ○ ASISTENCIA SANITARIA AMBULATORIA CON POSTERIORIDAD
○ ○ ASISTENCIA SANITARIA INMEDIATA EN CENTRO DE SALUD O MUTUA
○ ○ ASISTENCIA SANITARIA SOLO EN EL LUGAR DEL ACCIDENTE
○ ○ SIN ASISTENCIA SANITARIA
○ ○ SE DESCONOCE

HOSPITAL AL QUE SE TRASLADA (Nombre del hospital) ○ ○ SE DESCONOCE

ACCESORIOS DE SEGURIDAD
ADULTOS 4 RUEDAS
○ ○ CINTURÓN SI
○ ○ CINTURÓN NO
○ ○ SE DESCONOCE
2 RUEDAS O QUAD O BICI
○ ○ CASCO SI
○ ○ CASCO NO
○ ○ CASCO SUPUESTAMENTE EXPULSADO
○ ○ SE DESCONOCE
NIÑOS HASTA 3 AÑOS Y PERSONAS HASTA 135 CM Y NIÑOS HASTA 12 AÑOS EN ASIENTOS DELANTEROS
○ ○ SISTEMA DE RETENCIÓN INFANTIL SI
○ ○ CINTURÓN SI
○ ○ NI SRI NI CINTURÓN DE SEGURIDAD
○ ○ SE DESCONOCE

ACCIÓN ESPECIAL DEL PASAJERO
○ ○ BAJANDO O SUBIENDO DEL VEHÍCULO
○ ○ CAÍDA EN LA VÍA DESDE EL VEHÍCULO
○ ○ CAÍDA DENTRO DEL BUS

OTROS ACCESORIOS DE SEGURIDAD
EQUIPAMIENTO DE PROTECCIÓN (2 RUEDAS A MOTOR) :
☐ ☐ BRAZOS
☐ ☐ ESPALDA
☐ ☐ TORSO
☐ ☐ MANOS
☐ ☐ PIERNAS
☐ ☐ PIES
☐ ☐ PRENDA REFLECTANTE

NO CONTABILIZABLE POR
○ ○ MUERTE NATURAL
○ ○ SUICIDIO
○ ○ INTENTO DE SUICIDIO
○ ○ HOMICIDIO
○ ○ INTENTO DE HOMICIDIO

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

POSICIÓN EN EL VEHÍCULO
TURISMO/CAMIÓN/AUTOBÚS
○ ○ ASIENTO DELANTERO
○ ○ ASIENTO DELANTERO CENTRAL
○ ○ ASIENTO TRASERO IZQUIERDO
○ ○ ASIENTO TRASERO DERECHO
○ ○ ASIENTO TRASERO CENTRAL
○ ○ OTROS ASIENTOS O LITERAS
○ ○ DE PIE
☐ ☐ NIÑO EN BRAZOS
2 RUEDAS/QUAD
○ ○ POSICIÓN PASAJERO
○ ○ PASAJERO ADICIONAL

LESIVIDAD
○ ○ FALLECIDO 24 HORAS
○ ○ INGRESO SUPERIOR A 24 HORAS
○ ○ INGRESO INFERIOR O IGUAL A 24 HORAS
○ ○ ATENCIÓN EN URGENCIAS SIN POSTERIOR INGRESO
○ ○ ASISTENCIA SANITARIA AMBULATORIA CON POSTERIORIDAD
○ ○ ASISTENCIA SANITARIA INMEDIATA EN CENTRO DE SALUD O MUTUA
○ ○ ASISTENCIA SANITARIA SOLO EN EL LUGAR DEL ACCIDENTE
○ ○ SIN ASISTENCIA SANITARIA
○ ○ SE DESCONOCE

HOSPITAL AL QUE SE TRASLADA (Nombre del hospital) ○ ○ SE DESCONOCE

ACCESORIOS DE SEGURIDAD
ADULTOS 4 RUEDAS
○ ○ CINTURÓN SI
○ ○ CINTURÓN NO
○ ○ SE DESCONOCE
2 RUEDAS O QUAD O BICI
○ ○ CASCO SI
○ ○ CASCO NO
○ ○ CASCO SUPUESTAMENTE EXPULSADO
○ ○ SE DESCONOCE
NIÑOS HASTA 3 AÑOS Y PERSONAS HASTA 135 CM Y NIÑOS HASTA 12 AÑOS EN ASIENTOS DELANTEROS
○ ○ SISTEMA DE RETENCIÓN INFANTIL SI
○ ○ CINTURÓN SI
○ ○ NI SRI NI CINTURÓN DE SEGURIDAD
○ ○ SE DESCONOCE

ACCIÓN ESPECIAL DEL PASAJERO
○ ○ BAJANDO O SUBIENDO DEL VEHÍCULO
○ ○ CAÍDA EN LA VÍA DESDE EL VEHÍCULO
○ ○ CAÍDA DENTRO DEL BUS

OTROS ACCESORIOS DE SEGURIDAD
EQUIPAMIENTO DE PROTECCIÓN (2 RUEDAS A MOTOR) :
☐ ☐ BRAZOS
☐ ☐ ESPALDA
☐ ☐ TORSO
☐ ☐ MANOS
☐ ☐ PIERNAS
☐ ☐ PIES
☐ ☐ PRENDA REFLECTANTE

NO CONTABILIZABLE POR
○ ○ MUERTE NATURAL
○ ○ SUICIDIO
○ ○ INTENTO DE SUICIDIO
○ ○ HOMICIDIO
○ ○ INTENTO DE HOMICIDIO

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

PASAJERO
NOMBRE Y APELLIDOS ____________________
○ NIF ○ PASAPORTE ○ T. DE RESIDENCIA
○ OTRO ____________
☐ VEHÍCULO
SEXO ○ HOMBRE ○ MUJER ○ DESCONOCIDO
FECHA DE NACIMIENTO __ /__/ ____
NACIONALIDAD (SI EXTRANJERO) _ _ _ _ _ _ _ _ _ _ _ _ _
POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO) ____________ ○ SE DESCONOCE

POSICIÓN EN EL VEHÍCULO
TURISMO/CAMIÓN/AUTOBÚS
○ ○ ASIENTO DELANTERO
○ ○ ASIENTO DELANTERO CENTRAL
○ ○ ASIENTO TRASERO IZQUIERDO
○ ○ ASIENTO TRASERO DERECHO
○ ○ ASIENTO TRASERO CENTRAL
○ ○ OTROS ASIENTOS O LITERAS
○ ○ DE PIE
☐ ☐ NIÑO EN BRAZOS
2 RUEDAS/QUAD
○ ○ POSICIÓN PASAJERO
○ ○ PASAJERO ADICIONAL

LESIVIDAD
○ ○ FALLECIDO 24 HORAS
○ ○ INGRESO SUPERIOR A 24 HORAS
○ ○ INGRESO INFERIOR O IGUAL A 24 HORAS
○ ○ ATENCIÓN EN URGENCIAS SIN POSTERIOR INGRESO
○ ○ ASISTENCIA SANITARIA AMBULATORIA CON POSTERIORIDAD
○ ○ ASISTENCIA SANITARIA INMEDIATA EN CENTRO DE SALUD O MUTUA
○ ○ ASISTENCIA SANITARIA SOLO EN EL LUGAR DEL ACCIDENTE
○ ○ SIN ASISTENCIA SANITARIA
○ ○ SE DESCONOCE

HOSPITAL AL QUE SE TRASLADA (Nombre del hospital) ○ ○ SE DESCONOCE

ACCESORIOS DE SEGURIDAD
ADULTOS 4 RUEDAS
○ ○ CINTURÓN SI
○ ○ CINTURÓN NO
○ ○ SE DESCONOCE
2 RUEDAS O QUAD O BICI
○ ○ CASCO SI
○ ○ CASCO NO
○ ○ CASCO SUPUESTAMENTE EXPULSADO
○ ○ SE DESCONOCE
NIÑOS HASTA 3 AÑOS Y PERSONAS HASTA 135 CM Y NIÑOS HASTA 12 AÑOS EN ASIENTOS DELANTEROS
○ ○ SISTEMA DE RETENCIÓN INFANTIL SI
○ ○ CINTURÓN SI
○ ○ NI SRI NI CINTURÓN DE SEGURIDAD
○ ○ SE DESCONOCE

ACCIÓN ESPECIAL DEL PASAJERO
○ ○ BAJANDO O SUBIENDO DEL VEHÍCULO
○ ○ CAÍDA EN LA VÍA DESDE EL VEHÍCULO
○ ○ CAÍDA DENTRO DEL BUS

OTROS ACCESORIOS DE SEGURIDAD
EQUIPAMIENTO DE PROTECCIÓN (2 RUEDAS A MOTOR) :
☐ ☐ BRAZOS
☐ ☐ ESPALDA
☐ ☐ TORSO
☐ ☐ MANOS
☐ ☐ PIERNAS
☐ ☐ PIES
☐ ☐ PRENDA REFLECTANTE

NO CONTABILIZABLE POR
○ ○ MUERTE NATURAL
○ ○ SUICIDIO
○ ○ INTENTO DE SUICIDIO
○ ○ HOMICIDIO
○ ○ INTENTO DE HOMICIDIO

6. Peatón

DATOS DEL PEATÓN

NOMBRE Y APELLIDOS ____________________

○ NIF
○ PASAPORTE
○ TARJETA DE RESIDENCIA
○ OTRO _ _ _ _ _ _ _ _ _ _

FECHA DE NACIMIENTO
_ _ / _ _ / _ _ _ _

SEXO
○ H ○ M
○ D

NACIONALIDAD (SI EXTRANJERO)
_ _ _ _ _ _ _
○ SE DESCONOCE

POBLACIÓN DE RESIDENCIA (PAÍS EN CASO DE EXTRANJERO)
_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _
○ SE DESCONOCE

LESIVIDAD

○ FALLECIDO 24 HORAS
○ INGRESO SUPERIOR A 24 HORAS
○ INGRESO INFERIOR O IGUAL A 24 HORAS
○ ATENCIÓN EN URGENCIAS SIN POSTERIOR INGRESO
○ ASISTENCIA SANITARIA AMBULATORIA CON POSTERIORIDAD
○ ASISTENCIA SANITARIA INMEDIATA EN CENTRO DE SALUD O MUTUA
○ ASISTENCIA SANITARIA SOLO EN EL LUGAR DEL ACCIDENTE
○ SIN ASISTENCIA SANITARIA
○ SE DESCONOCE

HOSPITAL AL QUE SE TRASLADA ○ SE DESCONOCE

NO CONTABILIZABLE POR

○ MUERTE NATURAL
○ SUICIDIO
○ INTENTO DE SUICIDIO
○ HOMICIDIO
○ INTENTO DE HOMICIDIO

ACCESORIOS DE SEGURIDAD

○ SIN REFLECTANTES
○ CON CHALECO
○ CON OTRO REFLECTANTE
○ SE DESCONOCE

PRUEBA DE ALCOHOL

○ NO SE REALIZA PRUEBA
○ NO, PORQUE SE NIEGA
○ NO ,PORQUE NO PUEDE
○ PRUEBA EN AIRE
mg/l __________
mg/l __________
○ PRUEBA EN SANGRE
g/l __________

SIGNOS DE INFLUENCIA
○ SIN SIGNOS
○ CON SIGNOS

PRUEBA DE DROGAS

○ NO SE REALIZA PRUEBA
○ EN SALIVA
○ EN SANGRE
○ OTRAS

SIGNOS DE INFLUENCIA
○ SIN SIGNOS
○ CON SIGNOS

RESULTADO +/-		→ CONFIRMADO SI/NO (SI EL RESULTADO ES +)
AMP	☐	Si / No
BDZ	☐	Si / No
COC	☐	Si / No
THC	☐	Si / No
OPI	☐	Si / No
METH	☐	Si / No
OTRAS	☐	Si / No

▼ _ _ _ _ _ _ _ _ _ _

MOTIVO DE DESPLAZAMIENTO

○ SERVICIO DE LIMPIEZA, RECOGIDA DE BASURA
○ SERVICIO DE MANTENIMIENTO VIARIO
○ BOMBEROS, POLICÍA, AMBULANCIA
○ IN ITINERE
○ EN MISIÓN
○ OCIO Y ENTRETENIMIENTO
○ ESTUDIANTE HACIA CENTRO DE ESTUDIOS
○ TRANSPORTE DE MENORES AL COLEGIO
○ OTRAS ACTIVIDADES
○ SE DESCONOCE

ACCIÓN DEL PEATÓN PREVIA AL ACCIDENTE

○ SALIENDO ENTRE VEHÍCULOS APARCADOS
○ EN LA CALZADA DELANTE DE LA PARADA DEL BUS
○ CRUZANDO LA CALZADA JUSTO ANTES DE UNA INTERSECCIÓN
○ CRUZANDO LA CALZADA JUSTO DESPUÉS DE UNA INTERSECCIÓN
○ CRUZANDO LA CALZADA EN INTERSECCIÓN
○ CRUZANDO LA CALZADA EN SECCIÓN
○ CAMINANDO O PARADO EN LA ACERA O REFUGIO
○ CAMINANDO POR LA CALZADA O ARCÉN
○ PARADO EN LA CALZADA O ARCÉN
○ TRABAJANDO EN LA CALZADA O ARCÉN
○ REPARANDO EL VEHÍCULO
○ SERVICIO AUXILIO EN CARRETERA
○ PRECIPITACIÓN A LA VÍA (PUENTE, EDIFICIO…)
○ IRRUMPE EN LA CALZADA CORRIENDO/JUGANDO
○ AUXILIANDO ACCIDENTE ANTERIOR
○ SE DESCONOCE

PRESUNTAS INFRACCIONES DEL PEATÓN

○ NINGUNA INFRACCIÓN
○ NO RESPETA SEMÁFORO DE PEATONES
○ NO CRUZA POR PASO PARA PEATONES
○ ESTÁ O CAMINA POR LA VÍA ANTIRREGLAMENTARIAMENTE
○ NO OBEDECE LAS INDICACIONES DEL AGENTE
○ OTRAS INFRACCIONES
○ SE DESCONOCE

POSIBLE RESPONSABLE DEL ACCIDENTE
○ SI
○ NO
○ SE DESCONOCE

FACTORES QUE PUEDEN AFECTAR A LA ATENCIÓN

○ USO DE TELÉFONO MÓVIL
○ USO DE RADIO, DVD, VIDEO, AURICULARES...
○ PRESENCIA ACCIDENTE ANTERIOR
○ MIRAR EL ENTORNO (PAISAJE, PUBLICIDAD, SEÑALES…)
○ ESTAR PENSATIVO O ABSTRAIDO
○ ENFERMEDAD SÚBITA/INDISPOSICIÓN
○ NO SE APRECIA NINGÚN FACTOR

PRESUNTOS ERRORES DEL CONDUCTOR / PEATÓN

○ NO SE APRECIAN ERRORES
○ NO VER UNA SEÑAL
○ NO VER UN VEHÍCULO/PEATÓN/OBSTÁCULO...
○ NO ENTENDER UNA SEÑAL DE TRÁFICO O CONFUNDIRLA
○ INDECISIÓN, DEMORA O RETRASO EN TOMAR UNA DECISIÓN
○ EJECUCIÓN INCORRECTA DE MANIOBRA/MANIOBRA INADECUADA

SECUENCIA DEL ACCIDENTE

(CUMPLIMENTAR SÓLO EN CASO DE ACCIDENTES GRAVES O MORTALES)

Los vehículos se identificarán como V1, V2, V3, V...
Los peatones se identificarán como P1, P2, P3, P…
Los conductores que hayan sido atropellados (se han caído del vehículo, estaban subiendo o bajando del mismo…) se identificarán como C. Se le asignará un número C1, C2, C3 teniendo en cuenta el vehículo en que viajaban). En el caso de los pasajero se utilizará PA1, PA2… siguiendo la misma lógica.

MÉTODO METRAS DE SECUENCIACIÓN DEL ACCIDENTE			
UNIDADES IMPLICADAS		EVENTOS	SUCESO MÁS GRAVE

Ejemplar 1:	🟨	🟦	🟩
Ejemplar 2:	🟨	🟦	🟩
Ejemplar 3:	🟨	🟦	🟩

Como guía puede identificar en estos diagramas a qué ejemplar en papel corresponde cada vehículo o peatón (si hay más de dos vehículos o más de un peatón) y el color que lo representa en papel (V1, P1…).

NOTA: El vehículo o peatón que haya intervenido en primer lugar en un evento del accidente se situará en la primera columna de la secuenciación, y así sucesivamente.
En el caso de vehículos que han intervenido en el accidente pero no han sufrido directamente las consecuencias del mismo se indicarán en la tabla y se indicará: Evento 59.

TIPOS DE EVENTOS:

COLISIÓN ENTRE VEHÍCULOS
1. COLISIÓN FRONTAL
2. COLISIÓN FRONTOLATERAL AFECTANDO EL LADO DERECHO
3. COLISIÓN FRONTOLATERAL AFECTANDO EL LADO IZQUIERDO
4. COLISIÓN LATERAL O REFLEJA
5. RASPADO POSITIVO
6. RASPADO NEGATIVO
7. COLISIÓN POR DETRÁS, ALCANCE O EN CARAVANA
8. ALCANCE INVERSO
9. COLISIÓN POSTERIOR-LATERAL
10. EMPOTRAMIENTO

ATROPELLO
11. ATROPELLO A PERSONA
12. ATROPELLO A ANIMAL → ☐

CAÍDA
13. CAÍDA EN LA VÍA
14. CAÍDA DE PASAJERO DENTRO DE BUS

CHOQUE CONTRA OBSTÁCULO
15. ELEMENTOS DE OBRAS
16. CONOS U OTROS ELEMENTOS DE BALIZA MÓVILES
17. VALLA (NO BARRERA DE SEGURIDAD)
18. DESPRENDIMIENTOS DE PIEDRA O VEGETACIÓN
19. VEHÍCULO DETENIDO
20. CARGA O ELEMENTOS DE OTROS VEHÍCULOS
21. VEHÍCULOS IMPLICADOS EN ACCIDENTE PREVIO

SALIDA DE LA CALZADA
22. SALIDA POR LA DERECHA
23. SALIDA POR LA IZQUIERDA
24. SALIDA EN LÍNEA RECTA
25. CRUCE DE MEDIANA
26. INVASIÓN DE OTRA VÍA O CALZADA
27. RETORNO A LA VÍA

CHOQUE CONTRA ELEMENTOS FIJOS
28. GLORIETA
29. REFUGIO,ISLETA
30. BORDILLO
31. BOLARDOS
32. SEÑAL DE TRÁFICO
33. SETOS, ARBUSTOS
34. ÁRBOL
35. FAROLA O POSTE
36. CONTENEDOR
37. FUENTE O ESTATUA
38. PARADA DE BUS
39. BARRERA DE CONTENCIÓN DE VEHÍCULOS
40. BARRERA DE PASO A NIVEL
41. AMORTIGUADORES DE IMPACTO
42. PASO SALVACUNETAS
43. PUENTE O TÚNEL
44. DIQUE, MURO DE CONTENCIÓN
45. CASA, MURO O EDIFICIO
46. MURO DE NIEVE O HIELO
47. ROCA
48. OTROS ELEMENTOS

VUELCO, INCENDIO, REVENTÓN, OTRO TIPO
49. GIROS SOBRE SÍ MISMO
50. VUELTAS DE TONEL O DE CAMPANA
51. VUELCO DEL VEHÍCULO
52. INCENDIO DEL VEHÍCULO
53. DESPEÑAMIENTO
54. INMERSIÓN
55. DESPLAZAMIENTO DE LA CARGA
56. SEPARACIÓN DE UNIDADES DE CARGA
57. DESPRENDIMIENTO DE CARGA
58. OTRO TIPO DE SUCESO

VEHÍCULO IMPLICADO SIN EVENTO
59. SIN EVENTO O IMPLICADO SIN CHOQUE NI COLISIÓN

DESCRIPCIÓN DEL ACCIDENTE: NO PODRÁ CONTENER DATOS DE CARÁCTER PERSONAL

CROQUIS

OBSERVACIONES PODRÁN CONTENER DATOS DE CARÁCTER PERSONAL

FACTORES CONCURRENTES

A) CONDUCCIÓN DISTRAIDA O DESATENTA: ☐
C) NO RESPETAR PRIORIDAD: ☐
E) ADELANTAMIENTO ANTIRREGLAMENTARIO: ☐
G) CONDUCCIÓN NEGLIGENTE: ☐
I) IRRUMPIR ANIMAL EN CALZADA: ☐
K) ALCOHOL: ☐
M) ESTADO O CONDICIÓN DE LA VÍA: ☐
O) CANSANCIO O SUEÑO: ☐
Q) AVERÍA MECÁNICA: ☐
S) MAL ESTADO DEL VEHÍCULO: ☐
U) ESTADO O CONDICIÓN DE LA SEÑALIZACIÓN: ☐
W) OTRO FACTOR: ☐

B) VELOCIDAD INADECUADA: ☐
D) NO MANTENER INTERVALO DE SEGURIDAD: ☐
F) GIRO INCORRECTO: ☐
H) CONDUCCIÓN TEMERARIA: ☐
J) IRRUMPIR PEATÓN EN CALZADA: ☐
L) DROGAS: ☐
N) METEOROLOGÍA ADVERSA: ☐
P) INEXPERIENCIA CONDUCTOR: ☐
R) TRAMO EN OBRAS: ☐
T) ENFERMEDAD: ☐
V) OBSTÁCULO EN CALZADA: ☐

cve: BOE-A-2015-181