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Review

Advanced Driver Information System at Critical Points of the Multimodal Traffic Network

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Abstract: Enhancing traffic safety is one of the fundamental objectives of Intelligent Transport Systems (ITS), and it aligns closely with the principles of sustainable transport. Due to specific differences in infrastructure, vehicles, and users' behaviour, places where different modes of traffic intersect are recognized as critical points of the traffic system, making them crucial aspects of Sustainable Urban Mobility Plans (SUMPs) implementation. The SUMPs aim to create urban mobility that is not only environmentally friendly and efficient but also safe for all users. The continuous development and widespread adoption of innovative ITS technologies have paved the way for a system that could provide drivers with real-time information about both immediate and potential dangers at these critical points. This paper provides an overview of previous research in the field, investigating the impact of information systems on drivers' behaviour, various detection and communication solutions that can be effectively integrated into such a system, as well as a brief overview of models and solutions that have been developed to warn drivers in a similar context. The reviewed literature offered valuable insights on which a novel driver information system architecture framework is proposed. This framework can contribute to the ongoing safety improvement in multimodal transport networks within the context of sustainable transport.

Keywords: urban mobility; traffic safety; cooperative intelligent transport systems; traffic control

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1. Introduction

Sustainable transport refers to ways of moving people and goods that are ecologically, socially, and economically sustainable in the long term. This concept also promotes safe transport practices and measures to reduce the number of traffic accidents and injuries. That includes safety initiatives, infrastructure design, promotion of alternative modes of transport, education and raising awareness of risks and safety measures among road users.

The integration of Intelligent Transport Systems (ITS) is continuously enhancing the progress of sustainable transport. By its definition [1], ITS aims to increase the quality of the transport network, improve its performance, and provide a basis for the development of innovative services that, among other things, enable better information exchange and safer use of traffic network resources. In the domain of ITS, a whole range of services is available and defined through several functional areas, such as passenger information, traffic management, in-vehicle support, and personal safety. These services use information and communication technologies, mobile applications, sensors, and data platforms to provide relevant real-time traffic information, including information directed at passengers and drivers about road conditions, public transport, parking, alternative transport, location, road hazards and others. To achieve this, the concept of Cooperative Intelligent Transport Systems (C-ITS) is developed where the cooperation between the main actors of the transport network is considered: vehicles, drivers, and infrastructure [2]. With the same purpose, the concept of the Internet of Vehicles (IoV) is being developed, derived from its previous domain, the Internet of Things (IoT). IoV represents the evolving paradigm where vehicles maintain near-constant connectivity to the Internet, enabling the exchange of information with each other and with other

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services [3]. It is also considered as an extension of Vehicular Ad-Hoc Networks (VANETs) with a significant distinction that in VANETs vehicles are not directly connected to a shared network but require additional information and communication infrastructure for connectivity [4].

In this paper, the focus on safety is directed towards locations where multiple traffic flows or different modes of transport are integrated, such as intersections, pedestrian crossings, railway crossings, etc. Regarding the safety aspect, these spots of interweaving different modes of transport can be defined as critical points. Compared to other safety interventions, it is evident that in-vehicle warning systems have a great potential to increase safety at critical points in multimodal traffic, in terms of impact on user behaviour and considering that no major interventions are needed on existing infrastructure.

The rest of the paper is organized as follows: In Chapter 2, driver information systems and their impact on road users are briefly explained, following a short overview of proposed models found in the available literature. Chapter 3 includes methods and solutions for the identification and classification of critical points and communication methods applicable to the driver warning system. Discussion and Conclusion provide an analysis of the reviewed literature and guidelines for further research.

2. Driver information systems

Driving is a social phenomenon, which requires interaction between all involved road users to ensure efficient traffic flow and the safety of others [5]. Such interaction is very dynamic and includes tasks such as identifying other road users, analysing their behaviour, communicating with them and, if necessary, predicting their future actions and choosing an appropriate reaction accordingly [6]. With the development of ITS services, drivers are provided with additional decision support through various information systems. ITS is emerging towards systems based on the integration of a wide range of relevant technologies that can collect substantial amounts of data, process them, and then take appropriate actions in real-time [7]. Today, vehicles possess the potential of wireless communication with other vehicles and other entities in their immediate proximity to timely share safety-critical information (warnings) primarily to avoid or mitigate collisions. Furthermore, vehicles can be connected to traffic management systems via their accompanying network infrastructure to register any potential road hazards as well as for guidance to ensure more efficient traffic flow.

In terms of increasing traffic safety, one of the most used ITS approaches is driver information systems, which provide real-time information about incidents, possible dangerous conditions on the road, etc. Driver information systems were mentioned as early as 1975, and with the development of sensory and communication technologies, numerous driver warning systems were developed, and studies were conducted on their reliability and efficiency. Only with the rapid development of technologies in the last decade and their wide application, more specific research involving technologies such as C-ITS and IoV is being carried out. With the rapid development of autonomous driving and advanced telematics driver assistance systems, vehicle safety has improved significantly. These systems mainly use sensors installed on the vehicle and help drivers make decisions to increase driver self-awareness to prevent traffic incidents. While such systems are already widely used in road traffic across Europe and are paving the way for autonomous vehicles, there are very few attempts to achieve the same in a multimodal traffic environment.

2.1. Influence on driver's behaviour

The complex interaction between entities of different modes of transport is often unpredictable because of the road user's behaviour, and the impact of any system primarily depends on the impact on the road user himself, that is, on the degree of his obedience to the system. Driver disobedience can be intentional (when drivers or pedestrians are aware of their surroundings and understand warning signs but still deliberately ignore them) or unintentional (when they do not notice changes in the environment and/or do not understand warning signs and consequently approach critical point even in the case of danger). Furthermore, often the focus of the driver's attention is not on the location that they are approaching, nor on the observation of the environment, but drivers more often rely on

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the warning signals installed on the traffic infrastructure and on the behaviour of the surrounding vehicles as a way of warning of changes in road conditions, especially drivers with less experience in traffic [8]. Recent research shows that in-vehicle or smartphone warning systems can have a significant impact on driver/pedestrian behaviour if they can be perceived as credible and reliable. The impact on users through different research was analysed in simulation environments, through field tests or by surveys. The results of testing in the simulator showed that respondents are more inclined to use ITS technologies at critical points with passive signalling (traffic signs and protective fences) than with active signalling (changing light and sound signals or active barriers) and they prefer systems that are the simplest to use [9]. Also, displaying too much unnecessary information can further confuse drivers or distract them from the primary task of driving, so the system should display the minimum amount of information necessary to adequately assist the driver in making decisions [10]. Solutions for informing drivers at passive crossings resulted in driver behaviour similar to that at active crossings [11]. Also, behaviour improves in areas where drivers are more prone to riskier driving [12]. In general, the implementation of a driver information system significantly improves driver behaviour near critical points in terms of observing the environment (in multiple directions), braking response and approach speed [12]. Approach speed is reduced for all routes whose first segment is straight, while for horizontal routes that include sharp turns or stop signs, the approaching speed is slightly increased. Despite this slight increase in speed, drivers slow down more intensively during the application of the system [13]. On the negative side, with the active warning system, participants' obedience to the STOP sign decreased by 16.5%, but in case of system failure, most participants had no difficulty in detecting road hazards even though they did not receive any warning message [14], meaning that in-vehicle warning systems have a lasting effect on driver behaviour even after the system is no longer present [15]. Field research [16] shows that the predicted crash risk decreases as the approach speed decreases (Figure 1).

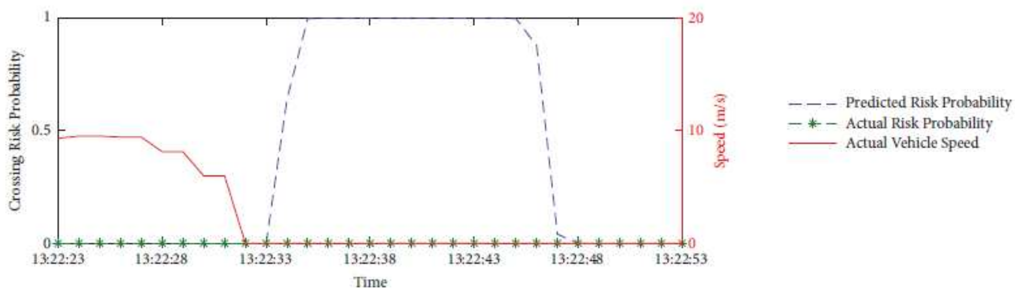

Figure 1. Field test results on the impact of the in-vehicle warning system [16].

Based on the conducted tests, a warning system improves drivers' behaviour over time, but no immediate effect has been confirmed. Also, the individual's personality plays a key role in the effectiveness of the system, so it is necessary to conduct more detailed research in different situations in the multimodal traffic network. Although there are many simulation tests with impressive results, field tests on multimodal critical points are still weak and it remains uncertain whether in-vehicle warning systems can be equally reliable in the field [17].

2.2. Existing examples of driver information systems

Several examples of driver information systems are described below, with an emphasis on level crossings as the most critical points in a multimodal environment. In the available literature, in-vehicle warning systems are mostly related to autonomous driving, and it is necessary to further investigate the possibilities of applying these technologies at a higher level.

2.2.1. Critical crossing points of rail and road traffic

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When observing the interaction of different traffic modes, the most critical points of the traffic system are level crossings, therefore, they are taken as a reference example for the analysis of the warning system application. Level crossings are defined as places where a railway line or an industrial track and a road cross at the same level, which may also include a crossing with a pedestrian and bicycle path, or other roads intended for the passage of people, animals, vehicles, or machines [18]. Although accidents at such critical points do not happen so often, their consequences are much more severe compared to other traffic accidents, on a personal, social, and financial level. Due to the large disparity between the train's mass and the road vehicle, most accidents involve serious injuries and fatalities. Also, secondary consequences include damages to vehicles, trains and infrastructure, disruption of critical supply chain links, environmental impact in case of transportation of hazardous materials, etc. [19]. Despite the increasing number of technological systems that aim to elevate safety at these critical points, the occurrence of accidents is consistent, and their consequences are classified as the most severe compared to other traffic accidents [20]. According to the Annual Safety Report for the year 2021, in the Republic of Croatia, out of 80 serious accidents and accidents in railway traffic, 35 of them occurred on level crossings, in which 6 people died (out of a total of 10), and 7 people were seriously injured [21]. At the EU level in the same year, 234 people were killed on level crossings, and an equal number of people ended up with serious or life-threatening injuries, which makes level crossings the second largest cause of death in railway traffic [22].

The most common safety solutions on level crossings refer to infrastructural operations that change the level of the roadway or pedestrian crossing or to physical warning signals for road users. Passive signalling is a simple and financially profitable solution, but it is far more susceptible to human disobedience than active signalling. Active signalling systems are most often based on a sensor device placed at a certain distance from the crossing, which registers the arrival of the train and sends information to signal-sound devices placed on the level crossings [23]. At the EU level, out of approximately 105,000 registered level crossings, only 45% of them are provided with active signalling [9], while in the Republic of Croatia, it is only slightly more than 20% of the 1500 registered crossings [9,21]. Most of the research in the field of level crossing safety deals with the improvement of existing technical solutions, such as more advanced train detection [24], more effective warnings [25], better information transmission within the railway environment [26], warnings to train drivers about obstacles on the track [27], etc. Although these and similar studies offer quality solutions, they lead to minor system design changes that have only marginal effects on safety, considering that accidents on level crossings mostly occur due to irresponsible drivers' and pedestrians' behaviour: their wrong decision-making or just unawareness of the environment.

According to previous research, driver information systems can be divided into two basic groups: warning systems about approaching a critical point based on historical data ([17,19]) and warning systems about approaching a train based on real-time data ([13,16,28]). The first group does not use real-time data of the approaching train, but they do use the location of the vehicle to decide to display the warning.

In the study [17], the authors developed and tested (in a real-world environment) a comprehensive in-vehicle Decision Support System (DSS) that provides information on critical points based on location analysis applied to a national set of accident historical data, composed over 266,000 accidents which is presented in Figure 2. The in-vehicle unit uses the Density-Based Clustering Algorithm (DBSCAN) algorithm to identify and classify critical points. The output informs the driver that he is approaching a critical crossing.

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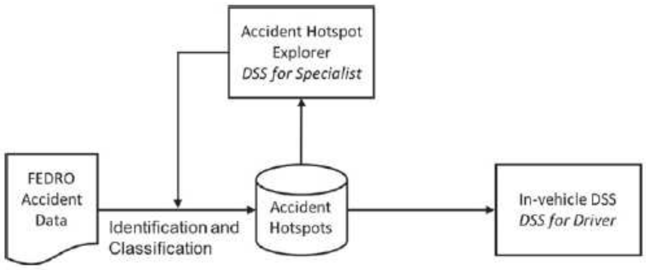

Figure 2. Decision support system based on DBSCAN [17].

The authors in [19] proposed an early warning system for oncoming trains based on a wide range of available data, including the train's schedule. The data sets are incorporated into a Geographic Information System (GIS), performing diverse analyses to better assess and characterize different locations. The system notifies drivers using the on-board navigation unit of an oncoming train, allowing users to efficiently assess the best available route.

In research involving real-time data, the system architecture consists of two main elements: on-board equipment in conflicting vehicles and infrastructure equipment. In the study [16], the device installed on the Roadside Equipment (RSE) contains static information that includes geometric characteristics and positioning accuracy parameters for crash risk assessment. The On-Board Equipment (OBE) receives location data from its Global Navigation Satellite System (GNSS) module and thus calculates approach speed and direction of travel. Together with the data archived in the RSE, the system first estimates the actual location considering latency and user behaviour. The system then estimates the probability of a collision through a mathematical collision risk assessment model. If the probability of a collision between a road user and a train is greater than a predetermined threshold, a warning is activated and immediately sent to road users. At the same time, the road user can get an estimate of the waiting time for the train to pass (Figure 3).

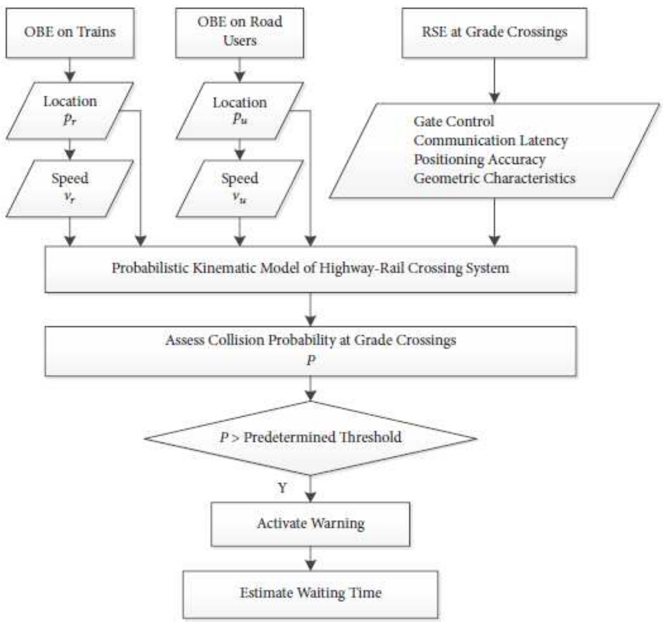

Figure 3. Information system framework based on GNSS real-time data [16].

Communication between devices takes place via Dedicated Short-Range Communication (DSRC).

The authors of the studies [13] and [28] investigated the safety impact of the C-ITS system service as part of the SAFER-LC project. The main elements of this system are a model for train monitoring and arrival time estimation, and a module for vehicle tracking and communication with a dedicated web service that enables data exchange and storage (Figure 4). This warning informs the driver about the presence of the level crossing (static message that is generated regardless of the real-time data) or informs him about the train approach and the estimated time of arrival (dynamic message).

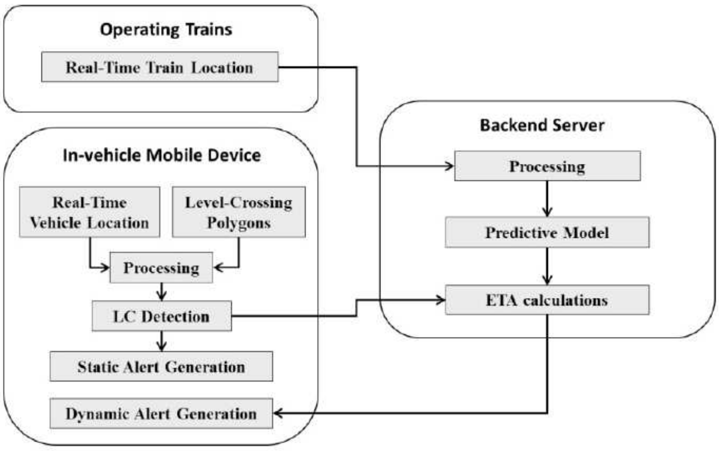

Figure 4. SAFER-LC system architecture [28].

The estimate of the train's arrival time is calculated based on the train's position and speed, and predictions are made using machine learning algorithms, i.e., neural networks. The warning system relies on mobile communication, and the warning is provided through a pop-up window on navigation devices inside the vehicle. The critical area is determined using two predefined polygons of the road and rail network: the road network polygon includes all sections of the road leading to the level crossing within a radius of 80 meters from the railway, while the railway polygon includes railway tracks in a length of approx. one kilometre from the level crossing in both directions. If the vehicle enters the polygon or the train and the vehicle is in the same group of polygons, an audio-visual warning is generated.

The LeCross study [29] analysed the concept of a satellite system that enables reliable information about approaching trains at level crossings with passive signalling. The service uses satellite communication and navigation systems. Instead of a trackside detection system, information about the train's arrival is delivered to the level crossing equipment using wireless communication systems. Implementation requires a back-end server for data transfer, as well as a communication platform that can distribute information across remote areas. The server maintains an up-to-date database on the train's position and calculates the train’s arrival time. Warnings are transmitted via satellite link whenever the train is within a certain distance of the crossing. The system requires the installation of a smaller satellite terminal unit on the level crossing with an interface for users, which enables a two-way connection with the central server. By default, the system runs in failsafe mode: the assessment is made by the trackside unit independently of other systems and is triggered by the lack of the train’s position message when expected. This architecture has the added advantage that a centralized data model and communication platform can be used to deliver additional information.

The authors [30] proposed a system that combines Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication based on DRSC. The system works in two cases, direct and indirect warning. In the case of a direct warning, the driver of the vehicle receives the warning directly from the train. This scenario is preferred for implementation where the radio channel between the train and the vehicle has a strong line-of-sight component. In the case of an indirect warning, the DSRC receiver on the level crossing receives the warning from the train and possibly resends it to the vehicle or generates a warning in the form of light or sound for vehicles that do not have a DSRC radio.

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A step further was taken by the authors [31]. In their work, they presented a DSRC/Wi-Fi hybrid system (Figure 5) that acts as a one-way broadcast mechanism for transmitting messages of interest to vehicles equipped with On-Board Units (OBUs) for Wi-Fi reception only. Basic safety messages transmitted from the DSRC OBU in the train are routed through the Road Side Unit (RSU) to the Wi-Fi OBU in the vehicle.

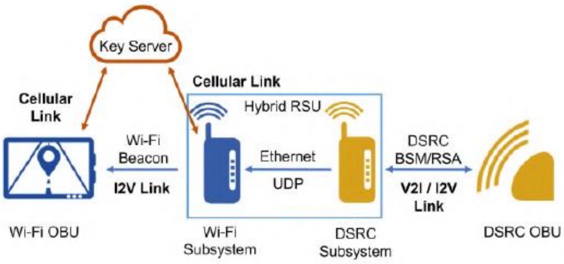

Figure 5. DSRC/Wi-Fi Hybrid System Architecture [31].

Communication within the Wi-Fi segment is based on custom beams that serve a similar function to roadside warnings in DSRC, but with a configurable repeat interval.

2.2.2. Extended driver information system – smart city concept

Authors [32] presented the concept of IoT architecture for collision avoidance systems in smart cities based on 5G mobile technology. The cloud-based system is in the function of traffic management and collects data about the environment through distributed applications and sensors and manages all traffic control procedures. With modern vehicles able to communicate with RSUs, the system encompasses all traffic entities including vulnerable road users. The system architecture (Figure 6) can be divided into three segments: data sources, data transmission and processing, and data sinks.

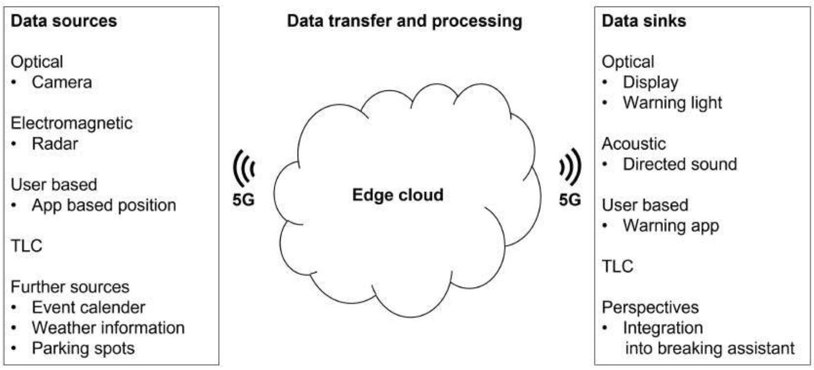

Figure 6. Generic IoT Architecture for smart cities [32].

The first pillar represents data sources, i.e., sensors used to detect and classify individual road users. AI-based processing enables the output of non-personal data such as identification, position, speed, and course, resulting in the ability to predict likely collisions. The advantages of this architecture are that even older vehicles without communication devices or vulnerable groups such as pedestrians can be integrated into the system. It is of particular importance to use the 5G network due to its low latency, high bandwidth, number of possible networked participants and data processing that cannot be achieved with the previous wireless technology.

In the study [33], the authors propose an in-vehicle warning system to avoid collisions with cyclists in the area of a bicycle path at an intersection in a Connected Vehicles (CV) environment.

Based on the collected 118 trajectories of vehicles turning to the right, the behaviour of drivers when turning was investigated. The authors proposed an algorithm for calculating the time of entry into the critical area in different situations and identifying potential places of collision between vehicles and bicycles around the bicycle path. The critical point can be predicted based on vehicle and bicycle speeds and their location information. The warning system is only conceptually based on Vehicle-to-Bicycle (V2B) communication; the assumption is that the driver/vehicle should know where the bicycle is based on GNSS data. The proposed system could help drivers to be more prepared for the upcoming right-turn manoeuvre, thereby improving traffic safety for both drivers and cyclists at intersections.

The study [34] considers a pedestrian collision avoidance system for low-speed autonomous shuttles based on Vehicle-to-Pedestrian (V2P) communication. When pedestrians cannot be detected by line-of-sight sensors such as cameras, radar, and Light Detection and Ranging (LIDAR), V2P communication based on pedestrian smartphones and DSRC is used for their detection and positioning. The vehicle then either stops or, if possible, goes around the pedestrian in a socially acceptable manner. In their study [35], the authors investigated the extension of vehicle crash avoidance systems to smartphone-equipped participants. Due to the reduced capabilities of smartphones compared to OBUs, the authors propose the support of Multi-access Edge Computing (MEC). The MEC-based system architecture includes three main segments: users (i.e., vehicles and vulnerable users), access points of different technologies, and collision detection servers. They conclude that thanks to MEC, a system traditionally used in vehicles can be extended to vulnerable users.

3. Driver information system architecture – components and technologies

For a high-quality information system solution, which could timely and reliably warn drivers of potential danger, it is necessary to combine several segments of different research areas, such as different methods for data analysis and processing, identification and classification, and available technologies for detection and communication that would be applicable in a multimodal environment. Also, regarding architecture definition, it is essential to define the physical, logical, and communication components of the system which is presented below.

3.1. Identification of critical points in a multimodal environment

Today, many solutions in the field of transport depend on reliable and consistent spatial data. For high-quality identification and classification of critical points, it is necessary to connect their individual safety features with the spatial component. So, the first step is the identification of potentially dangerous locations, which requires data on the locations of all registered places where multiple modes of transport meet at the same level. Furthermore, classification according to the hazard criteria requires data on technical equipment and detailed historical data on accidents for each location, with an emphasis on the severity of the consequences of the accident [23]. In the field of transport, data are available at the national and EU level, but they are quite limited. According to the Official European Data Portal, of the total number of available data sets, the area of traffic occupies only 3.75% (including all types of traffic), and their quality and quantity differ depending on the source [23]. Data sources are different in terms of functionality, characteristics and quality of service, and the main challenge, besides the lack of publicly available data sets, is their uneven distribution across subdomains [36]. Considering the limitation of available data and the incompatibility with more advanced processing methods, simpler risk assessment methods would be more suitable for identifying critical points, especially for parts of traffic networks where accidents are not frequent. Over the past sixty years, the topic of accident critical point analysis has been extensively researched and various methods have been developed, however, classical methods mostly ignore the spatial aspects and patterns of accidents, i.e., the actual locations of individual accidents [17].

According to the example of risk assessment at level crossings, the first step in identifying critical or high-risk points is to create a list of all crossings where incidents have been recorded in the last five years at least. For each transition, the frequency or number of accidents is determined, divided by the number of years taken into account. After determining the frequency, the consequence is determined, i.e., the number of fatalities in one accident. Using the following equation [37]:

$$\Re = X * Y \tag{1}$$

the frequency factor X and the consequence factor Y are multiplied to obtain the risk index $\Re$. Depending on the values of the risk index, based on qualitative methods, the intervals on which the transition classification is formed are determined.

In a more advanced analysis of the safety level [38], the total number of level crossings on one section of the railway was observed, including individual level crossings with passive signalling, which have a history of accidents. A multi-criteria fuzzy model consisting of 15 criteria and 8 alternatives was formed, and data on serious accidents, accidents, incidents, and the number of deceased and injured persons were taken into account. Based on the obtained results, the authors proposed measures to increase the safety of individual level crossing.

The mentioned risk assessment methods determine the level of danger at certain critical points but do not attach a spatial component to them. In the study [19], the features of critical places with their geospatial components were analysed through the Geographic Information System (GIS) to determine the causes of the reduction in the effectiveness of traditional security measures. The proposed method evaluates data from several sources, which relate to geospatial information about the multimodal transport network in the observed area, safety features of crossings, train schedules, historical information about accidents (frequency, financial damage, injuries, and deaths), daily population migrations, etc. Data analysis revealed patterns in transport traffic and the historical frequency of accidents, based on which locations were singled out as potential candidates for the installation of an advanced warning system.

The authors [17] used the DBSCAN to identify critical points using geolocated accident records. DBSCAN classifies the elements into clusters in such a way that inside the cluster the density of elements is higher compared to the outside of the cluster. Elements that are not part of any group are considered forests. As such, the identified clusters can be considered critical points with significantly higher accident density compared to other areas. Noise elements represent "random" accidents, which have no or very little spatial dependence on other accidents. Furthermore, a condition was defined for the identification of critical points: at least ten accidents must have occurred within 15 months at the observed location in five years. With these parameter settings, the authors successfully identified the critical points. Further classification was based on the output message to the user, consisting of three pieces of information: "What", "Why" and "Where", where more than 50% of the involved accidents must have shared the same predominant contextual detail information.

3.2. Detection of conflicting entities in a multimodal environment

Obstacle detection is one of the key aspects of research in the field of driver DSS. Reliable detection includes analysis of different types of obstacles, sensor characteristics and environmental conditions. While roadside driver assistance systems or autonomous driving systems are well-researched in this regard, methods developed for structured urban roads may fail in a multimodal environment due to their uncertainty and diversity. In principle, there are two sources of data about the environment: from the vehicle's built-in sensors and other vehicles or nearby infrastructure. Most of the researched warning systems on encountering a conflicting entity require the installation of an additional device near the critical points for detection and data transmission and/or processing. If we look at systems in terms of financial profitability, it is necessary to focus on systems of direct communication between vehicles.

Unlike the typical V2V and V2I communication environment, the one connected to a vehicle of a different mode of transport, such as a train, has different limitations. The communication environment near level crossings is similar to road intersections for vehicles, but the line of sight is a function of geometry where greater visual blockages are possible [30]. Therefore, commercial sensors installed on vehicles are not reliable for train detection. LIDAR sensors in autonomous vehicles have a typical detection range of 120 [m], but the range is limited by technical factors such as power

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requirements and target reflectivity. The intensity of infrared beams is also limited by eye safety regulations. Therefore, currently available automotive LIDAR cannot detect a train early enough [39]. Sensors capable of detecting objects up to one kilometre are cameras and radars. Radars intended for adaptive cruise control applications have a detection range of up to 250 [m] but have a narrow beam of detection field, usually ±6-9°, and vegetation or weather conditions can limit visibility [39]. Therefore, relying only on sensors does not provide sufficiently reliable data on the detection of conflicting entities from different modes of transport. The installation of GNSS devices in vehicles enables real-time monitoring, thus giving car drivers a reliable warning about the presence of other vehicles, but this technology also encounters difficulties in a multimodal environment. In a simulation of a railway environment [29], one of the main investigated questions was the impact of long-delay satellite communication on the warning time to road users. The first simulation test was done using terrestrial communication (with an average latency of 5 seconds), and the second using satellite communication (latency varies statistically between 15 and 40 seconds). The result shows that the developed communication protocol successfully manages delay problems, and the difference in warning time and reliability is negligible. Positioning accuracy is reduced by adding a worst-case error component to the original measured positioning data. The results show that the system is resistant to degradation of positioning performance, and standard GNSS accuracy (<30 [m]) is sufficient for timely train detection. Higher-level systems such as C-ITS and IoV rely on several components for data processing, communication, decision-making and information projection, including GNSS, LIDAR, camera, radar, and electronic control unit systems. Although the average accuracy of GNSS is about 10-15 meters, the mentioned sensor technologies can improve the accuracy of determining the position of the vehicle/user [40].

3.3. Communication technologies

Today, numerous wireless communication technologies can be applied in a multimodal environment, but one of the key implementation challenges is propagation effects – especially channel statistics and their correlation with obstacles, such as bridges, buildings, and tunnels [41]. In addition, as vehicles move quickly, the physical layers of the communication solution must support very high speeds.

Today's C-ITS research is mostly based on two main solutions: DSRC and Cellular Vehicle to Everything (C-V2X), based on the LTE standard. DSRC represents the main protocol for V2V and V2I communication, and the key technological driver for the development of ITS applications. The original band allocation contained 10 MHz channels between 5.855 and 5.925 GHz, but as a result of the development of C-V2X, a change in the operating band of DSRC to 5.895-5.905 GHz was adopted [30]. At these operating frequencies, the Doppler spread is around 2700 Hz, which makes channel fluctuation very fast and channel estimation much more challenging [42]. When comparing the performance of the two mentioned technologies at the link level and system level [42], in all aspects C-V2X either greatly outperforms DSRC or performs as well as DSRC. A critical advantage of C-V2X from a point of vehicle safety is greater communication range. However, the communication technology that is most often mentioned today in the context of C-ITS is DSRC. The authors [43] analysed the use of DRSC in a railway-road environment. Among the many features of the DSRC system is the ability to detect and then provide early warning of a potential collision. Although DSRC systems have a nominal range of one kilometre, the range is very sensitive to the surrounding environment and can be significantly reduced in crowded or out-of-sight conditions. The DSRC waveform contains mechanisms that enable the development of highly reliable and robust communication. The results of over 10,000 recorded measurements on two different test tracks suggest that signals at the assigned 5.8GHz signal frequency, even in moderately crowded environments, should be able to operate over relatively long distances and experience minimal fading or spectral distortion. Similar research [44] focused on direct communication between vehicles and trains using DSRC. The authors conducted simulations and field tests of DSRC communications and determined that about 80% of the sent security warnings arrived on time, about 10% early and about 10% late.

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The broader term for the dynamic network infrastructure that connects vehicles, users and other smart devices to the Internet is IoV. An increasing number of vehicles are connected to IoV systems, where each vehicle represents a node in the network [45], and they exchange information with each other in an open, wireless environment. There are various communication activities between IoV entities to share important information such as identification, location, speed, messages, and traffic information, necessary for network operation [40]. Many studies have established a three-layered architecture aimed at integrating different technologies within the IoV [40]. The first layer includes sensor nodes inside the vehicle, which are used to gather local information and detect specific important driving situations. The e-communications layer is the second level, which ensures that existing and emerging networks are seamlessly connected through communication standards. Layer three includes statistical hardware, storage capacity and processing unit, shaping IoV intelligence and providing large data-based processing capacity. IoV requires vehicles to be permanently connected to the Internet and is connected to an ad hoc network environment, where vehicles can also connect to the public Internet. Local data storage is also available in vehicles for future use, where information collected by different vehicles within a vehicle cloud is shared via IoV network [46].

IoV combines several directions of communication (Figure 7): V2V communication is a wireless connection between vehicles to obtain information about their location, speed, and other useful data; vehicle-to-pedestrian (V2P) connection enables the vehicle to monitor, check and communicate with pedestrians and cyclists on the roads to prevent accidents through high-risk road user awareness systems.

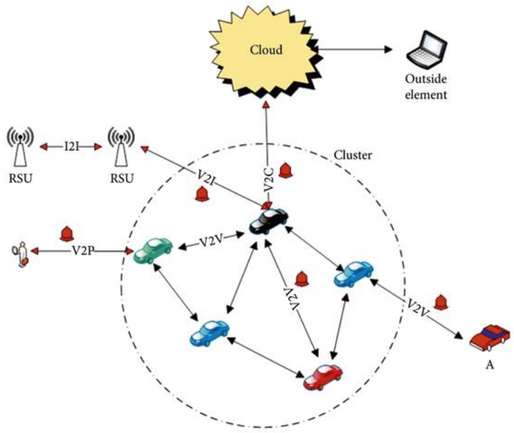

Figure 7. IoV communication [40].

There is a constant exchange of information between RSUs using V2I communication, providing services in wireless communication between the vehicle and the road service provider data centre. Finally, Vehicle-to-Cloud communication (V2C) allows the vehicle to collect and store data in the cloud and also provides access to the system to obtain additional information via the Application Programming Interface (API) [40].

4. Advanced driver information system architecture

In the available literature, in-vehicle warning systems are mostly related to autonomous driving. In terms of multimodal transport, several quality solutions were developed for level crossings specifically, while solutions for other critical points of the multimodal network have been very poorly researched, so it is necessary to further investigate the possibilities of applying these technologies at a higher level.

The primary objective of this paper was to study the available research in the field of C-ITS and IoV that can be used to create a robust solution, designed to deliver timely and reliable warnings to all drivers, and potentially other users of the traffic system, as they approach critical points of the multimodal network environment. The focus was on synthesizing available research findings to develop a solution that seamlessly integrates into the existing framework of sustainable transport.

Based on the reviewed literature, a framework for a refined system architecture is proposed. This framework combines two existing models of in-vehicle warning systems: the ones based on historical data and the ones based on real-time data, as shown in Figure 8.

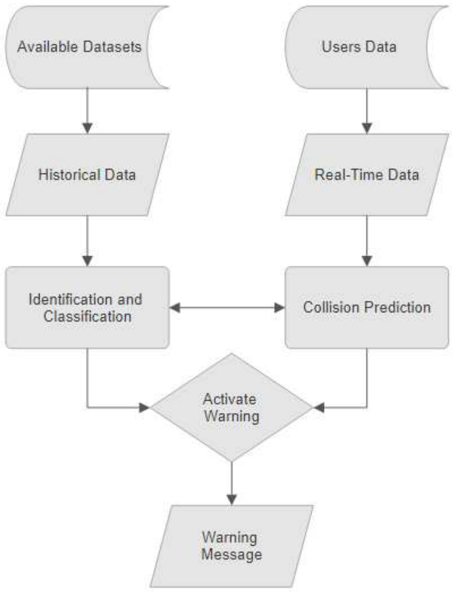

Figure 8. Proposed system architecture framework.

The first segment of the proposed architecture, based on historical data, is applicable to all critical locations for which there is available data. Historical data provide valuable information for conducting an identification and classification of locations with a history of traffic accidents. They are crucial for identifying patterns, assessing risks, and informing the system's response strategies. As traffic is an overly complex system composed of many interdependent elements, most of these elements, or subsystems, use a particular form of information system and data collection, so, for quality and usable data, it is necessary to connect datasets available from multiple sources, e.g., government, the scientific community, industry, and the public [23].

Simultaneously, the second segment deals with real-time location data and provides dynamic and timely information about the current state of the driver's environment. The sources are system users from different modes of transport. Based on the precise data about their location, the system calculates the collision probability of conflicting traffic entities. This process can also consider the results of the critical point classification process, and vice versa, to make a more reliable decision.

Based on the outputs of these two segments, the system will decide to warn the driver of potential or immediate danger.

Combining real-time data with historical data not only enhances the reliability of the system but also extends its applicability to locations lacking a history of incident situations. Integrating these system segments requires a comprehensive understanding of their functioning, mechanisms, and how they can complement each other to create a more robust and effective system.

5. Discussion

For a truly sustainable intelligent driver information system, the integration of new technologies including sensors, C-ITS, IoV and cloud data processing is required.

The available data sets on traffic accident history are quite limited, and data sources differ in terms of functionality, characteristics, and service quality, therefore, there is a need to establish stable and open access to this data.

Furthermore, one type of sensor can hardly meet the needs of obstacle detection due to sensor limitations in range, signal characteristics and detection operating conditions, and it is necessary to investigate in detail the methodology of combining multiple sensors and system integration. Regarding the transfer of information, the emphasis of future research should be on direct communication between transport entities, excluding the RSU if possible.

A reliable warning system requires a stable network connection with low latency and global coverage. Today, numerous wireless communication technologies can be deployed in a multimodal environment, but any mobile vehicle or device may face network disconnection, wireless bottlenecks, and security threats in different geographic locations. Over the years, mobile technologies have focused on improving the speed and efficiency of wireless networks, but there are still some application areas where current wireless networks struggle to deliver. New generations of mobile networks are expected to be able to meet performance criteria for low latency, high speed, and improved system reliability.

The C-ITS environment needs to address several future challenges before it becomes successful. Different C-ITS technologies should be complementary, and this requires the development of algorithms that provide intelligence to the communication devices installed inside the vehicle.

6. Conclusions

Traffic safety is a critical issue that concerns all sectors involved worldwide. Today, in the transport system, there are numerous high-quality solutions to increase safety, but in the field of multimodal transport networks such solutions are very limited. Critical points in a multimodal environment represent challenging situations where different modes of transport are in "physical conflict". Due to specific differences in infrastructure, vehicles, and users' behaviour, places where different modes of traffic intersect are recognized as critical points of the traffic system, making them crucial aspects of Sustainable Urban Mobility Plans (SUMPs) implementation. The unpredictable nature of these interactions is a result of road users' behaviour. Various passenger and driver information systems are already widely used within ITS, and recent research shows that warning systems inside vehicles or through smartphones can have a significant impact on driver/pedestrian behaviour if they can be considered credible and reliable.

In proposed system architecture, reliable and consistent spatial data play a key role. Identifying and classifying critical points requires linking security aspects with spatial components. The first step is to identify potentially dangerous places, considering different modes of transport at the same level. Detailed technical and historical accident data are essential for risk assessment. Classical methods do not consider spatial components, while more advanced methods include analyses where geospatial elements are combined with accident data to identify critical points. The choice of method depends on the specific parameters of the system and the degree of risk at the crossing points of different forms of traffic.

Advanced driver information system combines two existing models of in-vehicle warning systems: the ones based on historical data and the ones based on real-time data. Most of the research so far focuses on systems that require additional devices for detection and data processing, while the proposed system relies on solutions for direct communication between users and cloud-based processing. In the field of multimodal transport networks, communication challenges include various constraints. Commercial sensors, such as LIDAR, cameras and radars are not reliable due to limitations in range and reflections. The installation of GNSS devices enables monitoring and warning drivers in real-time, and research shows that the standard performance of GNSS meets the needs of the system, reducing its complexity and costs. Wireless communication technologies play a key role in the multimodal environment but face numerous challenges due to the effects of propagation and vehicle speed. The main technologies for communication are DSRC and C-V2X. C-V2X shows advantages in terms of communication range and security applications, but DSRC is more often mentioned in the context of C-ITS. A survey of DSRC communication between vehicles and trains shows that most safety warnings arrive on time. Since the integration of communication systems between multiple transportation modes is still in its infancy, there is little evidence in the literature to fully identify all the potential benefits and drawbacks for user safety that this technology could offer.

The implementation of the system proposed in this paper would be technologically and financially less demanding than classic solutions and could alleviate the stagnation of the effectiveness of existing security measures. However, it is important to point out that the gradual implementation of new technologies to increase traffic safety should not be considered a substitute for traditional approaches, but part of active protection that informs drivers of potential dangers in their environment.

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