KSÜ Mühendislik Bilimleri Dergisi, 29(1), 2026
Derleme Makalesi

KSU J Eng Sci, 29(1), 2026
Review Article

Kahramanmaras Sutcu Imam University
Journal of Engineering Sciences

Geliş Tarihi : 26.11.2025
Kabul Tarihi :08.01.2025

Received Date : 26.11.2025
Accepted Date : 08.01.2025

TECHNOLOGICAL AND PSYCHOSOCIAL DIMENSIONS OF AGGRESSIVE DRIVING AND ROAD RAGE: A PERSPECTIVE BASED ON INTELLIGENT TRANSPORTATION SYSTEMS, ARTIFICIAL INTELLIGENCE, AND SOCIETAL IMPACTS

AGRESİF SÜRÜŞ VE YOL ÖFKESİNİN TEKNOLOJİK VE PSİKOSOSYAL BOYUTLARI: AKILLI ULAŞIM SİSTEMLERİ, YAPAY ZEKÂ VE TOPLUMSAL ETKİLER TEMELLİ BİR PERSPEKTİF

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ABSTRACT

Traffic safety is a multidimensional field shaped not only by infrastructure and vehicles but also by driver behavior and its technological mediation within Intelligent Transportation Systems (ITS). Among these behaviors, aggressive driving and road rage are critical phenomena that directly affect safety and traffic flow. This review examines psychological and societal determinants such as anger, stress, impatience, and cultural norms; Artificial Intelligence (AI) and Machine Learning (ML)-based detection and management approaches using CAN-bus, biometric, and video data; and Advanced Driver Assistance Systems (ADAS) and ITS applications. The study explains how behavioral evidence supports AI-based risk assessment, early-warning mechanisms, and ITS applications by enhancing situational awareness and adaptive response. It also discusses the growing role of data-driven analytics and sensor fusion in predicting and mitigating risky driving patterns in conventional and connected vehicle environments. Recent research shows that aligning human factors insights with model design enhances reliability and supports adaptive, real-time safety functions. The review provides practical implications for researchers and policymakers regarding intelligent behavior modeling, ethical data use, and human-centric ITS design, and highlights future research areas such as cross-cultural analyses, biometric-aware modeling, and human–autonomy interaction in next-generation mobility systems.

Keywords: Aggressive driving, driver behavior, intelligent transportation systems, road rage, traffic safety

ÖZET

Trafik güvenliği, yalnızca altyapı ve araçlarla değil, sürücü davranışı ve bunun Akıllı Ulaşım Sistemleri (ITS) içindeki teknolojik karşılığıyla şekillenen çok boyutlu bir alandır. Agresif sürüş ve yol öfkesi, güvenliği ve trafik akışını doğrudan etkileyen kritik olgulardır. Bu derleme; öfke, stres, sabırsızlık ve kültürel normlar gibi psikolojik ve toplumsal belirleyicileri; CAN-bus, biyometrik ve video verilerine dayalı yapay zekâ ve makine öğrenmesi yaklaşımlarını; ayrıca ADAS ve ITS uygulamalarını birlikte ele almaktadır. Davranışsal verilerin, durumsal farkındalığı artırarak yapay zekâ tabanlı risk değerlendirmesi ve erken uyarı mekanizmalarını nasıl desteklediği açıklanmaktadır. Ayrıca veri odaklı analiz ve sensör füzyonunun, geleneksel ve bağlantılı araç ortamlarında riskli sürüş örüntülerinin öngörülmesi ve azaltılmasındaki rolü tartışılmaktadır. Bulgular, insan faktörleri ile model tasarımının uyumunun güvenilirliği artırdığını ve gerçek zamanlı güvenlik işlevlerini güçlendirdiğini göstermektedir. Çalışma, akıllı davranış modelleme, etik veri kullanımı ve insan merkezli ITS tasarımı için pratik çıkarımlar sunmakta ve kültürlerarası analizler ile insan–otonomi etkileşimi gibi gelecekteki araştırma alanlarına işaret etmektedir.

Anahtar Kelimeler: Agresif sürüş, sürücü davranışı, akıllı ulaşım sistemleri, yol öfkesi, trafik güvenliği

INTRODUCTION

Traffic safety stands out as one of the most critical global issues of our time. According to data from the World Health Organization (WHO), approximately 1.2 million people lose their lives each year due to traffic accidents, while millions of others are injured (WHO, 2023). One of the main causes of traffic accidents is human-related errors. Studies have revealed that driver behavior is a determining factor in more than 90% of accidents. This indicates that human behavior, particularly driver psychology and societal factors, lies at the core of traffic safety (National Highway Traffic Safety Administration-NHTSA, 2025). Among human behaviors, aggressive driving and road rage play a particularly critical role in traffic safety. Aggressive driving includes actions such as speeding, sudden lane changes, and exerting pressure through high beams or honking, while road rage refers to a deeper psychological process that emerges as the external manifestation of a driver's inner anger (Love and Nicolls, 2025; Shoma-Nir, 2023). These two concepts are not merely individual driving problems but also reflections of societal and cultural dynamics. Factors such as traffic congestion, stress, social norms, and weak enforcement mechanisms trigger both aggressive driving and road rage (Mohammed, 2025; Love et al., 2023). Road rage and aggressive driving affect not only drivers but also pedestrians and other road users directly. Pedestrians, in particular, as the most vulnerable group, are disproportionately impacted by such behaviors, leading to a deterioration in their perception of safety and a weakening of the overall sense of security at the societal level (Kim et al., 2025; Üzümcüoğlu and Yaşar, 2025). In this context, addressing pedestrian-driver interactions alongside psychological and sociological dimensions provides significant contributions to traffic safety studies. Emerging technologies also offer new opportunities for understanding and managing aggressive driving and road rage. Modern tools such as machine learning, artificial intelligence, and ITS enable the early detection and prediction of driver behaviors (Dong et al., 2025; Hou et al., 2025; Gupta et al., 2024; Azadani and Boukerche, 2021). Furthermore, with the rise of autonomous vehicles, the question of how human behaviors will be integrated into these systems has become one of the primary focal points of traffic safety research (Xie et al., 2025; Sun et al., 2024).

The aim of this study is to examine aggressive driving and road rage through psychological, social, and technological dimensions, to compile recent developments in the literature, and to reveal the multidimensional impacts of these phenomena on traffic safety. The study will first analyze the psychological foundations of aggressive driving and road rage, followed by a discussion on pedestrian–driver interactions as well as social and cultural determinants. Subsequently, the detection and management of aggressive driving will be addressed from the perspective of artificial intelligence and intelligent transportation systems, and finally, future implications and policy recommendations will be presented.

Contributions

The contributions of this article can be summarized as follows:

1. Aggressive driving and road rage, which are mostly examined separately in the literature, are addressed in this study from a holistic perspective, incorporating social, psychological, and technological dimensions.
2. Pedestrian-driver interactions are discussed within the context of aggressive driving and road rage, offering a comprehensive framework to fill a gap in the literature.
3. The role of modern technologies such as AI, ML, ITS, and autonomous vehicles in the detection and management of aggressive driving is examined, while also discussing the integration of human factors into these systems.

Through policy, education, and design-oriented recommendations, the study introduces approaches that contribute not only to individual driving safety but also to societal safety.

Methodology

The present study has been conducted as a systematic review following the PRISMA 2020 guidelines. The methodology comprised three key stages: (i) identification of literature through comprehensive database searches, (ii) screening and eligibility assessment using predefined inclusion and exclusion criteria, and (iii) synthesis of the final studies included in the review. The complete flow of study selection, including the numbers excluded at each stage and the specific reasons for exclusion, is illustrated in Figure 1, which follows the PRISMA flow diagram format.

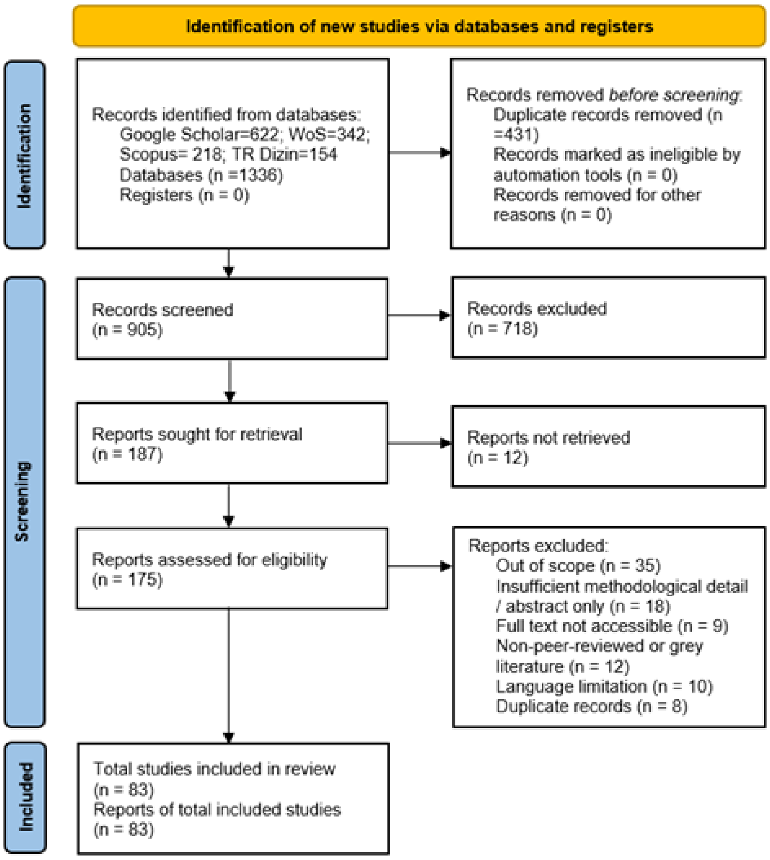

Figure 1. PRISMA Flow Diagram Illustrating the Study Selection Process, Including Screening, Eligibility, and Final Inclusion of Studies

Search Strategy

The literature search has been carried out in Google Scholar, Web of Science (WoS), Scopus, and TR Dizin, covering the period between 2020 and 2025. These databases have been selected to ensure a comprehensive scope that includes both international and national studies. To capture the multidimensional nature of aggressive driving and road rage, a structured search strategy was designed. Search terms were grouped into five thematic categories, and synonyms within each group were connected with OR, while groups were combined using AND operators:

1. *Aggressive driving and road rage behaviors:* “aggressive driving”, “risky driving”, “reckless driving”, “dangerous driving”, “road rage”, “driver anger”, “driving hostility”, “aggressive maneuvers”, “speeding”, “tailgating”.
2. Psychological and individual determinants: “psychology”, “driver psychology”, “stress”, “anger”, “anxiety”, “frustration”, “impatience”, “impulsivity”, “personality traits”, “risk-taking behavior”, “emotional regulation”.
3. Societal and cultural factors: “social norms”, “societal norms”, “cultural context”, “traffic culture”, “social behavior”, “societal determinants”, “public perception”, “community safety”, “cross-cultural comparison”.
4. Data sources and observational parameters: “CAN-bus data”, “vehicle telemetry”, “speed”, “acceleration”, “braking”, “steering”, “lane changing”, “facial expression”, “eye tracking”, “gaze”, “gesture”, “biometric signals”, “EEG”, “heart rate”, “galvanic skin response”, “video data”.
5. Technological and system-level approaches: “artificial intelligence”, “machine learning”, “deep learning”, “neural networks”, “CNN”, “LSTM”, “hybrid models”, “SVM”, “random forest”, “XGBoost”, “intelligent transportation systems (ITS)”, “advanced driver-assistance systems (ADAS)”, “autonomous vehicles”, “connected vehicles”, “smart cities”, “big data analytics”, “risk modeling”, “Hidden Markov Models (HMM)”, “Bayesian networks”.

Example search strings included:
- (“aggressive driving” OR “road rage”) AND (“traffic safety” OR “road safety”)
- (“driving anger” OR “risky driving”) AND (“machine learning” OR “deep learning” OR “neural networks”)
- (“facial expression” OR “eye tracking” OR “biometric signals”) AND (“aggressive driving”) AND (“intelligent transportation systems”)

Searches were carried out across Web of Science, Scopus, Google Scholar, and TR Dizin. The initial query yielded a total of 1336 records (Google Scholar: 622; Web of Science: 342; Scopus: 218; TR Dizin: 154).

Inclusion and Exclusion Criteria

Studies were included if they:
- focused on aggressive driving or road rage,
- examined psychological, societal, or technological aspects of traffic safety,
- were peer-reviewed journal articles or conference proceedings,
- were published in English or Turkish between 2020 and 2025.

Studies were excluded if they:
- did not address aggressive driving or road rage as a central theme,
- were editorial notes, non-academic reports, or grey literature,
- had insufficient methodological transparency, duplicated already screened records.

Screening and Eligibility

Following the removal of duplicates, a total of 905 records have been screened at the title and abstract level. At this stage, 718 records have been excluded as they did not directly address the scope of the study. The full texts of 187 studies have been retrieved for further evaluation, of which 12 could not be accessed. A detailed eligibility assessment has been then conducted for 175 reports, during which studies were excluded for reasons such as insufficient methodological detail, lack of full text, non-peer-reviewed or grey literature, language limitations, or duplication. As a result of this rigorous screening process, 83 studies met the inclusion criteria and were incorporated into the final review.

INDIVIDUAL AND SOCIETAL DETERMINANTS OF AGGRESSIVE DRIVING AND ROAD RAGE MATERIAL AND METHODS

Aggressive driving is a phenomenon that goes beyond individual driver behavior, emerging from the interplay of psychological and societal factors. At the core of these behaviors lie psychological processes such as anger, stress, impatience, and a tendency toward risk-taking (Singh and Dubey, 2025; Marian et al., 2024). In the literature, aggressive driving is defined through behaviors such as exceeding speed limits, lane violations, sudden maneuvers, and exerting pressure with high beams or honking, whereas road rage refers to the deeper psychological basis underlying these actions (Love and Nicolls, 2025; Wei and Shi, 2025).

Anger and stress directly affect drivers’ cognitive processes, leading to an increase in risky behaviors. In particular, traffic congestion, time pressure, and environmental stress factors elevate drivers’ impatience levels and trigger road rage (Öztürk and Varankaya, 2024; Wang et al., 2024). This represents not only a shift in individual mood but also an outcome that jeopardizes traffic safety at a societal level.

Personality traits stand out as key determinants of aggressive driving. Drivers with high levels of impulsivity, aggressiveness, and low self-control exhibit a greater frequency of aggressive behaviors in traffic (Kaveh et al., 2025; Liu et al., 2023). In contrast, drivers with higher levels of self-control and empathy tend to show lower tendencies toward road rage.

Cultural norms are also a significant component of aggressive driving. In some societies, competitive and individualistic behaviors among drivers are more prevalent, whereas in others, rule compliance and mutual tolerance are more dominant (Yousaf and Wu, 2024; Töre et al., 2023). These differences directly influence both the form and the frequency of road rage.

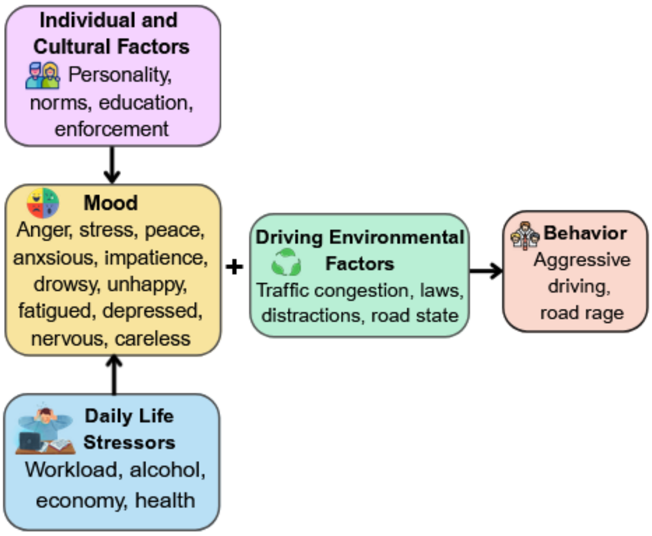

Figure 2. Relational Framework Between the Individual, Societal, and Behavioral Dimensions of Aggressive Driving and Road Rage, and Their Contribution to Traffic Safety Risks

Finally, societal sources of stress play a critical role in the increase of aggressive driving. Factors such as intense urbanization, inadequate traffic infrastructure, socioeconomic pressures, and stressors of daily life directly affect driver behavior (Mohammed, 2025; Qiang and Li, 2025). These factors not only undermine individual moods but also erode the collective perception of safety, thereby paving the way for the prevalence of aggressive driving and road rage. Aggressive driving and road rage are two fundamental behavioral patterns shaped by the interaction of individual and social factors, generating critical risks for traffic safety. To illustrate how these behaviors emerge and transform into risks, a conceptual framework is presented in Figure 2. As shown in Figure 2, individual factors such as personality traits, psychological tendencies, education, and control, daily life stressors such as workload, economic pressures, health, and alcohol, emotional states such as anger, stress, impatience, anxiety, and fatigue, as well as traffic-specific environmental conditions such as traffic density, legal regulations, and distracting elements directly shape driver behavior. These elements can trigger both road rage and aggressive driving, although the two concepts do not necessarily lead to one another. Road rage primarily reflects an internal emotional state, while aggressive driving may emerge as the behavioral outcome of that state. Therefore, distinguishing between the concepts of aggressive driving and road rage is critically important for developing effective intervention strategies at both the individual and societal levels.

While road rage is predominantly an internal psychological reaction, aggressive driving is characterized by outward behavioral patterns. Nevertheless, there are shared psychological factors where the two concepts intersect. This relationship is illustrated in Figure 3.

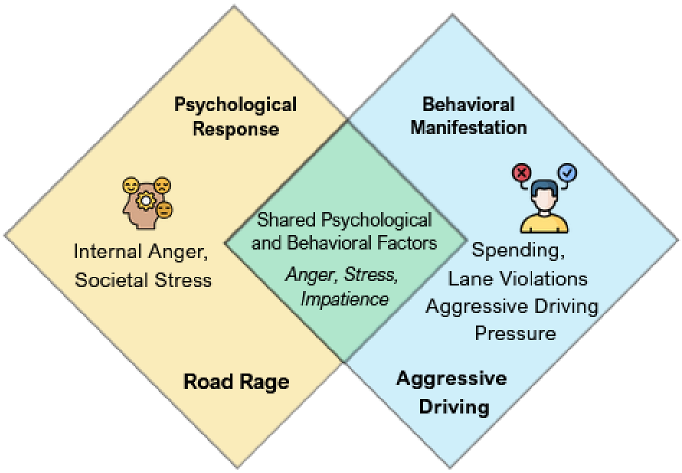

Figure 3. Partial Overlap Between Road Rage and Aggressive Driving, and Their Shared Psychological–Behavioral Factors

As shown in Figure 3, road rage is more closely associated with internal anger, societal stress, and psychological reactions, whereas aggressive driving manifests through behavioral outcomes such as speeding, lane violations, or the use of high beams. At the intersection of these two concepts lie anger, stress, and impatience, which represent both psychological and behavioral influences. Thus, while road rage and aggressive driving may occur independently, they converge on a common ground that amplifies traffic safety risks (Singh and Dubey, 2025).

The psychosocial foundations of aggressive driving and road rage have been examined in various studies from both individual and societal perspectives. These studies highlight the significant role not only of anger, stress, impatience, and personality traits but also of cultural norms and societal stress factors. The findings from the relevant literature are summarized in Table 1. In Table 1, it is evident that aggressive driving behaviors are influenced not only by psychological factors such as individual anger or impatience but also by cultural differences and societal stressors. In particular, societal conditions such as traffic congestion, economic pressures, and infrastructural deficiencies directly affect drivers' emotional states and can trigger road rage. Moreover, the role of cultural norms in shaping driver behavior reveals that aggressive driving is not merely an individual choice but also a social phenomenon.

Table 1. Summary of Literature on the Psychosocial Foundations of Aggressive Driving and Road Rage

Study	**Research Aspect**	**Key Findings**	**Method / Data**
Love et al., 2023	Road rage	Road rage can be both a trigger and an outcome of aggressive driving.	Literature review
Umar and Farooq, 2025	Anger and stress	High levels of anger and stress increase risky driving behaviors.	Survey + psychometric tests
Shokri and Behnood, 2022	Impatience, personality traits	Impulsivity and low self-control strengthen the tendency toward aggressive driving.	Driving simulator + survey
Ogwude et al., 2025; Labbo et al., 2025	Cultural norms	Road rage is more frequent in individualistic societies, while observed at lower levels in collectivist societies.	Comparative field study
Ogwude et al., 2025; Gu et al., 2025	Societal stress factors	Traffic congestion, economic pressures, and infrastructural deficiencies negatively affect driver behaviour.	Traffic data analysis

PEDESTRIAN-DRIVER INTERACTIONS

The traffic environment is a multi-actor system consisting not only of drivers but also of pedestrians and other road users. Therefore, addressing driver–pedestrian interactions is of great importance in traffic safety studies. Although drivers and pedestrians share the same environment, their perceptions, priorities, and risk assessments differ. Drivers typically prioritize fast mobility and traffic flow, whereas pedestrians place emphasis on safety and the protection of personal space (Nassereddine, 2025; Krizsik and Sipos, 2024; Yang et al., 2024). These differing perceptions increase the potential for conflict, especially under heavy traffic conditions. Perceptual differences lie at the core of driver-pedestrian interactions. When a driver perceives themselves as the primary user of the road, it can lead to the marginalization of pedestrian rights. Conversely, the imbalance between pedestrians' safety expectations and drivers' pressures of speed and time often results in tension within traffic (Krizsik and Sipos, 2024; Brill et al., 2024).

Conflicts are observed more frequently at pedestrian crossings, intersections, and urban roads. In the literature, role theory has been employed to explain how drivers and pedestrians perceive one another (Üzümcüoğlu and Yaşar, 2025; Kizawi and Borsos, 2021). According to this perspective, drivers tend to view themselves as "actors in control" while pedestrians are defined as "vulnerable users in need of protection". These role differences contribute to communication gaps and conflicts in traffic.
Road rage and aggressive driving affect not only drivers but also pedestrians directly. Aggressive driving behaviors increase feelings of stress, fear, and insecurity among pedestrians and, in some cases, even lead pedestrians to develop anger and reactive behaviors in traffic (Üzümcüoğlu and Yaşar, 2025; Wei and Shi, 2025; Shamoa-Nir, 2023). This undermines the collective perception of safety in the traffic environment and negatively impacts individuals' quality of daily life. From a cultural and societal perspective, it is observed that in some countries drivers are more

considerate toward pedestrians, whereas in others pedestrian rights are frequently violated. For example, in developed countries pedestrian priority has been internalized as a traffic culture, while in developing countries significant differences can be observed in drivers' yielding behaviors (Labbo et al., 2025; Askarizad et al., 2025; Yousaf and Wu, 2024). This situation is not only linked to legal regulations but is also closely tied to cultural norms and societal values.The interactions between drivers and pedestrians in the traffic environment have been examined in the literature through differing perceptions, points of conflict, and cultural variations. These studies highlight the critical role of pedestrian–driver interactions in traffic safety. The related research is summarized in Table 2. As shown in Table 2, pedestrian–driver interactions are not limited to the physical sharing of roads but are also shaped by perceptions, roles, and societal norms. Insensitivity toward pedestrians is more pronounced in developing countries, whereas in developed countries legal and cultural norms enhance pedestrian safety. These differences highlight the importance of the social context in ensuring traffic safety.

Table 2. Key Findings in the Literature on Pedestrian-Driver Interactions

Study	Research Aspect	Key Findings	Method / Data
Üzümcüoğlu and Yaşar, 2025; Wei and Shi, 2025; Shamoa-Nir, 2023	Impact on pedestrians	Aggressive driving generates fear, stress, and insecurity among pedestrians.	Psychometric tests and experimental/field analyses
Labbo et al., 2025; Askarizad et al., 2025; Yousaf and Wu, 2024	Cultural differences	Pedestrian priority is stronger in developed countries but weaker in developing ones.	Comparative field study
Zhang et al., 2025; Krizsik and Sipos, 2024; Brill et al., 2024	Perceptual differences	Drivers perceive themselves as holding control of the road, while pedestrians prioritize safety.	Experimental/simulation-based analysis
Üzümcüoğlu and Yaşar, 2025; Hyder and Subbarao, 2025; Kizawi and Borsos, 2021	Role theory	Divergent driver–pedestrian roles increase the likelihood of conflicts.	Literature review and field analysis

SOCIETAL AND CULTURAL DETERMINANTS

Aggressive driving and road rage are not only linked to individual psychological traits but are also closely related to the cultural structures and social norms of societies. Driver behaviors in traffic environments are shaped within a broad framework that includes societal value systems, education levels, enforcement mechanisms, and media influence. Therefore, examining the societal determinants of aggressive driving is critically important for developing solutions not only at the individual level but also at the societal level.

Differences Between Developed and Developing Countries

The literature highlights significant differences in driver behavior between developed and developing countries (Ogwude et al., 2025; Gracian et al., 2024; Granie et al., 2021). In European countries and North America, pedestrian priority has been internalized as part of the traffic culture and reinforced through legal sanctions. In contrast, in developing countries, pedestrian rights are more frequently violated, drivers tend to bend the rules, and road rage becomes more visible (Sharma, 2025; Mukherjee, 2025). This situation is not only associated with legal regulations but also with societies' collective behavioral habits.

Education and Enforcement Mechanisms

Traffic education is one of the fundamental elements shaping individuals' perceptions and behaviors toward traffic environments from an early age. Rules acquired through education play an important role in reducing aggressive driving behaviors (Boehme and Mourtgos, 2024). In addition, the visibility of traffic police, the deterrent effect of penalties, and the effectiveness of technological enforcement tools (cameras, radar systems) are critical factors in controlling aggressive driving behaviors. Research indicates that in areas with low enforcement intensity, road rage and aggressive driving behaviors are observed more frequently (Cheng et al., 2025; Factor et al., 2023).

Traffic Culture and Social Norms

Societal value systems directly influence driver behavior. In collectivist cultures, individuals tend to exhibit more cooperative behaviors in traffic, whereas in individualistic cultures, competitive and risky driving behaviors are more common (Yousaf and Wu, 2024; Fındık et al., 2022; Granie et al., 2021). In societies where compliance with rules is regarded as a form of social pressure, aggressive driving is observed at lower levels. Conversely, in societies where rule violations are considered ordinary, the social acceptance of road rage and aggressive behaviors increases (Labbo et al., 2025; Cubillos-Pinilla et al., 2025).

Media, Social Perception, and Collective Behavior

The influence of media and social media on traffic safety has become more apparent in recent years. News reports on accidents, public service announcements, and social awareness campaigns shape individuals' perceptions of traffic safety and transform social attitudes toward aggressive driving. On the other hand, the circulation of content on social media that encourages or normalizes aggressive driving creates a foundation for increased risky behaviors, especially among young drivers. This underscores that road rage and aggressive driving are not only individual but also cultural and social phenomena (Olii et al., 2024; Nicolls et al., 2024; Stefanidis et al., 2022). Studies indicate that the societal and cultural determinants of aggressive driving have been examined across different dimensions. These investigations encompass differences in behavior between developed and developing countries, the impact of education and enforcement mechanisms, the role of social norms, and the influence of media on driver behaviors. The findings from the literature are summarized in Table 3.

Table 3. Summary of Literature on the Societal and Cultural Determinants of Aggressive Driving and Road Rage

Study	Research Aspect	Key Findings	Method/Data
Sharma, 2025; Mukherjee, 2025; Gracian et al., 2024; Granie et al., 2021	Country comparisons	Pedestrian priority is strong in developed countries, while violations are more common in developing ones.	Comparative field study
Jha et al., 2026; Boehme and Mourtgos, 2024; Factor et al., 2023; Nadimi et al., 2021	Education and enforcement	Traffic education and intensive enforcement reduce aggressive driving.	Survey + observation
Labbo et al., 2025; Cubillos-Pinilla, 2025; Fındık et al., 2022; Granie et al., 2021	Traffic culture	Cooperative behavior is more common in collectivist societies, while competitive behavior prevails in individualistic ones.	Literature review
Olii et al., 2024; Nicolls et al., 2024; Stefanidis et al., 2022	Media influence	Public service announcements have a positive effect, while normalization on social media has a negative impact.	Content analysis

As seen in Table 3, aggressive driving is not merely an individual behavioral pattern but is closely related to societal structure, cultural values, and media influence. In developing countries, insufficient enforcement and traffic cultures inclined toward rule-bending create conditions that foster the rise of road rage and aggressive driving. In contrast, in developed countries, strengthening traffic safety awareness through education and media produces more positive outcomes in driver behavior. When the societal and cultural determinants of aggressive driving and road rage are examined, it becomes evident that these factors can be considered within a hierarchy. Societal and cultural infrastructures shape individual behaviors in the traffic environment, and these behaviors ultimately manifest as outcomes such as road rage and aggressive driving. This conceptual hierarchy is summarized in Figure 4.

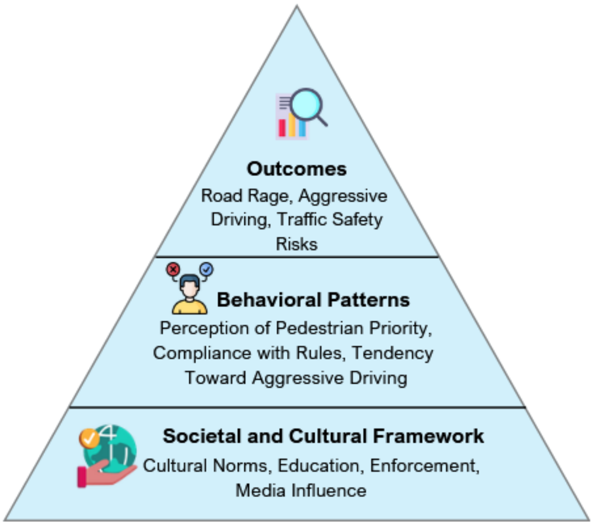

Figure 4. Pyramid Model of the Societal and Cultural Determinants of Aggressive Driving and Road Rage

As shown in Figure 4, the societal and cultural infrastructure, comprising cultural norms, education, enforcement, and media, forms the base layer of the pyramid and directly influences individuals' behavioral patterns in traffic environments. These behavioral patterns manifest in drivers' perceptions of pedestrian priority, their levels of compliance with rules, and their tendencies toward aggressive driving. Ultimately, as a consequence of these patterns, outcomes such as road rage, aggressive driving, and traffic safety risks emerge. This model emphasizes that aggressive driving is not only an individual phenomenon but also a societal and cultural one, highlighting the need to seek solutions within the same multilayered framework.

DETECTION OF AGGRESSIVE DRIVING: TECHNICAL APPROACHES

In addition to the social and psychological dimensions of aggressive driving, its detection through technical methods is of great importance for traffic safety. In recent years, machine learning and artificial intelligence-based approaches have made it possible to analyze driver behaviors using data collected from multiple sources (Dong et al., 2025). Through these methods, drivers can be classified as aggressive or normal, emotional states such as anger and stress can be identified, and this information can be integrated into intelligent transportation systems (Gatteschi, 2021). The methods used for detecting aggressive driving generally consist of three stages: data collection, processing through machine learning and AI techniques, and classification of the results. Figure 5 summarizes the conceptual flow of data sources, methods, and outputs used in the detection of aggressive driving.

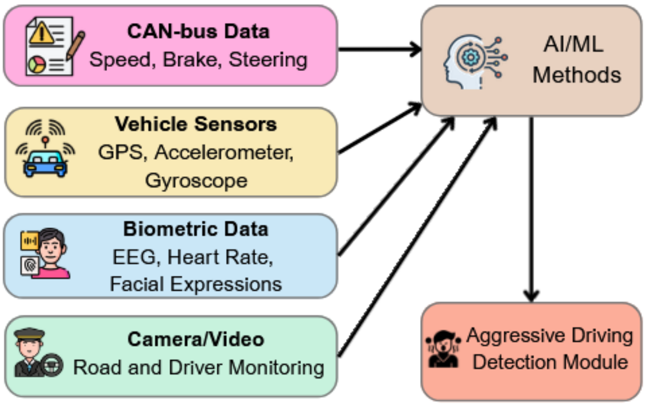

Figure 5. Conceptual Flow Model of Data Sources, Methods, and Outputs in Aggressive Driving Detection

In the first stage of the aggressive driving detection process, data are collected from various sources such as CAN-bus, vehicle sensors, biometric measurements, and video recordings. These data are then processed using machine learning and artificial intelligence algorithms, SVM, Random Forest, CNN, LSTM, and hybrid models, to extract the characteristics of driver behavior. Subsequently, the processed data are used to determine whether the driving is normal or aggressive. In addition, the driver's emotional state such as anger or stress is analyzed, thereby shedding light on both behavioral and psychological dimensions. This flow model illustrates the multidimensional nature of aggressive driving from a technical perspective.

Data Sources in the Perception of Aggressive Driving

Reliable detection of aggressive driving primarily depends on the collection of accurate and meaningful data. In the literature, different types of data sources are employed to analyze driver behaviors.

CAN-bus data include parameters obtained from sensors in modern vehicles such as speed, braking, steering angle, and engine RPM. These data have been found highly effective in detecting aggressive maneuvers and risky behaviors. For example, sudden accelerations, harsh braking, and sharp steering movements stand out as indicators of aggressive driving (Gheni and Abdul-Rahaim, 2024; Karabuluter et al., 2020).

Vehicle sensors, beyond CAN-bus, provide additional insights using technologies such as accelerometers, gyroscopes, and GPS-based location data, enabling a detailed modeling of driver behavior. These data can capture speed variations, lane violations, or sudden maneuvers with high precision in different driving scenarios (Khandakar et al., 2025; Lazar and Jarir, 2024; Abarghooei and Ahmadi, 2026).

Biometric data focus on directly measuring the driver's psychophysiological state. EEG (brain waves), heart rate, galvanic skin response (GSR), and facial expressions are used to reveal the connection between drivers' emotional states and aggressive behaviors. Such data play a critical role particularly in the early detection of driver anger and stress (Mateos-Garcia et al., 2023).

Camera- and video-based methods analyze drivers' facial expressions, eye movements, and gestures to capture visual cues of road rage and aggressive behaviors. In addition, video data from both the road environment and the vehicle interior are used to evaluate the relationship between driver behaviors and the surrounding traffic context (Lohare et al., 2025; Leone et al., 2021).

Machine Learning and Artificial Intelligence Methods

The meaningful interpretation of collected data is made possible through machine learning (ML) and artificial intelligence (AI) algorithms. In the literature, methods used for the detection of aggressive driving span a wide spectrum, from classical classification algorithms to deep learning–based models.

Classical classification algorithms play a fundamental role in detecting aggressive driving. Methods such as SVM (Support Vector Machines), Random Forest, KNN (K-Nearest Neighbor), and XGBoost are trained with CAN-bus or sensor data to classify driver behaviors as aggressive or normal. These algorithms provide high accuracy, particularly with small- and medium-sized datasets (Gheni and Abdul-Rahaim, 2024; Karabuluter et al., 2020).

Deep learning methods capture more complex patterns by considering the time-series nature of driver behaviors. CNNs (Convolutional Neural Networks) extract behavioral features from driving data, while recurrent architectures such as LSTM (Long Short-Term Memory) and GRU learn the temporal dynamics of driving behaviors. These methods are particularly effective with multidimensional data such as video inputs and biometric signals (Hou et al., 2025; Diaaeldin and Zaher, 2024; Qu et al., 2024).

Hybrid models have emerged as a notable trend in recent years. Approaches that combine CNN+LSTM or integrate attention mechanisms simultaneously evaluate both instantaneous driving behaviors and long-term driving patterns. Such models can reveal the relationship between aggressive driving and road rage with higher accuracy (Liu et al., 2025; Debbarmaet al., 2025).

Mood detection represents an innovative dimension that AI methods bring to aggressive driving research. Emotion analysis from facial expressions, anger detection from voice tone, or stress level estimation from biometric signals make it possible to directly identify the driver's psychological state. In this way, aggressive driving can be assessed not only through behavioral outputs but also in relation to the driver's internal condition (Chen et al., 2022; Xiao et al., 2022).

Risk Modeling and Early Warning Systems

Detecting aggressive driving is important, but predicting it in ways that enhance traffic safety is equally critical. At this point, risk modeling and early warning systems come to the forefront.

Hidden Markov Models (HMMs) consider the stochastic nature of driver behaviors and are used to distinguish between normal and abnormal driving patterns. By deriving probability distributions from sequential driving data, this method enables the early detection of aggressive behaviors (Qi, 2024; Deng and Söffker, 2021).

Bayesian networks serve as a powerful tool in decision-making under uncertainty, allowing the modeling of aggressive driving risks. By defining causal relationships among various factors, they can estimate the likelihood of aggressive driving under certain conditions (Carrodano, 2024; Rahman et al., 2022).

Real-time early warning systems aim to enhance safety by providing drivers with immediate feedback on detected risky behaviors. Integrated with advanced driver assistance systems (ADAS), these technologies deliver alerts through visual, auditory, or haptic signals (Masello et al., 2023).

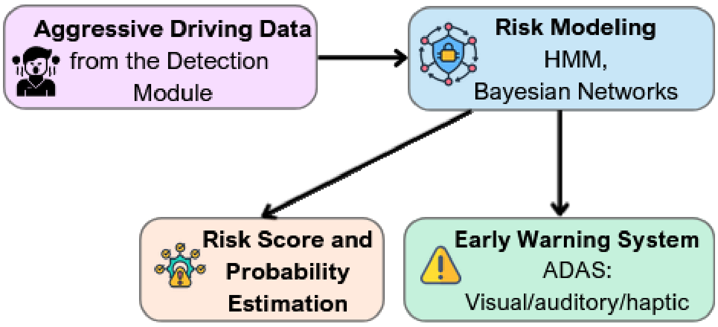

Figure 6. Integration Process of Aggressive Driving into Risk Modeling and Early Warning Systems

Scenario-based risk modeling is applied particularly in complex traffic situations such as overtaking, intersection use, and sudden lane changes. These scenarios are analyzed both in simulation environments and with field data to forecast potential accident risks caused by aggressive driving (Oh et al., 2024; Tan et al., 2024).

These methods go beyond detecting aggressive driving from historical data, enabling the prediction of potential future risks in advance. Detecting aggressive driving alone is not sufficient; modeling driver behaviors according to risk levels and forecasting possible accidents are also critical requirements. In this context, risk modeling methods account for the stochastic properties of driving data to estimate the probabilities of aggressive behaviors and supply input to early warning systems. Figure 6 summarizes the process extending from aggressive driving detection to risk modeling and driver feedback. As shown in Figure 6, once aggressive driving is technically detected, the data are processed through methods such as HMMs and Bayesian networks, thereby generating the driver's risk profile. The resulting risk scores are integrated into advanced driver assistance systems (ADAS), which deliver real-time visual, auditory, or haptic alerts to the driver. In this way, aggressive driving is not only defined as a behavioral phenomenon but also transformed into a preventive safety mechanism by predicting potential future risks.

Integration with Intelligent Transportation Systems

The technical detection of aggressive driving gains societal value when this information is integrated with intelligent transportation systems (ITS). The use of detected behaviors in traffic management, autonomous vehicles, and public safety further underscores the future significance of ITS. This integration process is summarized in Figure 7. As shown in Figure 7, data obtained from the aggressive driving detection module are transferred to ITS, where they are processed across different layers.

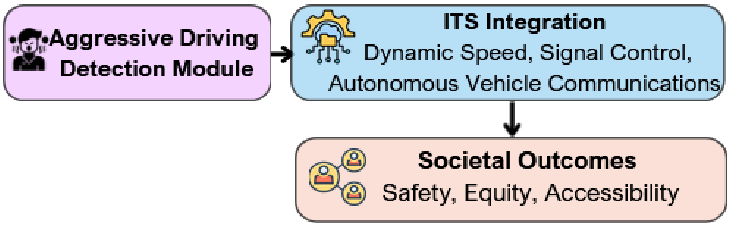

Figure 7. Integration of Aggressive Driving Detection into Intelligent Transportation Systems and Societal Outcomes

From a traffic management perspective, these data can be utilized in applications such as setting dynamic speed limits and optimizing traffic signals. For autonomous vehicles, the prior identification of aggressive driver behaviors enables more accurate safety-related decisions. At the societal level, this integration enhances traffic safety, supports fair road sharing among users, and strengthens accessibility. Thus, aggressive driving goes beyond being an individual behavior and becomes part of a system-level solution approach. The detection of aggressive driving through technical methods can only generate societal value when integrated with intelligent transportation systems (ITS). By combining sensor data, communication technologies, and AI algorithms, ITS aims to improve both traffic safety and efficiency. Integrating aggressive driving into ITS highlights the impact of individual driver behaviors on overall traffic flow. For example, when aggressive driving is detected, traffic management centers can use this information to set dynamic speed limits, optimize intersection control algorithms, or automatically notify police units (Gupta et al., 2024; Mohammed et al., 2023; Azadani and Boukerche, 2021). Integration with autonomous vehicles points to a critical future for aggressive driving detection. Autonomous systems must consider not only traffic signs and road data but also human driver behaviors when making decisions. Therefore, real-time detection of aggressive driving through machine learning and sensor-based methods becomes a fundamental component of autonomous vehicle safety (Hajiyev, 2024; Kang and Shen, 2021). At the societal level, this integration has significant implications for safety, fairness, and accessibility. Detecting and reporting aggressive behaviors in traffic creates a safer and fairer environment for rule-abiding drivers while also contributing to the reduction of traffic accidents and associated socioeconomic losses. Technical approaches to aggressive driving detection have been evaluated in the literature through different data sources and AI algorithms. The methods, advantages, and limitations of these studies are summarized in Table 4. When examining Table 4, it becomes clear that different methods stand out in the detection of aggressive driving. Classical machine learning methods provide practical solutions for small datasets, whereas deep learning-based approaches deliver superior performance with more complex data structures. Stochastic methods (HMM, Bayesian networks) are effective in modeling the uncertain nature of driver behaviors, while real-time ADAS integrations allow the development of directly applicable solutions. However, each method comes with its own limitations, making the use of hybrid models and multiple data sources increasingly important in recent years.

Table 4. Technical Methods, Data Sources, Advantages, and Limitations in the Detection of Aggressive Driving

Study	Method/Algorithm	Data Source	Advantages	Limitations
Gatteschi et al., 2021; Karabuluter et al., 2020	SVM, Random Forest	CAN-bus data	High accuracy, effective with small datasets	Performance may decrease with large datasets
Hou et al., 2025; Rudokaite et al., 2025; Diaaeldin and Zaher, 2024; Qu et al., 2024	CNN, LSTM	Video + sensor data	Captures temporal dynamics well, learns complex patterns	High computational cost, requires large datasets
Liu et al., 2025; Debbarma et al., 2025; Diaaeldin and Zaher, 2024	Hybrid CNN+LSTM	CAN-bus + biometric data	Combines behavioral and psychological factors	High model complexity, risk of overfitting
Qi, 2024; Deng and Söffker, 2021	HMM	CAN-bus+ speed / braking data	Models stochastic processes, provides probabilistic prediction	Sensitive to parameter selection, computational cost
Carrodano, 2024; Rahman et al., 2022;	Bayesian Networks	Multiple data sources	Strong decision support under uncertainty	Complex network structures may increase solution time
Masello et al., 2023; Mohammed et al., 2023	ADAS-based warning systems	Real-time sensor data	Provides immediate feedback to drivers	Possible issues with driver acceptance and compliance

INTELLIGENT TRANSPORTATION SYSTEMS (ITS) AND MODERN TECHNOLOGIES

ITS offer modern solutions that integrate information and communication technologies, sensors, artificial intelligence, and communication infrastructures to enhance traffic safety and efficiency. ITS enables aggressive driving and road rage to be addressed not only at the level of individual drivers but also at the societal level. In particular, autonomous vehicles, AI algorithms, and smart city infrastructures present critical opportunities for the real-time monitoring and management of driver behaviors.

The Role of Aggressive Driving and the Impact of Road Rage in Smart Cities

The smart city concept considers not only traffic flow but also the impact of individual behaviors on the broader city ecosystem. Aggressive driving is regarded as one of the main causes of traffic congestion, energy consumption, and accidents in smart cities (Algherbal and Ratrout, 2025; Jha et al., 2026). Road rage contributes to increased societal stress, fosters feelings of insecurity among road users, and diminishes overall quality of life. Therefore, addressing aggressive driving within the scope of ITS is essential for achieving the sustainability goals of smart cities.

Interaction of Autonomous Vehicles with Human Behavior

Autonomous vehicle technologies must account for not only road data but also human driver behaviors in their decision-making processes. Predicting aggressive drivers constitutes a critical parameter in the collision-avoidance systems of autonomous vehicles (Crosato et al., 2024; Ma and Zhang, 2024; Zhao et al., 2024). Moreover, modeling road rage behaviors in simulation environments contributes to more reliable performance of autonomous vehicles in real-world scenarios. In this respect, human–machine interaction will play a central role in the future of transportation ecosystems.

ITS + Artificial Intelligence Integration: Incorporating Driver Behaviors into Systems

Machine learning and AI-based systems have become core components of ITS. The perception and classification of driver behaviors provide real-time information flow to traffic management centers, enabling traffic policies to be dynamically shaped. Through this integration, once aggressive driving is detected:

- Dynamic speed limits can be applied to regulate traffic flow,
- Smart signal control can be activated at intersections,
- Autonomous vehicles can increase safety measures when encountering aggressive drivers.

This approach allows individual behaviors to be directly managed at the system level (Algherbal and Ratrout, 2025; Xie et al., 2025; Gupta et al, 2024; Mohammed et al., 2023).

Table 5. The Role of ITS and Modern Technologies in the Management of Aggressive Driving

Technology / Approach	Application Area	Contributions	Limitations
Smart city infrastructure	Traffic flow, sustainability	Energy efficiency, reduction of traffic congestion	High cost, infrastructure compatibility issues
Autonomous vehicles	Interaction with human behavior	Collision avoidance, enhanced safety	Unpredictability of human behaviors
AI-based ITS	Dynamic traffic management	Real-time analysis of driver behaviors	Data privacy concerns, high computational cost
Early warning systems	In-vehicle safety	Immediate feedback to drivers	User compliance and acceptance issues
Integrated data sharing	Traffic management centers	Fair road sharing, policy development	Lack of data standardization

Societal Impacts: Safety, Fairness, and Accessibility

The integration of aggressive driving detection into ITS produces not only technical but also social benefits. From a safety perspective, it contributes to reducing traffic accidents and improving emergency response times. In terms of fairness, it ensures more equitable road sharing for rule-abiding drivers, while aggressive drivers are identified and brought under control by the system. From an accessibility standpoint, safer road conditions make the traffic environment more inclusive, particularly for elderly individuals, children, and people with disabilities. Within this framework, modern technologies and ITS integrations used in the management of aggressive driving are summarized in Table 5. The table provides a conceptual framework for the role of different technological approaches in managing aggressive driving. Smart city infrastructures offer significant advantages in regulating traffic flow and improving energy efficiency, though they face challenges such as high costs and infrastructure compatibility. Autonomous vehicles hold strong potential for collision avoidance and improved safety through interaction with human behaviors, yet the unpredictability of drivers remains a major limitation. AI-based ITS enables dynamic traffic management through real-time behavioral analysis, but it raises concerns about data privacy and high computational demands. ADAS-based early warning systems enhance safety by delivering instant feedback to drivers, although issues of user acceptance and compliance may restrict their effectiveness. Finally, integrated data sharing mechanisms provide traffic management centers with opportunities for fairer policy development, but a lack of data standardization complicates implementation. The technological approaches presented in Table 5 demonstrate the multilayered structure of ITS, which also encompasses societal dimensions. Within this framework, ITS emerges not only as a technological integration but also as an ecosystem generating social benefits.

RESULTS

Psychosocial Findings: The review of literature demonstrates that psychological factors such as anger, stress, impatience, and personality traits play a central role in aggressive driving and road rage. These findings are consistent with the Frustration–Aggression Theory and Social Learning Theory, which explain how internal emotions and external stressors translate into risky driving behaviors.

Pedestrian–Driver Interaction Findings: The studies indicate that perception gaps between drivers and pedestrians, as well as role conflicts, significantly increase road tension. These insights align with Role Theory, which explains the conflict of expectations between actors in shared environments.

Societal and Cultural Findings: Comparative studies reveal significant differences between developed and developing countries in terms of pedestrian priority, rule compliance, and tolerance levels. These patterns reflect the impact of Traffic Culture and Social Norms, showing how cultural values shape individual driving behaviors.

Technical and Technological Findings: Machine learning, AI-based models, and risk modeling techniques (HMM, Bayesian networks) enable the detection and prediction of aggressive driving. These approaches are grounded in Human Factors Theory and Socio-technical Systems Perspective, where driver behavior is seen as both a psychological and technological phenomenon.

Future Research Directions: The integration of psychological, societal, and technological aspects points toward future directions such as cross-cultural comparisons, biometric-based mood detection, and human–autonomous vehicle interactions. These findings emphasize the need for a holistic research framework that incorporates both behavioral and technological layers.

DISCUSSION AND FUTURE DIRECTIONS

Integration of Social, Psychological, and Technical Dimensions: Aggressive driving and road rage are phenomena situated at the intersection of individual psychology and societal norms. However, addressing these behaviors through technical methods in addition to their psychological foundations enables more holistic solutions. While most studies in the literature focus either on social/psychological or technical approaches, integration of the two dimensions has remained limited (Love and Nicolls, 2025; Mohammed, 2025; Azadani and Boukerche, 2021). The model presented in this review demonstrates that when social factors are integrated with AI and ITS technologies, traffic safety can be enhanced more effectively.

Recommendations for Education, Policy, and Regulation: Reducing aggressive driving requires not only technical solutions but also interventions at the levels of education and policy. Incorporating anger management, stress-coping strategies, and empathy development programs into driver training may contribute to reducing road rage (Factor et al., 2023; Stephens et al., 2022; Nadimi et al., 2021). In addition, clarifying the definition and penalty criteria of aggressive driving through legal regulations can enhance deterrence. With ITS integration, the effectiveness of such policies can be monitored in real time.

Emerging Societal Risks of Artificial Intelligence and Autonomous Vehicles: Although AI and autonomous vehicles present significant opportunities for detecting and managing aggressive driving, they also introduce new societal risks. Data privacy, algorithmic bias, and user acceptance are among the most pressing issues (Kim et al., 2025; Xie et al., 2025; Sun et al., 2024). In particular, the continuous monitoring of aggressive driving behaviors may negatively affect drivers' perceptions of privacy. Therefore, ethical principles must be considered when developing technological solutions.

The Importance of Road Rage in Future Research: Future research should consider road rage not only as a factor leading to aggressive driving but also as a phenomenon influencing societal safety and social relations. Combining AI and biometric methods with early detection of road rage may help prevent both individual accidents and broader social unrest. Furthermore, cross-cultural comparative studies could provide deeper insights into how road rage emerges and is managed in different societies (Wei and Shi, 2025; Yousaf and Wu, 2024; Shamoa-Nir, 2023; Love et al., 2023; Töre et al., 2023). The existing literature on aggressive driving and road rage has made notable progress in both social/psychological dimensions and technical methods. However, these studies must be extended with forward-looking research agendas. Based on the gaps observed in the literature, potential future research directions are summarized in Table 6.

As shown in the table, future research requires a multidimensional approach. Social and psychological integration studies will help to understand how road rage emerges across different cultures, while combining biometric data with AI will contribute to more precise detection of aggressive driving. Scenarios focusing on the interaction between autonomous vehicles and human drivers will be a priority in terms of technological safety. In addition, interventions based on education and policy will support behavioral change at an institutional level. Finally, addressing ethical and legal aspects will enhance the social acceptance of technological solutions and contribute to the establishment of international standards.

Table 6. Suggested Directions for Future Research

Research Area	Proposed Approach	Expected Contribution	Potential Challenges
Social–psychological integration	Cross-cultural comparison of road rage and aggressive driving	Understanding the influence of social norms on driver behavior	Data collection and ethical sensitivities
Biometrics and AI	Analysis of EEG, heart rate data using ML, and facial expressions	More accurate detection in early warning systems	Privacy and data security concerns
Autonomous vehicles and human interaction	Simulation-based modeling of aggressive driving scenarios	Enhancing autonomous vehicle safety	Unpredictability of human behaviors
Policies and education	Anger management, stress-control training + ITS-based monitoring	Reduction of accidents and road rage	Driver adaptation and societal resistance
Ethics and legal aspects	Addressing data privacy and algorithmic biases	Strengthening trust in technology and increasing social acceptance	Lack of international standards

Limitations, Trade-offs, and Future Directions

This study has several limitations. First, a considerable portion of the reviewed literature has focused either on social/psychological or technical dimensions, with relatively few studies integrating both. This creates a gap in fully understanding the multidimensional nature of aggressive driving. Second, much of the existing data has been derived from controlled experiments, surveys, or simulation environments. The limited availability of real-world field data constrains the generalizability of developed models. Moreover, while AI and machine learning methods provide high accuracy, these approaches also introduce trade-offs such as data privacy concerns, computational costs, and algorithmic biases. Future research should prioritize the collection of field data encompassing diverse cultural contexts, the more holistic integration of biometric and behavioral data, and the examination of transparency–performance trade-offs in AI-based models. These steps would contribute to more effective management of aggressive driving at both individual and societal levels.

Future Research Roadmap

To provide direction for future studies, the social, psychological, and technical dimensions discussed in this paper are evaluated from a temporal perspective. The priorities and interrelationships among short-, medium-, and long-term research goals are summarized in Figure 8.

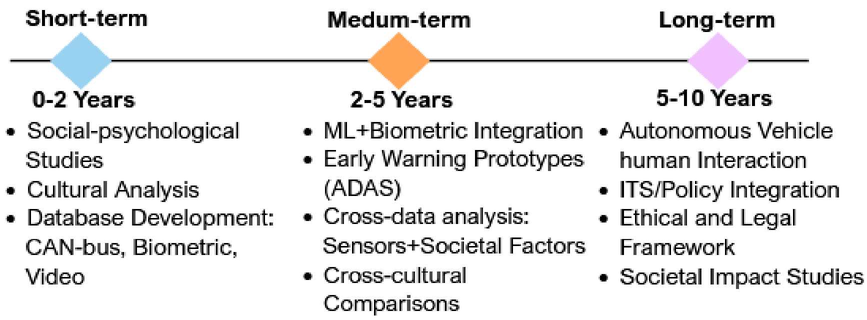

Figure 8. Roadmap for Short, Medium, and Long-Term Future Directions in Research on Aggressive Driving and Road Rage

As illustrated in Figure 8, in the short term, greater emphasis should be placed on investigating the socio-psychological and cultural dimensions of aggressive driving and road rage, supported by efforts to build comprehensive databases. In the medium term, the integration of machine learning and biometric data, the development of early-warning prototypes, and cross-cultural comparisons come to the forefront. In the long term, the interaction between autonomous vehicles and human drivers, the integration of ITS with policy frameworks, the consideration of ethical and legal aspects, and the deepening of societal impact studies gain importance. Together, these elements outline a comprehensive roadmap to ensure that research progresses in a multidimensional and sustainable manner.

CONCLUSIONS

This study has examined aggressive driving and road rage through a holistic perspective encompassing social, psychological, and technical dimensions. It demonstrates that these concepts, often studied in fragmented ways in the literature, directly influence traffic safety at both the individual and societal levels. Psychological factors such as anger, stress, and personality traits interact with social factors such as cultural norms, societal pressures, and traffic congestion to trigger aggressive driving behaviors. From a technical standpoint, machine learning and AI methods offer significant opportunities for the perception and classification of aggressive driving. Multidimensional data sources, including CAN-bus records, biometric measurements, and video recordings, make real-time analysis of driver behaviors possible. With the integration of these data into ITS, aggressive driving ceases to be a purely individual issue and becomes a parameter that enhances traffic safety at the system level. From a societal perspective, the detection and management of aggressive driving provide important benefits in terms of safety, fairness, and accessibility. Rule-abiding drivers gain more equitable road sharing, while risky behaviors are detected instantly, preventing accidents. Thus, aggressive driving is not only an individual psychological phenomenon but also a factor that directly affects social welfare and quality of life. In conclusion, future research must adopt an interdisciplinary approach. Integrating social and psychological research with technical methods, combining them with ITS and autonomous vehicle technologies, and securing them within ethical and legal frameworks will not only enrich the academic literature but also contribute in practice to building a safer and fairer transportation ecosystem.

Artificial Intelligence Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence tools. All content, including text, data analysis, and figures, was solely generated by the authors.

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