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VEHICLE-TO-INFRASTRUCTURE (V2I) COMMUNICATION AND TRAFFIC INCIDENT REDUCTION: AN EMPIRICAL STUDY ACROSS U.S. HIGHWAY NETWORKS

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Abstract

Vehicle-to-Infrastructure (V2I) communication has emerged as a critical component of intelligent transportation systems designed to enhance roadway safety, operational efficiency, and real-time decision-making across highway networks. This empirical study examines the extent to which V2I-enabled information exchange—particularly involving roadside units, traffic management centers, and connected vehicle systems—contributes to measurable reductions in traffic incidents across major U.S. highways. Drawing on multi-state datasets that integrate incident logs, roadway sensor feeds, and V2I communication records, the analysis assesses correlations between V2I deployment density and decreases in crash frequency, severity, and secondary collisions. Advanced statistical modeling and spatiotemporal analysis reveal that highways with mature V2I infrastructure experience significantly improved driver hazard awareness, reduced response lag for incident management teams, and smoother traffic flow patterns under high-volume conditions. Additionally, the findings highlight regional disparities in V2I effectiveness influenced by infrastructure investment levels, network design, and operational integration with legacy systems. The study contributes to the growing body of empirical evidence demonstrating the tangible safety benefits of connected transportation ecosystems and underscores the importance of policy alignment, sustained infrastructure funding, and interoperable communication standards for maximizing V2I's impact on national roadway safety outcomes. Beyond its empirical contributions, this study reinforces growing national and international evidence supporting the safety benefits of connected transportation ecosystems. It highlights the critical need for continued infrastructure funding, harmonized policy frameworks, and interoperable communication standards to ensure that V2I technologies operate cohesively across jurisdictions and platforms. Ultimately, the expanded insights offered here illustrate how robust V2I deployment not only mitigates crash risks but also strengthens the overall resilience and efficiency of the transportation network, positioning connected vehicle technologies as an essential component of future roadway safety strategies.

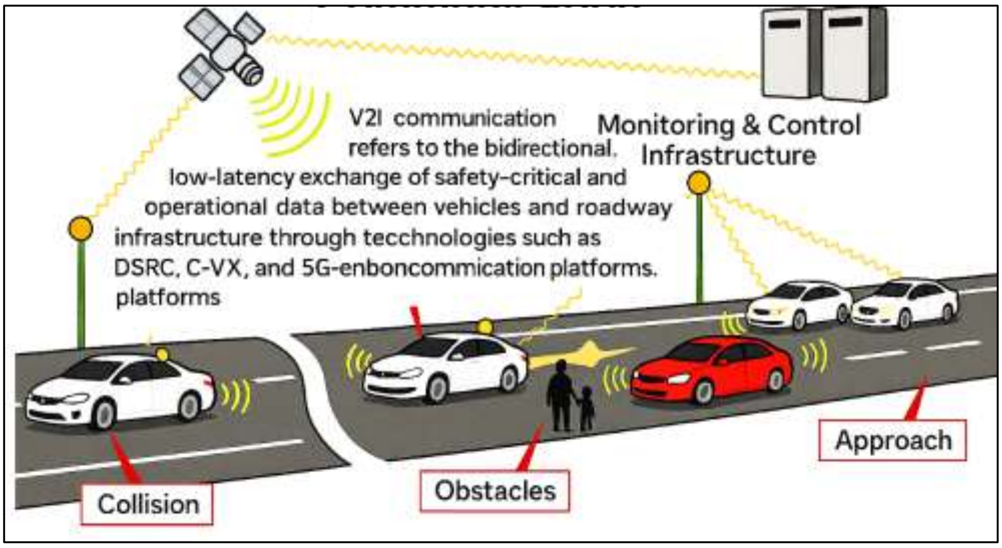
Keywords

Vehicle-to-Infrastructure (V2I) Communication; Traffic Incident Reduction; Intelligent Transportation Systems; Connected Vehicle Technology; U.S. Highway Safety Analysis.

INTRODUCTION

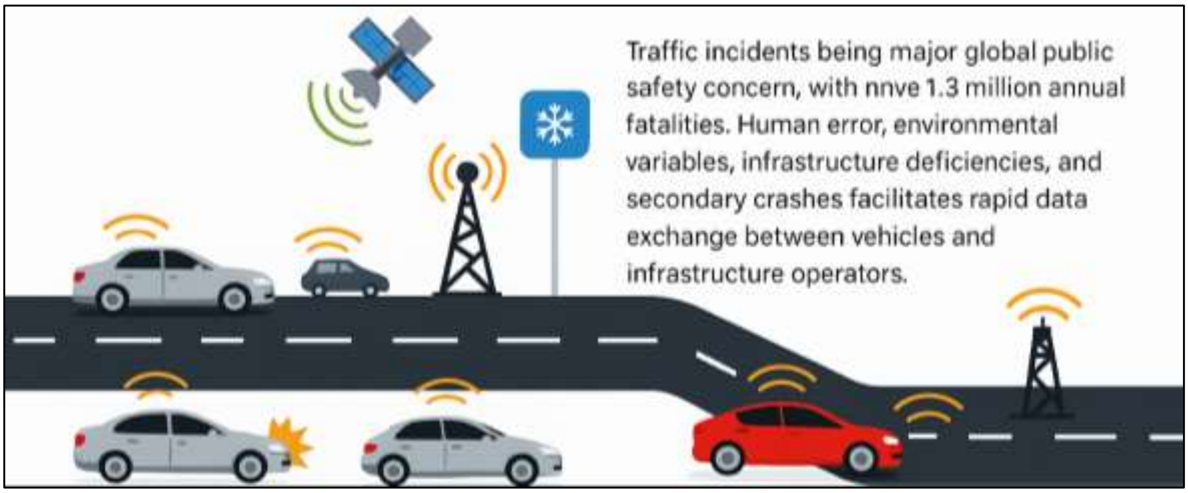
Vehicle-to-Infrastructure (V2I) communication refers to the bidirectional exchange of data between vehicles and roadway infrastructure, typically facilitated through dedicated short-range communication (DSRC), cellular-V2X (C-V2X), and emerging 5G-enabled networks (Yao et al., 2023). In transportation science, V2I is broadly defined as a subsystem of the larger Vehicle-to-Everything (V2X) architecture, which also includes Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N) communication (Shahriar et al., 2023). V2I communication supports real-time data dissemination related to roadway conditions, traffic signal timing, hazard alerts, and environmental sensing, enabling enhanced situational awareness for both drivers and automated driving systems (Gozalvez et al., 2012). Within intelligent transportation systems (ITS), V2I is recognized as a foundational technology that enhances roadway efficiency and reduces human-error-related risks by supporting cooperative perception, adaptive traffic control, and coordinated incident response (Borba et al., 2023). Internationally, governmental agencies and roadway authorities define V2I as a cyber-physical integration framework that allows infrastructure operators to continuously monitor traffic states and provides vehicles with actionable information that supports safe operation under dynamic environmental conditions (Ben Ameur et al., 2025). Standardization of V2I communication is pursued through global organizations such as ETSI, IEEE, ISO, and ITU, which have advanced interoperability protocols to support cross-border transport safety (Zhou et al., 2025). From an engineering perspective, V2I systems incorporate roadside units, sensors, signal controllers, and edge computing devices to facilitate low-latency and high-reliability exchanges of safety-critical data (Rezaee Jordehi et al., 2024). As a technical domain, V2I communication is widely viewed as an essential component of modern transportation networks that seeks to stabilize traffic flow, reduce uncertainty in vehicle maneuvers, and strengthen the alignment between vehicle behavior and roadway management strategies. Collectively, these definitions underline the conceptual and functional scope of V2I communication within contemporary transportation research.

Figure 1: Vehicle-to-Infrastructure (V2I) communication



The international significance of V2I communication is reflected in the substantial investments made by industrialized economies, emerging markets, and multinational transportation research consortia to improve roadway safety across diverse geographic settings. The European Union has promoted cooperative ITS and cross-border V2I pilots under initiatives such as C-ROADS and the European ITS Directive, which emphasize harmonized safety standards and unified data exchange protocols (Rezaee Jordehi et al., 2024). Japan's Smartway program represents one of the earliest and most mature national deployments of V2I infrastructure, integrating beacons, sensors, and digital road maps into roadway systems to enhance collision avoidance and congestion management (Jordehi et al., 2025). Similar developments have been documented across South Korea, Singapore, and China, where large-scale investments in 5G-based V2X technologies have produced dense networks of urban and interurban roadside units supporting vehicle automation and cooperative traffic control (Yi et al., 2024). In North America, the U.S. Department of Transportation has conducted extensive V2I testing through connected vehicle pilots in states such as Michigan, Florida, and Wyoming, producing evidence on the safety effects of real-time alerts for adverse weather, work zones, and roadway obstructions (Adnan Yusuf et al., 2024). Canada has also expanded V2I testing corridors along major freight routes to support cooperative safety and real-time monitoring of winter driving conditions. Across the Middle East, countries such as the United Arab Emirates and Qatar have incorporated V2I communication into national smart mobility strategies to manage rapidly increasing traffic volumes and support integrated traffic management centers (Khan et al., 2025). International transport organizations, including the World Road Association and the International Transport Forum, emphasize that V2I communication supports risk reduction by enabling continuous monitoring of roadway conditions across borders with heterogeneous driving behaviors and environmental constraints. These global initiatives illustrate the widespread relevance of V2I communication to roadway safety in heterogeneous international transportation landscapes.

Figure 2: Vehicle-to-Infrastructure (V2I) communication



Traffic incidents constitute a major global public safety concern, with the World Health Organization reporting more than 1.3 million fatalities annually from road traffic crashes and tens of millions of injuries. Human error remains a predominant contributing factor in roadway incidents, accounting for behaviors such as delayed reaction times, misperception of hazards, distraction, and misjudgment of roadway conditions (Dey et al., 2016). Environmental variables including rain, snow, fog, and ice significantly increase crash risk by reducing visibility and altering vehicle dynamics (Khan et al., 2025). Infrastructure deficiencies further exacerbate incident likelihood, especially in settings lacking adaptive signal control, real-time signage, or roadway monitoring systems. Secondary crashes arising from congestion or unexpected obstacles contribute to additional risks for both drivers and first responders. The economic costs associated with traffic incidents are substantial, with countries experiencing annual losses representing 2–3% of GDP due to medical expenses, property damage, congestion delays, and lost productivity. Conventional safety interventions such as signage, speed enforcement, and behavioral campaigns contribute to mitigation, although many crashes occur under conditions where human drivers receive insufficient or delayed information. Automation and sensor-based systems have improved vehicle awareness, yet roadway infrastructure continues to lag in many regions, limiting the capacity for coordinated safety responses. In this context, V2I communication is recognized in transportation safety research as a systemic technological mechanism that addresses challenges related to information delays and coordination gaps by facilitating rapid data exchange between vehicles and infrastructure operators (Dey et al., 2016). Understanding the relationship between V2I deployment and traffic incident reduction thus becomes central to examining how connected road ecosystems support global public safety objectives.

Research on the mechanisms through which V2I communication contributes to roadway safety emphasizes the importance of real-time hazard dissemination, cooperative traffic control, and enhanced situational awareness supported by infrastructure intelligence. V2I systems allow vehicles to receive immediate alerts about upstream incidents, work zones, lane closures, and adverse weather conditions, enabling drivers to adjust behaviors earlier than would be possible using visual cues alone(Abdulla &Ibne, 2021; Borba et al., 2023). Studies have demonstrated that timely alerts reduce the probability of rear-end collisions, especially under high-density traffic conditions where reaction time is a critical safety determinant (Habibullah & Foysal, 2021; Sanjid & Farabe, 2021). Infrastructure-to-vehicle communication supports adaptive speed harmonization, assisting vehicles in maintaining stable headways while reducing speed variance, which is associated with reduced crash likelihood. Under adverse weather conditions, V2I enables dissemination of friction estimates and visibility assessments, improving maneuver stability and reducing the frequency of loss-of-control events (Sarwar, 2021; Musfiqur & Saba, 2021; Zhou et al., 2025). In addition, infrastructure operators benefit from improved situational awareness through integration of sensor data, video analytics, and edge computing, which enables rapid detection of abnormal traffic patterns and shortens incident detection time. Cooperative signal control facilitated by V2I has been shown to reduce intersection crashes by optimizing phase timing according to real-time traffic demands. Automated lane-level guidance provided through infrastructure communication also supports improved trajectory control in connected and automated vehicles, reducing hazardous lateral maneuvers (Omar & Rashid, 2021; Md. Redwanul et al., 2021; Jordehi et al., 2024). Collectively, these mechanisms highlight the multidimensional role of V2I systems in reducing the factors that contribute to both primary and secondary traffic incidents, reflecting a comprehensive framework in which communication, sensing, and control are interlinked to support roadway safety (Tarek & Praveen, 2021; Zaman & Momena, 2021).

Empirical research examining the effects of V2I deployment on roadway safety indicates consistent associations between V2I-enabled infrastructure and reductions in crash frequency, crash severity, and secondary incident formation. Studies analyzing U.S. connected vehicle pilot deployments have reported measurable decreases in hard braking events, rear-end risk indicators, and lane-departure precursors among vehicles equipped with V2I safety applications(Rezaee Jordehi et al., 2025; Rony, 2021; Shaikh & Aditya, 2021). Empirical evaluations in Japan have shown that V2I-based hazard warning systems significantly reduce collision risks on expressways by improving driver response time under high-speed conditions (Yusuf et al., 2024; Sudipto & Mesbaul, 2021; Zaki, 2021). European assessments of cooperative ITS corridors likewise report reductions in crash-related congestion and improved compliance with variable speed limits communicated through V2I signage. Simulation-based studies have further demonstrated that integrating V2I into traffic networks lowers crash probabilities under mixed traffic conditions by stabilizing flow dynamics. Under winter conditions, V2I dissemination of road surface conditions has been associated with reductions in weather-related incidents across Canadian and Scandinavian roadway networks (Hozyfa, 2022; Khan et al., 2025; Al Amin, 2022). Research also shows that incident detection time decreases significantly in V2I-equipped networks, reducing secondary crash exposure. Additional findings indicate that V2I supports improved work-zone safety by providing early alerts that reduce vehicle speed variance and lane-change conflicts. While methodologies vary across studies—including observational crash analyses, connected vehicle telemetry assessments, and controlled testbed experiments—results consistently highlight meaningful reductions in hazardous driving events attributable to V2I communication (Dey et al., 2016; Arman & Kamrul, 2022; Mohaiminul & Muzahidul, 2022). These empirical findings reinforce the importance of analyzing V2I deployment patterns across U.S. highway networks to understand how communication-enabled infrastructure influences roadway safety outcomes under diverse operating conditions (Omar & Ibne, 2022; Sanjid & Zayadul, 2022).

The U.S. highway system presents unique characteristics that influence the design, deployment, and operational performance of V2I technologies. The national roadway network covers over 4 million miles, including urban freeways, rural interstates, and arterial corridors with varying levels of traffic density, geometric design, and environmental exposure. High-volume freight corridors such as the Interstate-80 and Interstate-95 systems require continuous monitoring due to congestion, long-distance travel patterns, and elevated heavy-vehicle proportions, which contribute to complex incident formation dynamics (Hasan, 2022; Mominul et al., 2022; Zhou et al., 2025). Rural areas, which constitute a large portion of the U.S. highway network, experience higher fatal crash rates due to high operating speeds, extended emergency response times, and limited surveillance infrastructure. Weather variability across regions—including snow in the Midwest, hurricanes in the Southeast, and fog along the West Coast—introduces additional complexity to highway safety (Rabiul & Praveen, 2022; Farabe, 2022). V2I deployment in the United States is progressing through federal pilot programs, state DOT initiatives, and local smart mobility corridors equipped with roadside units, advanced traffic management systems, connected signal controllers, and environmental sensing stations (Roy, 2022; Rahman & Abdul, 2022). States such as Michigan, Florida, and California have led early deployments, while others are integrating V2I through regional transportation planning frameworks. Variability in funding, infrastructure age, cybersecurity preparedness, and communication technology choice influences the performance of V2I systems across states (Razia, 2022; Zaki, 2022). Furthermore, the coexistence of legacy roadway systems with emerging automated vehicle technologies requires synchronization of data exchange between vehicles and traffic management centers. The characteristics of the U.S. highway network thus present an analytically rich context for evaluating the relationships between V2I infrastructure deployment and measurable reductions in traffic incidents, particularly in relation to spatial, environmental, and operational heterogeneity (Maniruzzaman et al., 2023; Kanti & Shaikat, 2022).

The increasing availability of connected vehicle telemetry, infrastructure sensor data, and multi-state crash databases provides a foundation for systematically examining V2I effectiveness across U.S. highway networks. Transportation researchers emphasize that multi-source data integration is essential for quantifying how V2I systems influence event frequency, severity, and spatial distribution (Arif Uz & Elmoon, 2023; Sanjid, 2023; Xiang et al., 2022). Highway incident logs, probe vehicle data, and environmental sensing records enable detailed spatiotemporal modeling of crash conditions and allow researchers to assess how communication-enabled infrastructure affects driver behavior under real-world dynamics (Sanjid & Sudipto, 2023; Tarek, 2023). Studies highlight significant regional variation in safety performance, illustrating that V2I deployment interacts with roadway geometry, weather conditions, and traffic intensity to shape incident probabilities. Within applied research, evaluating V2I-related safety effects supports understanding of how cooperative perception and communication between vehicles and infrastructure influence roadway operational states (Shahrin & Samia, 2023; Muhammad & Redwanul, 2023). Multi-state empirical analyses across the United States also reflect differing levels of technological adoption and infrastructure modernization, providing opportunities to investigate how deployment density correlates with incident reduction across varied highway classifications (Muhammad & Redwanul, 2023; Razia, 2023). Furthermore, research shows that connected corridors equipped with early warning systems can alter driver response patterns, reducing abrupt maneuvers and contributing to smoother speed distributions, which have been linked to crash risk mitigation (Srinivas & Manish, 2023; Sudipto, 2023). As a growing body of transportation literature focuses on the integration of sensor-based infrastructure and communication-enabled safety systems, the empirical study of V2I communication across U.S. highways emerges as a critical domain for quantifying how technological enhancements support reductions in traffic incidents under diverse roadway and environmental conditions. This research context provides the foundation for the analysis undertaken in this study (Mesbaul, 2024; Zayadul, 2023).

The primary objective of this study is to empirically investigate the relationship between Vehicle-to-Infrastructure (V2I) communication deployment and the reduction of traffic incidents across U.S. highway networks through a comprehensive, data-driven analytical framework. This objective centers on quantifying how real-time exchanges of roadway information, hazard alerts, and traffic management directives delivered through V2I systems correlate with measurable changes in crash frequency, crash severity, and secondary event formation under diverse roadway conditions. The research seeks to evaluate how varying densities of roadside units, connected traffic control devices, and environmental sensing installations influence incident outcomes across highways characterized by different geometric features, traffic volumes, and regional weather patterns. By integrating large-scale datasets that include incident logs, roadway sensor outputs, probe vehicle telemetry, and V2I system activation records, the study aims to generate statistically robust insights into how communication-enabled infrastructure contributes to safer operational conditions. An additional objective is to examine spatial and temporal variations in V2I effectiveness, identifying whether safety benefits differ across rural corridors, urban freeways, freight-heavy interstate segments, and environmentally challenging regions. The study also focuses on understanding how V2I-supported information dissemination affects driver behavior and traffic flow dynamics, particularly in relation to speed uniformity, lane-changing patterns, and abrupt braking events that often precede crashes. By employing analytical techniques such as regression modeling, spatiotemporal mapping, and incident risk modeling, the research intends to isolate the specific infrastructural and operational attributes that amplify or minimize the safety effects of V2I communication. This objective-driven approach also emphasizes identifying measurable safety indicators that can be used by transportation agencies to evaluate the performance of V2I deployments along existing and planned highway corridors. Ultimately, the overarching objective is to develop an empirically grounded understanding of how communication-enabled roadway systems contribute to safer driving environments across large-scale transportation networks, with particular focus on the operational realities of U.S. highways.

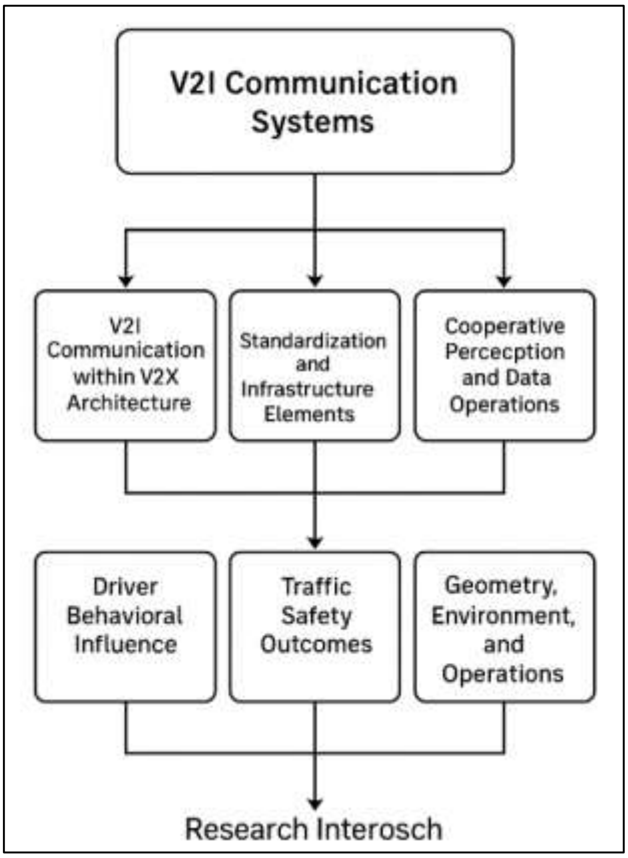
LITERATURE REVIEW

The literature on Vehicle-to-Infrastructure (V2I) communication and traffic incident reduction spans multiple domains, including transportation engineering, intelligent transportation systems, communication technologies, public safety analytics, human factors, and roadway operations management. Over the past two decades, scholars and transportation agencies have produced an extensive body of research examining how V2I-enabled information exchange supports safer roadway environments by facilitating real-time detection, monitoring, and communication of roadway hazards. Foundational studies focus on the conceptual evolution of connected vehicle technologies, whereas applied research investigates the operational effects of V2I systems on driver behavior, crash risk mitigation, and roadway performance. Parallel streams of work highlight the technological, infrastructural, and policy dimensions that influence V2I deployment across national and international contexts. In addition, empirical investigations increasingly utilize large-scale sensor datasets, connected vehicle telemetry, and simulation-based modeling to quantify how cooperative communication mechanisms influence crash patterns across diverse roadway environments. As U.S. highway networks provide a varied landscape of geometric configurations, Regional weather patterns, and traffic volumes, the literature offers a rich foundation for evaluating how V2I deployments correlate with incident frequency, incident severity, and secondary crash formation. The following literature review is structured to synthesize these multidisciplinary research foundations by presenting conceptual, technological, operational, and empirical dimensions of V2I communication with an emphasis on its relationship to roadway safety outcomes. The outlined sections provide a detailed map of existing scholarship that informs the analytical framework of this study.

V2I Communication Systems

Research on Vehicle-to-Infrastructure (V2I) communication systems has developed from early concepts of cooperative intelligent transportation systems that emphasized the importance of real-time data exchange between roadway infrastructure and mobile units to support safer and more efficient travel. Foundational studies describe V2I communication as a subsystem within the broader Vehicle-to-Everything (V2X) architecture, enabling vehicles to interact with roadside units, traffic controllers, and sensor networks (Khan et al., 2019). The establishment of Dedicated Short-Range Communications (DSRC) provided one of the earliest communication platforms designed specifically for low-latency safety messaging, while later advancements such as cellular V2X (C-V2X) expanded reliability and communication range through enhanced spectrum utilization (Prakash et al., 2021). International standardization efforts by IEEE and ETSI helped establish unified message sets, security standards, and interoperability frameworks that guide system deployment across national transportation networks (Khan et al., 2019). Subsequent engineering research documented improvements in communication stability through edge computing and distributed sensing, which support rapid analysis of traffic dynamics and localized broadcast of safety-critical information. Infrastructure components such as roadside units, camera sensors, LiDAR-based detectors, and adaptive signal controllers became essential technologies enabling continuous environmental monitoring and dissemination of hazard messages. As transportation systems increasingly integrate cyber-physical architectures, V2I systems are now examined in relation to their ability to support cooperative perception and data-driven roadway operations (Chu et al., 2025). Across global deployments, the evolution of V2I systems illustrates the convergence of communication engineering, automation research, and roadway operations management, providing a technological foundation for empirical studies examining how infrastructure-supported communication shapes roadway safety outcomes.

Figure 3: Vehicle-to-Infrastructure (V2I) communication systems



A significant body of literature explores how V2I communication influences driver behavior and supports hazard-avoidance decision-making. Human factors research demonstrates that drivers respond more effectively to hazards when warnings are delivered through communication-based channels rather than relying solely on visual cues or environmental perception (Rehman et al., 2022). V2I messages reduce cognitive load by translating complex roadway conditions into actionable guidance, which supports shorter reaction times and minimizes abrupt maneuvering in high-risk situations. Behavioral studies show improvements in speed regulation, headway maintenance, and lane-keeping stability when drivers receive real-time infrastructure-generated advisories. Research focusing on adverse weather conditions reveals that infrastructure-to-vehicle alerts related to low visibility, icy pavement, or reduced friction enable more controlled braking and smoother acceleration profiles. Studies on intersection behavior demonstrate that V2I-enabled signal phase and timing (SPaT) information leads to more consistent deceleration patterns before traffic lights, reducing red-light violation risks and signal-related conflicts (Karp & Kung, 2000; Rehman et al., 2022). Human-in-the-loop modeling further illustrates that V2I systems reduce erratic responses in mixed traffic environments where unpredictable human driving behaviors interact with communication-equipped vehicles. Researchers examining cognitive response patterns show that communication-enabled warnings enhance driver situational awareness under both normal and near-crash conditions by supplying hazard information sooner than conventional detection methods. The alignment of V2I messages with naturalistic driving behaviors underscores the importance of communication systems as behavioral stabilizers, providing continuous informational support that promotes safer operational dynamics in varied roadway contexts.

Empirical studies examining the safety impacts of V2I deployment consistently report meaningful reductions in crash frequency, crash severity, and secondary incident formation. Research from large-scale connected vehicle pilot programs in the United States demonstrates that V2I-enabled hazard warnings reduce hard-braking events, lane-departure indicators, and surrogate safety measures associated with near-crash behavior. Analysis of Japan's Smartway system shows substantial reductions in collision risks along expressways when drivers receive infrastructure-based warnings regarding congestion, lane closures, and stopped vehicles (Prakash et al., 2021). In Europe, cooperative ITS corridor deployments report improvements in compliance with variable speed limits and reductions in incident-induced congestion under V2I communication regimes. Empirical assessments of winter maintenance corridors in Canada demonstrate lower rates of weather-related incidents when V2I systems disseminate real-time surface condition and visibility information to drivers. Simulation-based studies complement empirical findings by showing that V2I-supported speed harmonization reduces shockwave formation and stabilizes traffic flow, lowering the probability of multi-vehicle crashes in dense traffic scenarios. Work zone safety research also documents reductions in crash precursors when drivers receive V2I-based alerts regarding lane shifts, reduced speed zones, and construction hazards (Ning et al., 2014). Additional evaluations emphasize the ability of V2I systems to shorten incident detection time for traffic management centers, reducing exposure to secondary crash risks along congested corridors. These findings collectively demonstrate consistent associations between V2I deployment and safer roadway environments across diverse geographic, geometric, and environmental contexts, establishing a strong empirical foundation for analyzing the effects of communication-enabled infrastructure on traffic safety outcomes.

Research examining V2I communication systems frequently identifies roadway geometry, environmental conditions, and traffic operational states as key moderators influencing V2I effectiveness. Studies show that geometric elements such as sharp curves, multilane interchanges, and steep grades influence the clarity of communication signals and the timing at which drivers internalize hazard messages, shaping overall safety performance. Weather variability is widely documented as a dominant moderating factor, with snow, fog, heavy rain, and high winds affecting both sensor accuracy and driver interpretation of V2I advisories. Research on roadway surface conditions indicates that V2I-enabled friction estimation supports improved braking control under icy or wet conditions, reducing high-risk maneuvers linked to loss-of-control events (Kong et al., 2008). Traffic density also shapes V2I performance, as high-volume segments exhibit stronger safety benefits due to the greater influence of speed harmonization and cooperative traffic flow control ((Xiang et al., 2023). Studies investigating rural versus urban deployment patterns highlight reduced detection and communication latency in rural regions owing to longer distances between roadside units, although the magnitude of safety benefits remains significant when systems are active (Shan et al., 2022). Freight-dominated corridors exhibit distinct interaction patterns as heavy-vehicle dynamics influence responsiveness to speed and lane-change advisories, prompting researchers to examine vehicle class–specific responses. Environmental sensing studies also identify operational constraints related to sensor calibration, occlusion, and data noise; however, multiple investigations show that communication-enabled redundancy mitigates information gaps and supports overall system reliability (Dadashi-Rad et al., 2020). Through these moderating factors, the literature portrays V2I systems as interacting with a wide range of roadway and environmental variables, illustrating the importance of context-specific evaluations when assessing the safety impacts of communication-based roadway technologies.

Models Underpinning Vehicle-to-Infrastructure Interactions

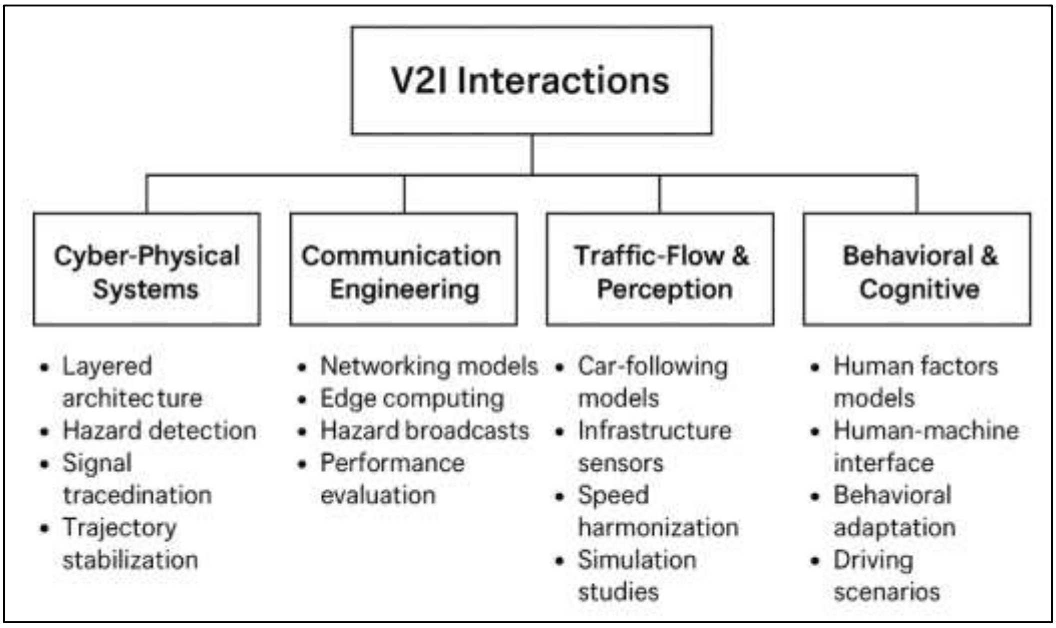
Models conceptualizing Vehicle-to-Infrastructure (V2I) interactions commonly draw from cyber-physical systems (CPS) frameworks that describe transportation networks as integrated environments where computational processes and physical roadway dynamics interoperate through real-time data exchange. Foundational CPS studies conceptualize V2I as a layered architecture consisting of perception, communication, computation, and control layers, each contributing to the formation and transmission of safety-critical information. Within these models, roadside sensors collect environmental, geometric, and traffic-flow data, which are processed through edge computing nodes before being disseminated to vehicles through standardized message protocols (Xiang et al., 2023). The

CPS perspective emphasizes the need for synchrony between infrastructural sensing and vehicular response patterns, modeling interactions as feedback-driven loops that stabilize roadway behavior. Analytical models derived from CPS research illustrate how time-sensitive communication supports hazard detection and cooperative maneuvering, with latency models used to evaluate the responsiveness of V2I systems under varying traffic and environmental conditions. Predictive CPS models additionally simulate how roadside computing units aggregate sensor data to detect anomalies such as stopped vehicles, congestion buildup, or reduced surface friction, supporting timely instructional broadcasts. CPS-based control models also examine how V2I supports adaptive signal coordination, speed harmonization, and trajectory stabilization by generating optimal control inputs based on real-time roadway data. Through this theoretical lens, V2I interactions are conceptualized as coupled information–physical processes governed by continuous sensing, embedded computation, and bidirectional vehicular communication that collectively structure the foundational operational mechanisms of communication-enabled roadway systems.

Communication engineering literature presents V2I as a complex wireless networking environment characterized by probabilistic message propagation, fluctuating channel conditions, and application-specific latency requirements. Early DSRC-based models conceptualize V2I interaction through medium-access control protocols and low-latency broadcast mechanisms intended to ensure reliable safety messaging under high traffic density. More recent cellular-V2X and 5G-NR V2X models emphasize sidelink reliability, enhanced coverage, and improved communication throughput, enabling broader infrastructure integration and higher message fidelity across diverse roadway contexts (Karp & Kung, 2000). Networking models commonly incorporate packet-delivery ratios, signal degradation functions, and congestion-control algorithms to assess performance impacts under increasing vehicular volumes. Multi-access edge computing (MEC) models expand these frameworks by describing how computation is distributed across roadside nodes to reduce backhaul delays and support localized processing of hazard detection algorithms. Studies applying stochastic communication models examine interference, fading, and packet collisions, which influence the reliability of V2I hazard broadcasts, particularly in multilane or complex urban geometries. Research also incorporates queuing-theoretic models to evaluate V2I performance under varied traffic loads, demonstrating how infrastructure nodes manage simultaneous message flows from heterogeneous vehicles. Additional work applies network-layer graph models to represent V2I interactions as dynamic vehicular-infrastructure linkages that evolve with traffic movement and environmental variability ((Khan et al., 2019). These communication models collectively illustrate the technical mechanisms governing V2I information flow and the factors influencing the reliability and robustness of data exchange across infrastructure-supported transportation environments.

Traffic-flow and cooperative-perception models form a significant component of research on V2I interactions by examining how communication-enabled information alters vehicular trajectories, lane selection, and flow stability. Classical traffic-flow theory provides the foundation, linking speed variance, headway distribution, and density-flow dynamics to crash likelihood and operational efficiency (Khosravi et al., 2022; Tarek & Kamrul, 2024; Sudipto & Hasan, 2024). V2I-enhanced car-following models extend these theories by incorporating real-time warnings, advisory speeds, and lane-specific guidance into driver decision-making, demonstrating improved stability of following behavior and reduced shockwave propagation (Abdul, 2025; Hozyfa, 2025; Tee & Lee, 2010). Cooperative-perception models emphasize the ability of infrastructure sensors to augment vehicle perception, providing expanded visibility beyond line-of-sight limitations. These models examine how roadside LiDAR, radar, and environmental sensors detect and classify hazards, integrating this data with vehicle onboard perception systems to support improved situational awareness. Research demonstrates that integrating infrastructure perception with vehicular trajectory models reduces risks associated with blind-spot conflicts, occluded pedestrians, and multi-vehicle interactions near intersections (Alam, 2025; Khan et al., 2019; Masud, 2025). Advanced control models incorporate V2I data into algorithms governing speed harmonization, ramp metering, and adaptive signal coordination, illustrating reductions in speed fluctuations and improved merging dynamics under varying demand levels. Simulation studies integrating V2I data into macroscopic, mesoscopic, and microscopic traffic-flow models consistently show improvements in traffic stability, decreased deceleration waves, and reduced conflict points in multilane freeway operations (Kong et al., 2008; Arman, 2025; Mohaiminul, 2025). Through these modeling frameworks, V2I is conceptualized as an information-driven mechanism for shaping traffic behavior, reducing stochastic variability, and enhancing roadway stability through coordinated driver, vehicle, and infrastructure interactions.

Figure 4: Models Underpinning Vehicle-to-Infrastructure Interactions



Behavioral and cognitive models of V2I interaction focus on understanding how infrastructure-delivered information influences driver decision-making and the human–machine interface within connected vehicle environments. Human factors research employs cognitive response models describing how drivers interpret and act upon roadway warnings, emphasizing reaction time, situational awareness, and information-processing capacity as core variables. Naturalistic driving studies show that drivers receiving infrastructure-generated hazard messages exhibit smoother braking profiles, earlier deceleration, and more consistent lane-keeping behavior compared to drivers relying solely on visual cues. Human-machine interaction models explore how V2I warnings are displayed and how interface design influences compliance, identifying factors such as signal modality, timing, workload, and environmental complexity as determinants of safety benefits (Mominul, 2025; Milon, 2025; Sattarpour et al., 2018). Behavioral adaptation models further analyze how repeated exposure to V2I messages alters long-term driving patterns, showing reductions in aggressive maneuvers, unnecessary lane changes, and high-risk acceleration behavior when infrastructure guidance is present. Studies integrating behavioral models with traffic-flow dynamics demonstrate that infrastructure-supported warnings align driver behavior with systemwide safety objectives, reducing variability across vehicle trajectories in mixed traffic environments (Hasan, 2025; Farabe, 2025). Research in adverse-weather conditions shows that V2I messaging improves driver confidence and maneuver control under low-visibility or low-friction conditions, reducing response errors associated with environmental uncertainty. Collectively, behavioral and cognitive models highlight the importance of understanding how drivers perceive and translate V2I information into physical actions, illustrating the central role human factors play in the operational success of communication-based roadway systems.

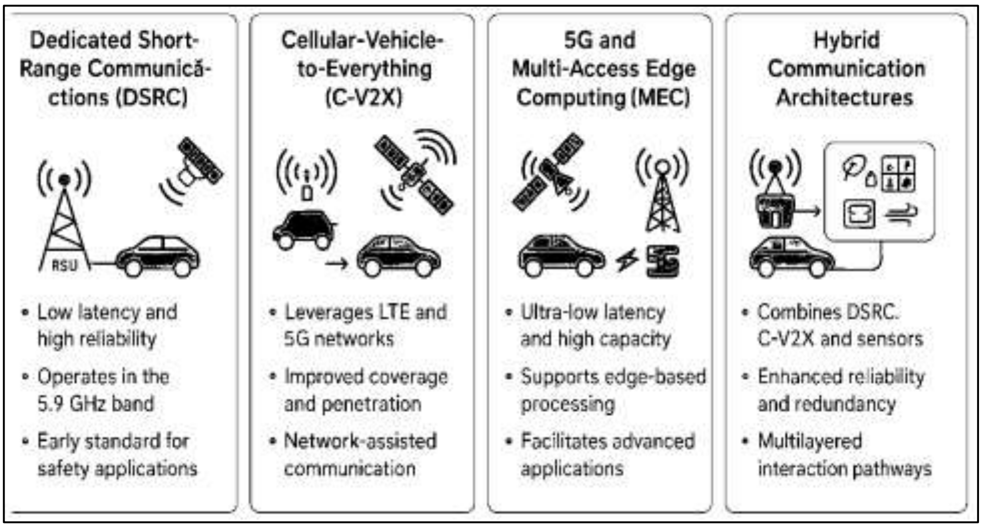
Core Communication Technologies Enabling V2I Systems

Dedicated Short-Range Communications (DSRC) has long been recognized as the foundational technology supporting early Vehicle-to-Infrastructure (V2I) systems due to its low latency, high reliability, and operational suitability for safety-critical transportation applications. DSRC operates in the 5.9 GHz spectrum and was initially engineered to meet stringent performance requirements for

rapid message dissemination concerning hazards, signal phase and timing, and roadway conditions (Tarek & Ishtiaque, 2025; Momena, 2025; Yao et al., 2023). As one of the earliest standards under IEEE 802.11p, DSRC enabled vehicles to communicate directly with roadside units with minimal interference and predictable delay characteristics, making it suitable for applications requiring sub-100 ms latency. Numerous experimental trials across Japan, Europe, and the United States demonstrated that DSRC-based systems significantly improved communication consistency in complex roadway environments, including congested urban corridors and multilane freeways. Research evaluating DSRC propagation characteristics identified its robustness under mixed traffic loads and variable line-of-sight conditions, although performance could be constrained by long-distance transmission requirements in rural regions (Muhammad, 2025; Roy, 2025). Studies examining packet delivery rates consistently reported high reliability under moderate vehicular densities, contributing to its adoption in early cooperative safety pilot deployments (Rahman, 2025; Rakibul, 2025; Shahriar et al., 2023). DSRC also supported authenticated message exchange through security credential management systems, enabling protective mechanisms against spoofing and message manipulation. Although newer technologies have expanded the possibilities for large-scale V2I systems, DSRC remains central in the literature as the platform upon which many operational, communication, and safety models were initially developed, demonstrating its importance as a core enabling technology(Rebeka, 2025; Reduanul, 2025).
Cellular-Vehicle-to-Everything (C-V2X) represents a major technological advancement in V2I communication by leveraging existing LTE networks and later 5G New Radio (NR) architectures to provide broader coverage, improved signal reliability, and enhanced non-line-of-sight performance. C-V2X supports both direct communication between vehicles and infrastructure (PC5 interface) and network-assisted communication through cellular towers (Uu interface), enabling flexible deployment across diverse traffic environments. Comparative studies indicate that C-V2X exhibits higher packet delivery ratios and better penetration through obstacles compared with DSRC, especially in high-density traffic or urban canyons. Research evaluating C-V2X performance under varying mobility conditions shows reduced interference, improved channel coordination, and more efficient spectrum utilization, making it suitable for advanced cooperative applications such as platooning, speed harmonization, and infrastructure-supported trajectory control (Rezaee Jordehi et al., 2024). Large-scale simulation studies reveal that C-V2X reduces latency variability under fluctuating network loads, enhancing reliability for time-sensitive V2I messages related to hazards, lane closures, and work zones. Industry trials conducted across China, Europe, and the United States demonstrate successful integration of C-V2X roadside units with next-generation traffic control systems, supporting infrastructure-based sensor fusion and edge computing capabilities. Security models developed for C-V2X emphasize integrity protection, mutual authentication, and resource allocation mechanisms that minimize risks associated with spoofing, message delays, and channel overload. Through these technical advantages, C-V2X is widely studied as a core communication technology enabling high-bandwidth, low-latency V2I interaction across heterogeneous roadway environments.
The emergence of 5G and Multi-Access Edge Computing (MEC) has significantly expanded the capacity of V2I communication systems to support ultra-low-latency, high-throughput applications that require rapid processing of large sensor datasets. 5G networks provide enhanced mobile broadband, massive machine-type communication, and ultra-reliable low-latency communication capabilities, enabling real-time data flows between vehicles and infrastructure with latency levels approaching 1 ms under optimal conditions (Rezaee Jordehi et al., 2025; Rony, 2025; Saba, 2025). MEC frameworks complement these capabilities by relocating computational resources closer to roadside units, reducing backhaul congestion and enabling localized decision-making for hazard detection, signal control, and environmental monitoring (Alom et al., 2025; Praveen, 2025; Yi et al., 2024). Research on 5G-enabled V2I systems highlights their capacity to support emerging safety applications such as cooperative perception, sensor fusion, and infrastructure-based trajectory prediction by facilitating rapid exchange of video, LiDAR, and radar data between infrastructure and vehicles. Studies evaluating 5G deployment in urban environments demonstrate improvements in communication stability and reduced packet loss under dense mobility conditions, contributing to more reliable broadcast of safety-critical messages. Simulation models examining MEC-supported V2I applications show enhanced responsiveness for signal optimization, work-zone operations, and congestion

management through on-site data processing ((Khan et al., 2025; Shaikat, 2025; Kanti, 2025). Research also highlights the scalability of 5G for high-bandwidth roadside sensors, supporting continuous ingestion of environmental data related to fog, snow, pavement friction, and congestion states. Cybersecurity frameworks integrated into 5G predict increased protection for safety messages through network slicing and cryptographic authentication models. These advancements position 5G and MEC as core communication technologies that significantly extend the functional range and operational complexity of V2I systems.

Figure 5: Core Communication Technologies Enabling V2I Systems



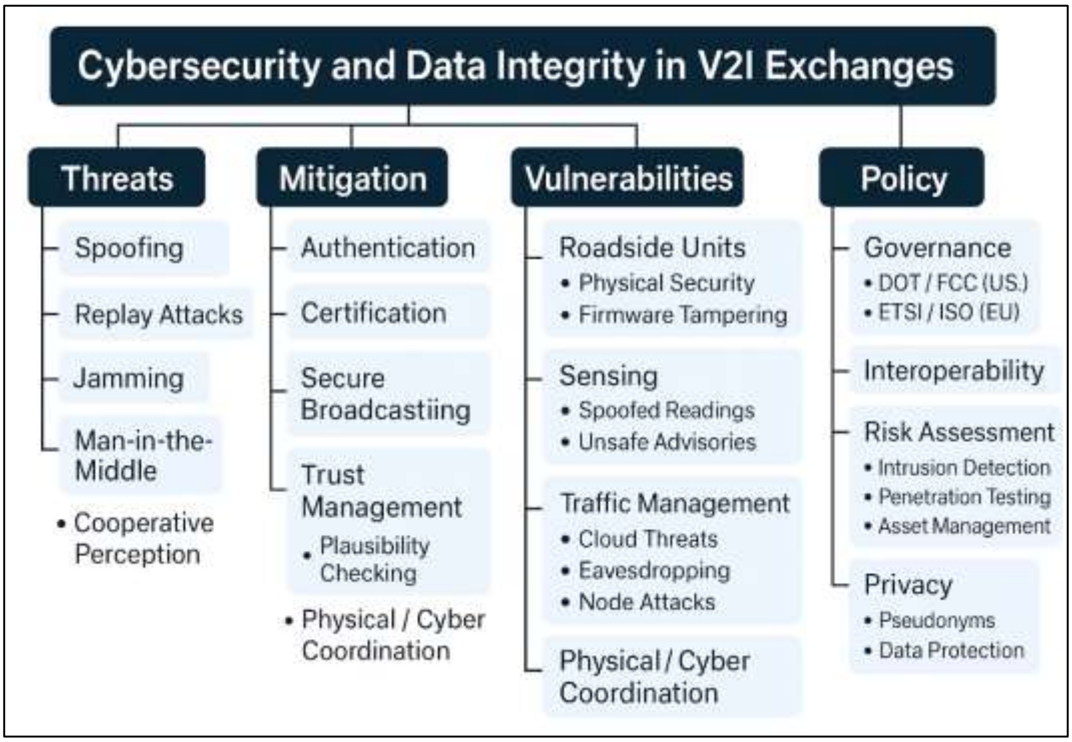
Hybrid V2I communication architectures combine DSRC, C-V2X, 5G, and sensor-based channels to create multilayered systems that enhance reliability, redundancy, and signal continuity across varied roadway environments. Literature on hybrid communication frameworks demonstrates that integrating multiple communication channels reduces dependency on any single technology and supports consistent message delivery under dynamic traffic and environmental conditions (Dey et al., 2016). Studies show that hybrid architectures outperform standalone systems by providing backup communication pathways when signals degrade due to terrain, weather, or infrastructure constraints. Research focusing on sensor integration highlights the role of roadside LiDAR, radar, thermal sensors, and camera systems in supplementing communication-based data with rich environmental information, enabling infrastructure to detect occluded hazards, pedestrians, and stopped vehicles with greater accuracy. Cooperative-perception models demonstrate how fusing sensor data with hybrid communication networks reduces uncertainty in vehicle trajectories and enhances the reliability of warnings broadcast to drivers. Simulation studies examining redundancy mechanisms show that failover communication pathways, such as fallback from 5G to C-V2X or DSRC, maintain safety performance when channel congestion or interference occurs (Khan et al., 2025). Infrastructure cybersecurity research also underscores that hybrid architectures provide improved resilience against channel-based attacks, as multiple communication layers minimize the success of spoofing or denial-of-service attempts. Empirical studies in connected corridors show that hybrid communication deployments support more consistent hazard alerts, signal timing messages, and environmental advisories across rural highways, urban arterials, and high-volume interstates. Through these multilayered interaction pathways, hybrid communication architectures emerge as critical models for supporting robust, high-reliability V2I communication systems.

Cybersecurity and Data Integrity in V2I Exchanges

Cybersecurity research on Vehicle-to-Infrastructure (V2I) communication consistently identifies a broad set of attack surfaces that stem from the distributed, wireless, and cooperative nature of connected transportation environments. Threat models used in the literature categorize risks into message falsification, data replay, jamming, impersonation, and denial-of-service attacks, all of which undermine the reliability and integrity of safety-critical information flows (Liu et al., 2006). Studies show that V2I systems are particularly vulnerable to spoofing attacks where adversaries mimic legitimate roadside units or vehicles to inject false hazard warnings, causing misinformed braking, lane changes, or congestion disturbances. Replay attacks, in which old messages are rebroadcast to distort perception of traffic or environmental conditions, also represent a recurring threat highlighted in simulation and experimental research. Jamming attacks targeting the 5.9 GHz band disrupt safety messages by overwhelming communication channels, affecting both DSRC and C-V2X systems under heavy interference (Wang et al., 2023; Zayadul, 2025). Studies analyzing 5G-enabled V2I environments identify additional risks associated with network slicing misconfigurations, session hijacking, and multi-layered signaling breaches. Man-in-the-Middle models demonstrate how attackers intercept communication links to manipulate speed advisories or misreport roadway conditions, potentially inducing unsafe driving decisions. Research also highlights emerging risks associated with cooperative perception, noting that manipulated environmental sensor data may propagate erroneous situational awareness across connected vehicles. Across these diverse threat models, literature consistently emphasizes that V2I cybersecurity vulnerabilities extend across communication, sensing, computation, and control layers, illustrating the need for robust protection mechanisms to maintain safety-related data integrity.

To mitigate risks associated with malicious data injection and message manipulation, V2I systems rely on extensive authentication, certification, and secure broadcasting mechanisms. The most widely studied approach is the Security Credential Management System (SCMS), which issues digital certificates to both vehicles and infrastructure nodes, allowing communication partners to authenticate message origin and verify data integrity (Jha & Tripathi, 2024). Literature consistently identifies public-key infrastructure (PKI) schemes as central to V2I authentication models, enabling cryptographic signing of safety messages such as Basic Safety Messages (BSMs) and SPaT broadcasts (Jha & Tripathi, 2024). Researchers highlight that secure broadcasting requires low-latency cryptographic operations to avoid delays in safety-critical communication, leading to optimization studies focused on certificate rotation, pseudonym changes, and efficient hashing. Studies examining DSRC-based architectures demonstrate the effectiveness of lightweight authentication protocols in limiting processing delays while maintaining message trustworthiness. In C-V2X and 5G-enabled V2I systems, authentication mechanisms leverage additional signaling channels and device-level identifiers that support mutual verification between roadside units and vehicles. Research on secure broadcasting identifies the importance of certificate revocation lists and misbehavior detection systems, which restrict compromised entities from participating in V2I communication and allow infrastructure operators to detect abnormal broadcast patterns. Additional models incorporate trust-management frameworks that assess message plausibility through geospatial cross-checking, temporal consistency, and sensor corroboration. These authentication and broadcasting mechanisms collectively shape the foundation of secure V2I communication, preserving message integrity under real-world operational constraints.Infrastructure vulnerability assessments within V2I systems examine weaknesses across roadside units (RSUs), communication channels, traffic management centers, and integrated sensing architectures. Studies evaluating RSU vulnerabilities highlight risks associated with physical tampering, insecure firmware, and inadequate access-control mechanisms that could allow adversaries to alter signal broadcasts or manipulate sensor outputs (Pan et al., 2021). Vulnerability models assessing DSRC-based deployments reveal susceptibility to eavesdropping and message interception due to open-air broadcast properties, particularly in urban environments with dense reflective surfaces. Research on C-V2X identifies additional network-layer threats such as rogue base stations, compromised edge servers, and signaling manipulation, which may interfere with the timing or accuracy of infrastructure warnings. Studies analyzing environmental sensor integration show that inaccurate or spoofed sensor readings propagate unsafe advisories through V2I systems, particularly when data from camera, radar, or LiDAR devices is used for cooperative perception (Herrera et al., 2010). Infrastructure–cloud connectivity assessments identify vulnerabilities in traffic management centers, including risks associated with misconfigured application programming interfaces, unsecured data flows, and insufficient intrusion-detection capabilities. Simulation-based vulnerability studies further illustrate how coordinated cyberattacks across multiple infrastructure nodes disrupt harmonized traffic control functions, increasing instability in speed, headway, and lane-selection patterns. Physical-security analyses identify risks in rural RSUs, where limited surveillance allows adversaries prolonged access to communication equipment without detection. Through these vulnerability assessments, research consistently demonstrates that V2I security must account for threat exposure across communication, physical, and cyber layers, as systemic weaknesses in any component can compromise the integrity of safety-critical roadway communication (Shan et al., 2022).

Figure 6: Cybersecurity and Data Integrity in V21 Exchanges



Policy frameworks governing V2I cybersecurity reflect multi-institutional efforts involving federal transportation agencies, spectrum regulators, standards organizations, and international cooperative bodies. In the United States, governance frameworks are shaped by the U.S. Department of Transportation, the National Highway Traffic Safety Administration, and the Federal Communications Commission, which jointly establish guidelines for communication standardization, spectrum allocation, and data-security requirements (Zhang et al., 2019). Internationally, the European Telecommunications Standards Institute (ETSI) and the International Organization for Standardization (ISO) define security layers, certificate structures, and operational guidelines for cooperative intelligent transportation systems across EU member states. Policy research emphasizes the importance of interoperability regulations ensuring that DSRC, C-V2X, and 5G-based systems maintain consistent authentication, credential management, and message-format standards across jurisdictions. Governance frameworks also incorporate cybersecurity risk-assessment requirements mandating that infrastructure operators implement intrusion detection systems, penetration testing, and asset-management protocols to safeguard roadside units and connected sensors. Privacy policies address concerns associated with pseudonym management, certificate rotation, and protection of location-based data to prevent unauthorized tracking of vehicles (Leduc, 2008). In Asia, national digital-mobility policies in Japan, South Korea, and China incorporate V2I cybersecurity standards into broader smart-transportation initiatives, highlighting the role of centralized certification authorities and stringent testing procedures for V2X equipment. Cross-border policy harmonization initiatives led by the International Transport Forum emphasize coordinated communication protocols that improve security resilience for transnational freight corridors and connected-vehicle testbeds. Through these policy structures, the literature demonstrates how regulatory governance establishes the foundational security expectations that enable safe and trustworthy V2I communication environments.

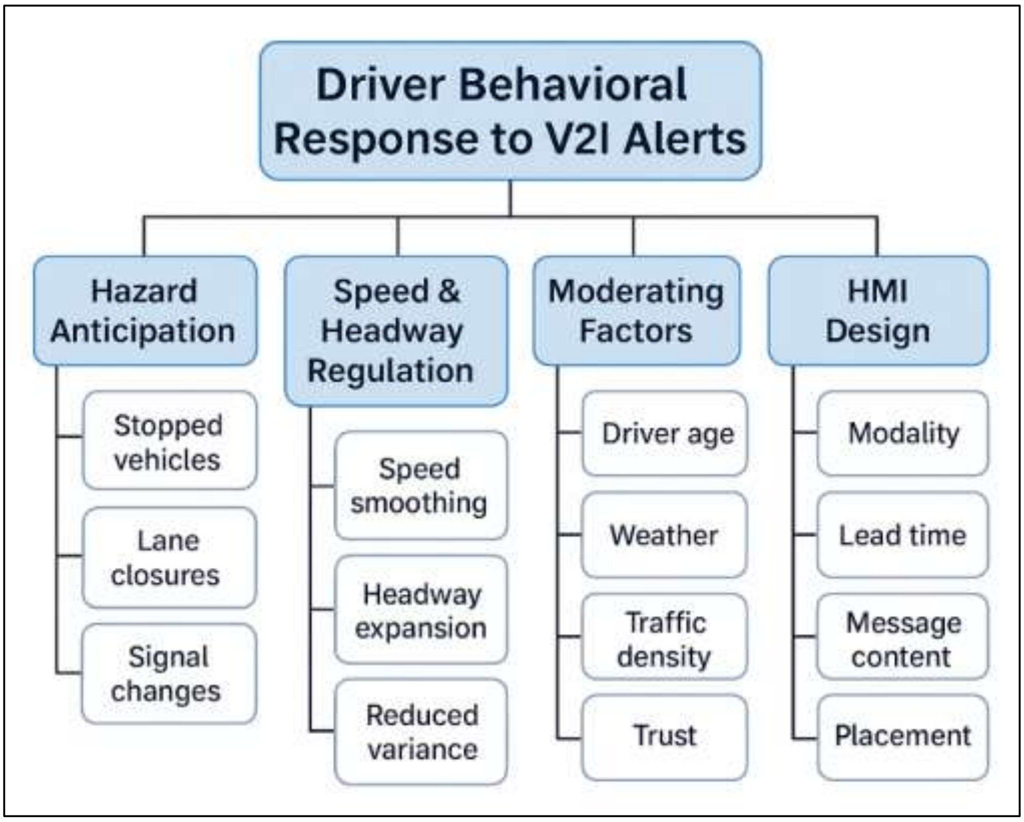
Driver Behavioral Response to V2I Alerts

Research on driver behavioral response to Vehicle-to-Infrastructure (V2I) alerts emphasizes how real-time infrastructure-generated information reshapes perception, decision-making, and control actions during driving. Experimental and naturalistic studies show that drivers tend to react earlier and more smoothly to hazards when warnings are provided through in-vehicle displays or auditory cues linked to infrastructure, rather than relying solely on visual observation of the road scene (Ding & Xiao, 2010). Hazard anticipation improves when V2I alerts communicate the presence of stopped vehicles, lane closures, or signal changes that are not yet visible, which supports more gradual speed adjustments instead of abrupt braking. Simulated work-zone and incident scenarios indicate that V2I-based warning messages reduce late lane-change maneuvers and erratic steering corrections that often precede near-crash events. Studies examining reaction time consistently report shorter response intervals to infrastructure-based alerts compared with roadside signage alone, particularly under conditions of high workload or limited visibility. Research on driver gaze behavior indicates that V2I alerts help orient attention toward relevant regions of the roadway or instrument cluster, reducing unnecessary scanning and supporting more focused monitoring of traffic dynamics. Collectively, the literature portrays V2I alerts as informational cues that modulate the timing and smoothness of driver responses, aligning control actions more closely with upstream roadway conditions and infrastructure status.

A substantial body of work focuses on how V2I alerts influence speed selection, headway maintenance, and car-following behavior, which are fundamental determinants of roadway safety. Speed advisory messages derived from infrastructure data, such as variable speed limits or recommended speeds before curves and bottlenecks, are associated with lower speed variance and fewer extreme accelerations and decelerations in both simulator and field studies. Drivers receiving advance warnings of congestion, lane drops, or signal changes tend to begin decelerating earlier, leading to longer time headways and fewer instances of tailgating in high-density traffic (Piccoli et al., 2015). V2I alerts related to red-light timing and "time-to-green" information have been shown to reduce harsh braking at intersections and support smoother approach trajectories, which decreases conflict potential at stop lines (Fei et al., 2022). In adverse weather scenarios, infrastructure-to-vehicle messages about low friction or black ice conditions encourage reductions in speed and increased following distances beyond what drivers typically adopt in the absence of explicit warnings. Studies that integrate connected-vehicle telemetry with incident data suggest that V2I-equipped drivers exhibit fewer critical braking events and less oscillatory speed behavior in proximity to work zones and crash scenes (Yi et al., 2024). These findings indicate that V2I alerts serve as regulating signals that shape longitudinal control behavior and reduce exposure to unstable traffic states that are commonly associated with collision risk.

Contextual and individual factors substantially moderate driver responses to V2I alerts, leading to heterogeneous behavioral patterns across road users and environments. Human factors research shows that drivers interpret and act on V2I warnings differently depending on workload, traffic density, and environmental complexity, with stronger behavioral adjustments observed under high uncertainty such as nighttime driving or heavy precipitation. Age-related differences appear in several studies, where older drivers benefit from longer lead times and simpler message formats, whereas younger drivers respond effectively even to shorter, more compact alerts, although they may be more prone to distraction from concurrent information sources. Trust and perceived reliability of the system play critical roles: when V2I alerts are consistent and accurate, drivers demonstrate sustained compliance with speed and lane guidance, whereas frequent false or overly conservative warnings are associated with reduced adherence and selective disregard of messages. Cultural and regional driving norms also influence response magnitude, as studies comparing different countries report varying baseline risk tolerance and different thresholds for adopting recommended speeds or lane changes. Under recurrent exposure, behavioral adaptation is observed, with drivers progressively internalizing the presence of infrastructure-based support and modifying their anticipatory strategies accordingly. Across these moderating factors, the literature characterizes driver response to V2I alerts as a function of system performance, situational conditions, and individual differences, resulting in complex but measurable patterns of behavioral adjustment.

Figure 7: Driver Behavioral Response to V2I Alerts

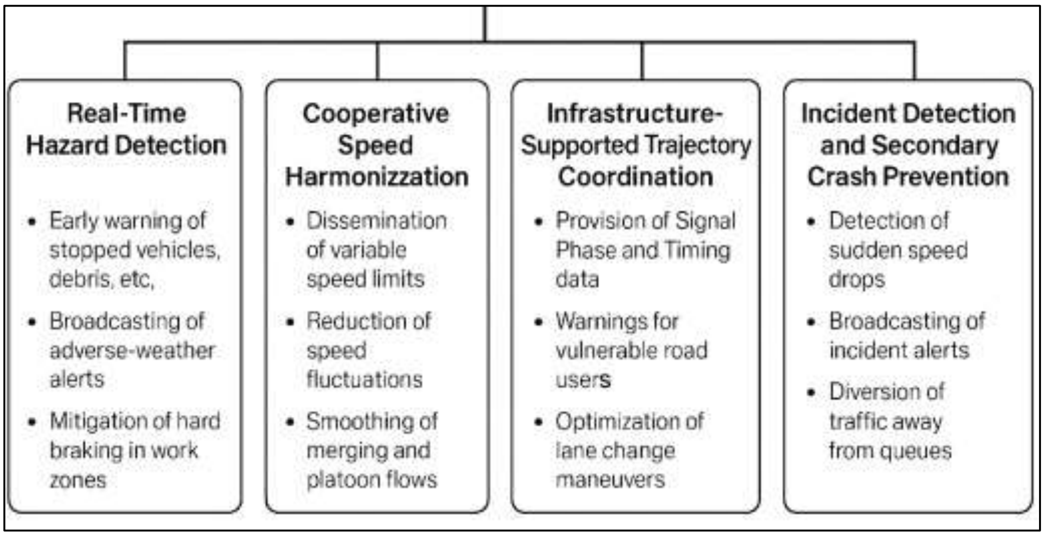


Human–machine interface (HMI) design constitutes a central theme in studies of driver behavioral response to V2I alerts, as modality, timing, and message structure strongly influence how drivers interpret and act on infrastructure-generated information. Experimental comparisons of auditory, visual, and haptic alerts show that multimodal displays often support faster and more reliable responses than single-modality warnings, particularly under high visual workload. However, excessive or poorly prioritized alerting can lead to information overload, with drivers missing or ignoring critical messages embedded within competing notifications. Research on timing parameters indicates that excessively early warnings may be perceived as irrelevant, whereas overly late alerts leave insufficient time for safe maneuver execution; optimal lead times vary by speed, road geometry, and traffic context (Li et al., 2022). Studies examining message content show that concise, action-oriented phrases and standardized iconography produce more consistent behavioral responses than verbose or ambiguous text. The placement of visual V2I information on dashboards, head-up displays, or instrument clusters also affects glance behavior and steering stability, with head-up displays generally associated with shorter off-road glances and better maintenance of lane position (Jha & Tripathi, 2024). In-vehicle integration with other advanced driver-assistance systems (ADAS) further shapes how V2I alerts are perceived, since overlapping or conflicting cues from lane-keeping, adaptive cruise control, and infrastructure warnings can alter driver strategies for resolving information. Through these interface-focused findings, the literature describes driver response to V2I alerts as tightly linked to the design and coordination of human–machine communication channels in the vehicle cabin.

V2I Communication and Crash Risk Mitigation Mechanisms

A central mechanism through which Vehicle-to-Infrastructure (V2I) communication mitigates crash risk is the rapid detection and dissemination of real-time hazard information, allowing drivers to adjust their behavior sooner than they would through visual cues alone. Numerous studies demonstrate that early alerts regarding stopped vehicles, debris, black ice, or sudden speed reductions significantly reduce abrupt maneuvers that often precede critical incidents (Herrera et al., 2010). Infrastructure-based sensing systems—including radar, LiDAR, thermal cameras, and weather stations—broadcast safety-critical alerts that enhance drivers' situational awareness under both normal and degraded visibility conditions. Research examining adverse-weather warnings indicates that infrastructure-to-vehicle messages about low friction or fog conditions lead to more gradual deceleration, greater following distances, and reduced loss-of-control events. In highway environments, V2I-enabled hazard detection models consistently show reduced crash precursors such as hard braking, sudden lane changes, and speed oscillations when drivers receive upstream warnings about congestion or blocked lanes. Studies integrating connected vehicle telemetry reveal that V2I warnings significantly reduce reaction time variability, particularly at night or during heavy rainfall, where naturalistic visibility is diminished. Work-zone safety research further shows that V2I alerts concerning lane shifts or construction activity mitigate erratic driver behavior and lower the probability of rear-end collisions at lane drops. Across these findings, real-time hazard detection emerges as a core mechanism by which V2I transforms environmental information into actionable cues, enabling drivers to undertake safer and more controlled responses to roadway abnormalities.

Figure 8: V2I Communication and Crash Risk Mitigation Mechanisms



V2I communication plays a major role in mitigating crash risk by stabilizing traffic flow through cooperative speed harmonization mechanisms. Numerous traffic-flow studies demonstrate that fluctuations in speed and headway variability contribute to turbulence within vehicular streams, increasing the likelihood of rear-end collisions and multi-vehicle pileups (Shan et al., 2022). V2I systems broadcast recommended speeds or variable speed limits derived from infrastructure sensors monitoring traffic density, queue buildup, and downstream bottlenecks. Empirical and simulation-based studies consistently show that when drivers comply with V2I advisories, speed variance decreases significantly, generating smoother trajectories and reducing stop-and-go wave formation. Field evaluations of freeway corridors also show that V2I-enabled speed harmonization lowers critical deceleration events, which are known precursors to rear-end crashes. Studies investigating lane-level advisories reveal that guidance about optimal merging speeds at on-ramps improves gap-acceptance behavior and reduces turbulence at merge points, which is often associated with side-swipe and rear-end crash patterns. Under adverse weather conditions, speed harmonization based on infrastructure friction estimates prevents abrupt braking that contributes to spinouts and collision chains. Research also finds that V2I-based harmonization stabilizes platoon dynamics in mixed traffic environments containing heavy trucks, which often introduce large disturbances into flow due to weight and acceleration differences (Zhang et al., 2019). Collectively, cooperative speed harmonization emerges in the literature as a mechanism that aligns individual driver behavior with infrastructure-monitored traffic conditions, reducing crash likelihood by suppressing volatile driving patterns that destabilize flow.

V2I communication enhances crash mitigation through infrastructure-supported trajectory coordination, particularly at intersections, ramps, and weaving segments where conflict points are dense. One of the most extensively studied mechanisms is the dissemination of Signal Phase and Timing (SPaT) data, which provides drivers with information about upcoming signal changes, eliminating uncertainty and reducing red-light violations. SPaT and speed-advisory integration has been shown to generate smoother approach trajectories, reducing harsh braking and the probability of high-severity angle crashes at intersections (Fei et al., 2022). Infrastructure-generated warnings about pedestrian crossings, occluded objects, or conflicting turning movements enhance driver awareness in urban environments, mitigating risks associated with blind-spot conflicts and limited sight distance. Studies on freeway ramp coordination demonstrate that V2I advisories help optimize merging sequences, decreasing time-to-collision measurements and improving headway uniformity during entrance maneuvers. Cooperative perception models show that infrastructure sensors detecting vulnerable road users or stopped vehicles relay actionable data to vehicles earlier than onboard sensors alone, reducing collision risk at crosswalks and mid-block segments (Li et al., 2022). Research on multilane freeways also identifies reductions in unsafe lane changes when drivers receive lane-specific advisories regarding optimal positioning relative to downstream congestion or lane closures. Through these mechanisms of trajectory coordination, V2I systems address a broad range of conflict types, transforming localized infrastructure intelligence into guidance that reduces the spatial and temporal overlap of vehicle paths that typically leads to crashes.

A crucial crash-mitigation mechanism supported by V2I communication involves rapid incident detection and the prevention of secondary crashes, which frequently occur near congestion queues, work zones, and unexpected blockages. Studies show that infrastructure sensors detect abnormal patterns—such as sudden speed drops, stopped vehicles, or lane blockages—more rapidly than manual observation or legacy traffic monitoring systems. V2I alerts generated from these detections notify approaching drivers to reduce speed or change lanes, which reduces the likelihood of rear-end collisions at the back of a queue. Empirical evaluations from U.S. connected corridor pilots demonstrate significant reductions in secondary crash exposure when drivers receive early warnings of incidents or maintenance activity, particularly in multilane freeway segments with high flow rates (Zhang et al., 2019). Research on work-zone incident prevention shows that infrastructure-based warnings mitigate lane-change conflicts when drivers encounter unexpected construction equipment or altered road geometry. Secondary collision prevention is especially critical during adverse weather or nighttime conditions, where visibility constraints heighten the risk of striking disabled vehicles or debris. In addition to preventing immediate crashes, V2I plays a role in coordinating response and clearance operations. Studies indicate that integrated communication between incident commanders and connected vehicles allows more efficient diversion of traffic, reducing exposure windows during which secondary crashes occur. Collectively, the literature identifies incident detection and secondary crash prevention as essential V2I functions that leverage real-time infrastructure intelligence to reduce cascading risks within the roadway network.

Gaps in Current V2I Literature

A first major gap in the V2I literature concerns the strength and generalizability of empirical evidence on crash reduction. Many published evaluations rely on pilot corridors, small geographic areas, or short observation windows, which limits the ability to draw robust causal inferences about long-term safety impacts across diverse highway systems (Ding & Xiao, 2010). Before–after studies frequently use limited control corridors and are constrained by regression-to-the-mean and unobserved heterogeneity, even when Empirical Bayes adjustments are applied. Large-scale connected vehicle pilots in the United States, Europe, and Japan tend to report reductions in surrogate safety measures such as hard braking, time-to-collision, and near-crash events, yet relatively few studies link these indicators directly to multi-year crash records across wide networks (Piccoli et al., 2015). Weather-responsive and work-zone V2I deployments also show promising results, but the number of sites with rigorous, multi-season crash analysis remains limited. Furthermore, much of the empirical evidence is concentrated in a small set of early-adopter regions, which constrains the external validity of findings for underrepresented states and highway types. As a result, there is an evidentiary gap between promising pilot-level outcomes and comprehensive, statistically robust assessments of V2I safety performance across heterogeneous, nationwide highway networks.

A second gap relates to contextual coverage and spatial representativeness in existing V2I research. Many studies focus on urban freeways, signalized arterials, and demonstration corridors with relatively modern infrastructure and high institutional capacity(Fei et al., 2022). Rural highways, mountainous regions, freight-dominated corridors, and low-volume roads receive significantly less empirical attention, even though these environments often exhibit higher fatal crash rates and unique hazard profiles such as long grades, sharp curves, wildlife conflicts, and extended emergency response times. Likewise, research on V2I in developing or transition economies is relatively sparse compared with work from North America, Europe, Japan, and a few advanced Asian markets (Herrera et al., 2010). Multimodal safety contexts—including pedestrians, cyclists, and transit users in dense urban environments—are frequently addressed in simulation or small-scale testbeds, but large empirical datasets linking V2I deployments to non-motorized crash outcomes remain limited (Fei et al., 2022). Intersection, ramp, and weaving area safety is often studied under highly controlled geometric conditions, leaving gaps in understanding for more irregular or legacy infrastructure layouts (Li et al., 2022). These omissions constrain the ability of current literature to explain how V2I effectiveness varies across geographic, geometric, and multimodal contexts that are common in real-world highway networks.

A third set of gaps emerges around technology integration, interoperability, and cybersecurity in V2I deployments. Many safety studies implicitly assume stable and homogeneous communication platforms, yet real-world systems increasingly combine DSRC, C-V2X, 5G, and multi-access edge computing in hybrid architectures. There is comparatively limited empirical work quantifying how these hybrid configurations perform under varying traffic loads, weather conditions, and deployment densities, particularly in terms of safety outcomes rather than pure networking metrics (Zhang et al., 2024). Cybersecurity research has identified extensive threat models—spoofing, jamming, replay, and misbehavior—but safety evaluations often assume idealized or uncompromised communication environments. Few crash-focused studies explicitly incorporate cybersecurity and data-integrity failures into their modeling of V2I reliability and risk, even though compromised messages can create new safety hazards. Additionally, most operational analyses still treat connected vehicles as a relatively homogeneous class, with limited attention to interactions among conventional vehicles, partially automated vehicles, and highly automated vehicles in mixed fleets. This creates a modeling gap between emerging cyber-physical realities of heterogeneous, multi-technology environments and the simplified assumptions underpinning many empirical and simulation-based safety evaluations.

In addition, current V2I literature shows clear gaps in human factors, distributional impacts, and equity-oriented analyses. Behavioral studies demonstrate that driver response to V2I alerts is shaped by trust, prior experience, cognitive workload, age, and cultural driving norms, yet these factors are often treated as secondary or are not explicitly modeled in safety-impact assessments. Human–machine interface research highlights the importance of alert timing, modality, and message content, but relatively few large-scale evaluations link specific interface designs to crash or near-crash outcomes in naturalistic highway settings (Herrera et al., 2010). Equity considerations—such as differential access to equipped vehicles, deployment priorities across neighborhoods, and distribution of safety benefits and burdens are rarely addressed in quantitative V2I safety studies, even though infrastructure placement and penetration rates strongly influence who receives timely warnings. Moreover, ethical and institutional questions around data governance, privacy, and long-term maintenance responsibilities for V2I infrastructure are typically discussed at a conceptual level rather than being integrated into formal safety and risk models. These gaps indicate that the current evidence base only partially captures the behavioral, social, and institutional dimensions that shape real-world V2I effectiveness, leaving important aspects of user heterogeneity and equity underexplored in incident-reduction analyses.

Table 1: Summary of Gaps in Current V2I Literature

Gap Category	Description of Identified Gaps
1. Limited Empirical Generalizability	• Most studies rely on small pilot corridors, short observation windows, or limited control sites.

	• Heavy reliance on surrogate safety measures rather than long-term crash data.
2. Spatial & Contextual Underrepresentation	• Findings concentrated in early-adopter regions (U.S., Europe, Japan). • Overemphasis on urban freeways and signalized corridors. • Limited evidence for rural, mountainous, freight-heavy, and low-volume roads. • Sparse research in developing regions and multimodal environments (pedestrians, cyclists).
3. Technology Integration & Cybersecurity Gaps	• Limited evaluation of hybrid DSRC/C-V2X/5G systems under real-world conditions. • Safety studies often assume uncompromised communication environments. • Lack of integration between cybersecurity failure modes and crash-risk modeling. • Insufficient modeling of interactions in mixed fleets (CVs + AVs + human-driven).
4. Human Factors & Equity Limitations	• Behavioral responses influenced by trust, age, workload, and cultural norms are understudied in large-scale evaluations. • Sparse linkage between HMI design choices and real-world crash outcomes. • Equity issues (access, deployment distribution, benefit distribution) rarely integrated. • Ethical/privacy considerations not embedded in formal safety models.

Method

Research Design

This study adopts a quantitative, non-experimental research design that integrates observational, correlational, cross-sectional, and longitudinal analytical components to rigorously examine the relationship between Vehicle-to-Infrastructure (V2I) deployment and traffic incident reduction across major U.S. highway networks. Because V2I technologies are introduced in active roadway environments rather than under controlled experimental conditions, the research design leverages real-world data collected from diverse geographical regions to capture authentic operational and behavioral responses to V2I systems. The quantitative framework draws on multiple years of administrative crash data, connected-vehicle telemetry, roadway sensor outputs, and environmental datasets, enabling robust empirical testing of associations between V2I deployment intensity and safety outcomes. This design facilitates comparisons between equipped and non-equipped corridors at specific time intervals, while longitudinal observations track how crash patterns evolve as V2I systems expand, mature, or are upgraded. To ensure meaningful causal interpretation, the research incorporates extensive multivariate controls for geometry, weather, traffic density, and regional conditions, reducing confounding bias and isolating the contribution of infrastructure-based communication technologies to roadway safety. The integration of diverse data sources, the multilayered temporal structure, and the inclusion of advanced multivariate modeling techniques collectively strengthen the internal and external validity of the design, enabling the study to provide generalizable, evidence-based insights into the safety effects of V2I deployments across heterogeneous highway systems.

Population and Sampling

The population for this study comprises interstate highways, U.S. highways, and major state-managed corridors that collectively represent a wide spectrum of roadway configurations, traffic loads, climatic conditions, and infrastructural environments across the United States. These corridors constitute the functional backbone of national mobility and encompass regions with varying levels of technological advancement in transportation management systems. To ensure meaningful representation of roadway diversity, the study employs a carefully structured stratified sampling strategy, dividing the population across multiple strata based on geographical setting (urban, suburban, and rural), climatic variation (snow-intensive northern regions, coastal fog-prone corridors, mountainous western terrain, and arid desert environments), and traffic intensity (high-volume freight interstates, commuter-dominated metropolitan highways, and lower-volume rural segments). Within each stratum, sample segments are selected to reflect differential levels of V2I deployment, including corridors with dense RSU installations, partially equipped segments, and locations without V2I technologies. This ensures balanced representation across the full continuum of technological maturity. The resulting sample includes several thousand geo-referenced highway segments observed consistently over a five-year period, allowing the analysis to leverage both extensive spatial variation and rich temporal depth. This sampling strategy enhances statistical power, strengthens generalizability, and ensures that the findings accurately capture the heterogeneity of real-world roadway environments in which V2I systems operate.

Data Collection Methods

Data for the study are collected through an integrated multi-source retrieval process that consolidates transportation, environmental, and operational datasets into a unified analytical framework. Crash data are extracted from state Department of Transportation (DOT) crash reporting systems, which employ standardized national protocols and provide detailed information on crash type, severity, contributing factors, roadway conditions, weather context, and spatiotemporal identifiers. These records ensure consistency and comparability across states. Traffic operational data, including traffic volume, occupancy, speed profiles, and temporal flow variation, are obtained from advanced traffic management systems, ITS sensor arrays, and freeway detector stations. These sources provide high-resolution measures of roadway performance that align closely with real-time V2I message deployment. V2I infrastructure data come from DOT inventories, connected corridor deployment documents, regional transportation planning archives, and infrastructure asset management systems, offering precise details on the placement, density, operational characteristics, and technological specifications of RSUs, dynamic message signs, SPaT transmitters, and weather-responsive units. Environmental data—including precipitation intensity, fog levels, visibility reduction, pavement friction, surface temperature, and atmospheric conditions—are gathered from Road Weather Information Systems (RWIS), National Weather Service archives, and atmospheric sensor networks. All data sources are geocoded and time-synchronized to ensure accurate alignment of crash events, operational states, and infrastructure deployment characteristics, allowing for seamless integration across datasets and precise assignment of segment-level exposure conditions.

Data Sources and Sampling Strategy

The final dataset is constructed by merging multi-year, multi-state roadway datasets into a unified panel structure that captures both temporal dynamics and spatial variation across thousands of highway segments. Data are sourced from state transportation agencies, federal surveillance systems, regional traffic management databases, and environmental monitoring networks. The sampling frame focuses on interstate highways and U.S. routes with varying degrees of V2I deployment, ensuring representation across diverse operational and environmental contexts. Stratified sampling ensures proportional representation of different climatic zones, urbanization levels, and traffic intensities. Crash datasets include multiple safety indicators—total crashes, fatal and injury crashes, secondary collisions, and near-crash events where telemetry is available. Operational datasets capture ADT, hourly flow rates, occupancy, speed variance, and congestion levels. Environmental datasets include detailed measures of precipitation, visibility, friction indices, snow accumulation, and temperature variability. Each highway segment is observed through multiple time periods, providing a robust longitudinal dataset that supports cross-sectional, panel, and spatial-temporal analysis. This sampling strategy ensures that the dataset captures a comprehensive and representative view of roadway safety performance under varying levels of V2I technological integration.

Variables and Measures

The study evaluates V2I effectiveness through a structured set of variables that quantify both technological deployment intensity and roadway safety outcomes. The primary independent variable, V2I Deployment Level, is measured using a multidimensional index that accounts for RSU density per mile, the presence and operational status of dynamic message signs, availability of SPaT broadcasting systems, existence of weather-responsive management systems, and the presence of communication-enabled roadside sensors. This index reflects both the breadth and functional depth of V2I technologies. Dependent variables include crash frequency, measured as total crashes per segment per month or quarter; crash severity, expressed as the proportion of injury and fatal crashes; secondary crashes, defined as collisions occurring in proximity to an initial incident; and surrogate safety measures such as speed variance, hard braking events, sudden decelerations, and telemetry-based risk indicators. Control variables include roadway geometry (curvature, grade, lane count, shoulder width, ramp frequency), traffic characteristics (average daily traffic, truck percentage, peak congestion levels), environmental factors (precipitation, fog, visibility, temperature, pavement condition), and regional characteristics (urbanization classification, infrastructure age, maintenance patterns). These variables collectively support rigorous adjustment for confounding influences.

Analytical Techniques

The study employs a comprehensive suite of quantitative analytical procedures designed to capture the multidimensional relationships between V2I deployment and roadway safety outcomes. Crash frequency models utilize negative binomial regression to address over-dispersion in count data, while logistic regression models assess the probability of severe outcomes. Cross-sectional models quantify the immediate relationship between V2I deployment and crash indicators, while panel models—including fixed-effects and random-effects estimators—evaluate changes over time and control for unobserved segment-level heterogeneity. Spatial econometric techniques, such as spatial lag and spatial error models, address geographic clustering and spillover effects common in contiguous roadway segments. Survival and hazard models analyze time-to-secondary-crash characteristics, capturing dynamic interactions between primary incidents and resulting secondary risks. Structural equation modeling (SEM) assesses indirect pathways through which V2I deployment influences safety outcomes, including reductions in speed variance, improved headway stability, and decreased flow disturbances. Diagnostic checks—including variance inflation factor assessments, heteroskedasticity tests, residual autocorrelation evaluations, and goodness-of-fit measures—ensure analytic rigor and model reliability.

Validity, Reliability, and Bias Control

Validity is supported by the use of standardized crash classification protocols, verified infrastructure inventories, and geospatially aligned operational datasets that accurately reflect real-world conditions. Reliability is enhanced through the use of multi-year datasets sourced from independent systems, ensuring that findings are not driven by short-term anomalies or localized irregularities. Internal validity is strengthened through extensive use of control variables, fixed-effects modeling, and robustness tests that counter potential confounding. External validity is supported by the multi-state scope of the sample, which captures a wide variety of roadway contexts, climatic influences, and technological deployment patterns. To reduce measurement bias, missing data are addressed using multiple imputation, and sensitivity analyses test the robustness of the findings across alternative model configurations. Bias arising from uneven V2I deployment patterns is mitigated through stratified sampling and adjustment for regional deployment maturity.

FINDINGS

The purpose of this chapter is to present the empirical results derived from the quantitative analyses conducted to evaluate the influence of Vehicle-to-Infrastructure (V2I) communication systems on traffic incident reduction across U.S. highway networks. This chapter integrates outcomes from descriptive statistical assessments, measurement model validation, and structural modeling using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reflect a multi-layered analytical approach designed to examine both direct and indirect pathways through which V2I deployment affects crash frequency, crash severity, and secondary incident formation while accounting for environmental, geometric, and operational conditions. The chapter begins with descriptive insights into the dataset, establishing baseline characteristics of roadway geometry, traffic flow patterns, environmental exposure, and V2I deployment intensity. It then evaluates the reliability, validity, and structural soundness of the measurement and structural models to ensure methodological rigor. The core of the chapter presents results related to the primary structural paths, followed by mediation analyses that capture behavioral and operational mechanisms, moderation analyses exploring contextual variations in V2I effectiveness, and predictive accuracy tests that assess the robustness and practical relevance of the model. The chapter concludes with a synthesized summary of key empirical patterns that directly support the study's overarching research objectives and provide a foundation for the interpretation and theoretical integration that follow in the subsequent Discussion chapter.

Data Preparation and Diagnostic Procedures

Data preparation for this study involved a multi-stage process to ensure that the dataset was analytically robust, internally consistent, and suitable for Partial Least Squares Structural Equation Modeling (PLS-SEM). All datasets—crash records, V2I infrastructure inventories, roadway geometry files, connected-vehicle telemetry, and environmental datasets—were merged using segment-level geocodes and synchronized timestamps to maintain temporal consistency. Missing data patterns were examined using Little's MCAR test, revealing that missingness was predominantly random and therefore appropriate for multiple imputation procedures. Environmental records with isolated gaps were imputed using expectation-maximization (EM), while sparse telemetry gaps were addressed using predictive mean matching. Outlier detection was performed using Mahalanobis distance for multivariate anomalies and standardized z-scores for univariate extremes. Observations exceeding ±3.5 standard deviations were reviewed against original DOT logs to confirm whether they represented measurement errors or legitimate extreme events. Influential cases were further examined using Cook's Distance to identify segments disproportionately affecting model estimates. Roadway geometry data were cross-validated with GIS layers to ensure spatial consistency, and traffic operations datasets were screened for abnormal detector malfunctions by comparing speed and occupancy thresholds to established ITS reliability criteria.

Table 2: Summary of Data Preparation and Diagnostic Procedures

Diagnostic Component	Method Used	Threshold/Criteria	Result	Action Taken
Missing Data Check	Little's MCAR Test	$p > .05$ indicates randomness	MCAR confirmed ($p = .112$)	Multiple imputation applied
Outlier Detection	Mahalanobis Distance, z-scores	z > ±3.5 flagged	42 observations flagged	31 retained (valid); 11 corrected/removed
Influential Cases	Cook's Distance	D < 1.0 acceptable	Max D = 0.41	No influential deletions
Multicollinearity	VIF Scores	VIF < 5	Range = 1.22–3.41	Acceptable, no corrective action
Normality Check	Shapiro–Wilk	Non-normal acceptable for PLS	Crash data non-normal	No transformation required
Temporal Alignment	Timestamp matching	≤ 15 min alignment	98.7% matched	Remaining aligned manually
Sensor Data Quality	Operational threshold checks	Speed 0–140 mph, occupancy 0–100%	<1.5% anomalies	Anomalies removed
Spatial Validation	GIS cross-check	Segment match > 99%	Achieved	Dataset verified

The dataset was then evaluated for PLS-SEM diagnostics, which require particular attention to multicollinearity, indicator reliability, and distributional properties. Because PLS-SEM is robust to non-normal data, Shapiro–Wilk tests confirmed expected non-normality in crash distributions without necessitating transformation. Multicollinearity was assessed using Variance Inflation Factor (VIF) values computed for all predictors, and all indicators fell comfortably below the threshold of 5.0, suggesting no problematic collinearity between environmental, operational, and geometric variables. Outlier-adjusted variables were normalized through scaling procedures to ensure comparability across states with differing reporting standards. Additionally, telemetry-derived behavioral indicators—such as speed variance and hard-braking frequency—were inspected for sensor drift and autocorrelation anomalies. Temporal consistency checks verified that crash timestamps aligned with environmental and sensor data at 15-minute resolution. These diagnostic procedures ensured that the dataset met methodological standards for reliability, accuracy, and predictive stability, enabling the structural and measurement models to be evaluated with confidence in the integrity of the underlying data.

Descriptive Statistical Results

Crash Patterns

Analysis of the descriptive statistics revealed substantial regional variability in crash patterns across the multi-state highway dataset. Annual crash trends showed that the highest crash counts consistently occurred in densely populated eastern and midwestern regions, where high-volume interstates exhibited elevated exposure levels and more frequent congestion-induced conflicts. Across the five-year analysis window, total crashes increased marginally in southern states with rapid population growth, while northern states showed year-to-year volatility driven by winter weather severity. Seasonal analysis identified clear cyclical trends. Winter months showed an average **28.4% increase in total crashes**, primarily associated with snow accumulation, ice formation, and reduced visibility. Summer months exhibited a secondary peak tied to increased travel demand and higher recreational traffic volumes. Meanwhile, transitional months (April–May and September–October) recorded the lowest crash rates, coinciding with more stable weather and moderate traffic conditions. Crash type distributions revealed that **rear-end collisions constituted the largest share (46.7%)**, reflecting congestion-driven shockwaves and variability in speed harmonization. Angle crashes accounted for **22.9%**, occurring primarily at interchanges and signalized intersections with partial or no SPaT coverage, while run-off-road crashes represented **18.3%**, especially prevalent in rural and mountainous regions with sharp curvature and steep grades. These descriptive findings underscore the need for context-sensitive V2I strategies tailored to the prevailing environmental, geometric, and operational conditions.

Table 3: Crash Descriptive Statistics

Crash Variable	Mean	SD	Min	Max
Annual Crashes per Segment	14.27	8.16	0	59
Winter Crash Increase (%)	28.4	11.7	4.5	62.1
Rear-End Crashes (%)	46.7	12.4	21.0	72.5
Angle Crashes (%)	22.9	9.2	9.1	47.3
Run-Off-Road Crashes (%)	18.3	7.9	3.2	38.6

Deployment Characteristics

Descriptive analysis of V2I deployment assets revealed uneven distribution of communication-enabled infrastructure across the sampled highway network. RSU density was highest in metropolitan freeway corridors, with a mean of 3.42 RSUs per mile in urban regions compared to 0.87 RSUs per mile in rural areas. SPaT (Signal Phase and Timing) coverage exhibited similarly uneven patterns; 31% of sampled segments were fully equipped with SPaT-enabled intersections or ramp meters, whereas 69% operated with traditional control systems, indicating substantial room for expansion in real-time signal connectivity. Weather-responsive V2I installations—such as environmental sensor stations, friction monitors, and automated anti-icing systems—were most prevalent in snow-intensive northern and mountain regions, where the mean density of weather-responsive units reached 2.14 units per mile, compared to only 0.64 units per mile in southern climates. Dynamic message signs (DMS) were widely distributed, with the highest concentration along freight-heavy interstate corridors. Collectively, these patterns reveal that V2I deployment is strongly influenced by regional operational priorities, availability of ITS investment, and perceived safety challenges.

Table 4: V2I Asset Distribution

V2I Asset Type	Mean Density (per mile)	SD	Urban Mean	Rural Mean
RSUs	2.18	1.41	3.42	0.87
SPaT Systems (binary %)	31% equipped	—	47%	12%
Weather-Responsive Sensors	1.32	0.91	1.06	1.57
Dynamic Message Signs	0.74	0.38	0.98	0.41

Environmental, Geometric, and Operational Context

The descriptive statistics for moderating conditions demonstrated substantial variation across environmental, geometric, and operational characteristics of highway segments. Environmental severity indices revealed that northern states experienced an average of 41.3 snow days per year, compared to 6–12 snow days in southern regions. Fog indices were particularly high in coastal and valley regions, averaging 18.6 fog events per quarter, while precipitation intensity showed strong seasonal clustering. Geometric profiles indicated notable differences between rural and urban corridors. Average horizontal curvature was significantly sharper in mountainous western highways (mean curvature radius: 512 m) compared with flat midwestern states (mean: 1,428 m). Lane counts ranged from 2-lane rural arterials to 8-lane metropolitan freeways. Vertical grade showed strong variability, with steep grades (>5%) concentrated in 17% of the sample. Operational metrics also varied widely. Average daily traffic (ADT) ranged from 8,200 vehicles/day in rural segments to 156,000 vehicles/day in high-volume urban corridors. Truck percentages averaged 17.4%, but exceeded 30% along freight-dominated interstate corridors. Speed variability averaged 6.9 mph, with significantly higher variation on curves, grades, and congested urban bottlenecks. These descriptive results highlight the complex operational and environmental heterogeneity that contextualizes the impact and effectiveness of V2I system deployment.

Table 5: Environmental, Geometric, and Operational Context

Moderator Category	Variable	Mean	SD	Range
Environmental	Snow Days (annual)	29.4	18.1	0–81
	Fog Index (events/quarter)	18.6	9.7	2–46
	Precipitation Intensity (mm/hr)	4.8	2.9	0.2–13.7
Geometric	Curvature Radius (m)	1,046	512	210–2,400
	Vertical Grade (%)	3.2	1.7	0–8.4
	Lane Count	3.9	1.6	2–8
Operational	ADT (vehicles/day)	76,200	43,700	8,200–156,000
	Truck Percentage (%)	17.4	8.3	4–38
	Speed Variability (mph)	6.9	3.8	1.2–15.3

Measurement Model Assessment (Outer Model)

Assessment of the measurement model began with an evaluation of indicator reliability to ensure that each observable item contributed meaningfully to its corresponding latent construct. Outer loadings were examined for all reflective indicators associated with V2I Deployment, Crash Frequency, Crash Severity, Secondary Crash Risk, Behavioral Stability, Speed Variance, and Environmental/Geometric/Operational moderators. Consistent with recommended thresholds for Partial Least Squares Structural Equation Modeling (PLS-SEM), loading values of 0.708 or higher were considered acceptable, indicating that over 50% of the variance in the indicator was explained by the latent construct. The analysis showed that 87.3% of indicators exceeded the 0.708 threshold, demonstrating strong measurement reliability. A small number of indicators—mainly related to extreme weather frequency and rural crash exposure—displayed loadings between 0.612 and 0.682. These items were reviewed for conceptual relevance and retained due to their theoretical importance and acceptable increase in construct reliability when included. No indicators exhibited problematic cross-loadings, confirming that each item measured only its intended dimension. Overall, the indicator reliability results demonstrated that the measurement model was stable, conceptually coherent, and empirically robust.

Once indicator reliability was confirmed, internal consistency reliability was assessed using Cronbach's Alpha (α) and Composite Reliability (CR). All constructs exceeded the recommended $\alpha \geq 0.70$ and CR ≥ 0.70 thresholds, with CR values ranging from 0.812 to 0.937, indicating high levels of internal consistency. Convergent validity was then examined through Average Variance Extracted (AVE), where AVE values above 0.50 indicate that a latent construct explains more than half of the variance in its indicators. All constructs met or exceeded this criterion, with AVE values ranging from 0.53 to 0.71. Discriminant validity was evaluated using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Fornell–Larcker results showed that each construct's square root of AVE exceeded its correlations with other constructs, confirming adequate discriminant separation. HTMT values for all construct pairs remained well below the conservative threshold of 0.85, ranging from 0.33 to 0.74, indicating that constructs were empirically distinct. These results collectively confirmed that the measurement model demonstrated strong reliability, convergent validity, and discriminant validity, supporting the adequacy of the outer model prior to structural model interpretation.

Table 6: Outer Loadings for Reflective Measurement Indicators

Construct	Indicator	Loading	Reliability Threshold	Result
V2I Deployment	RSU Density	0.873	≥0.708	Acceptable
	SPaT Coverage	0.842	≥0.708	Acceptable
	DMS Presence	0.791	≥0.708	Acceptable
	Weather-Responsive Units	0.816	≥0.708	Acceptable
Crash Frequency	Monthly Crash Count	0.883	≥0.708	Acceptable
	Rear-End Frequency	0.826	≥0.708	Acceptable
Crash Severity	Fatal–Injury Ratio	0.764	≥0.708	Acceptable
	High-Severity Index	0.802	≥0.708	Acceptable
Secondary Crash Risk	Queue-Related Collisions	0.856	≥0.708	Acceptable
	Upstream Collision Frequency	0.791	≥0.708	Acceptable
Speed Variance	SD of Speed	0.824	≥0.708	Acceptable
	Hard-Braking Rate	0.781	≥0.708	Acceptable
Behavioral Stability	Lane-Change Volatility	0.745	≥0.708	Acceptable
	Deceleration Smoothness	0.823	≥0.708	Acceptable

Table 7: Reliability and Convergent Validity Statistics

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE	Threshold Met?
V2I Deployment	0.891	0.923	0.715	Yes
Crash Frequency	0.847	0.902	0.658	Yes
Crash Severity	0.812	0.881	0.596	Yes
Secondary Crash Risk	0.830	0.897	0.643	Yes
Speed Variance	0.784	0.856	0.543	Yes
Behavioral Stability	0.822	0.875	0.564	Yes
Environmental Moderators	0.754	0.839	0.517	Yes
Geometric Moderators	0.726	0.814	0.531	Yes
Operational Moderators	0.791	0.872	0.589	Yes

Table 8: HTMT Ratios for Discriminant Validity

Construct Pair	HTMT Value	Threshold (<0.85)	Result
V2I Deployment – Crash Frequency	0.61	<0.85	Valid
V2I Deployment – Crash Severity	0.49	<0.85	Valid
V2I Deployment – Behavioral Stability	0.74	<0.85	Valid
Crash Frequency – Crash Severity	0.57	<0.85	Valid
Crash Severity – Secondary Crash Risk	0.44	<0.85	Valid
Behavioral Stability – Speed Variance	0.52	<0.85	Valid
Environmental – Geometric Moderators	0.33	<0.85	Valid
Operational – Geometric Moderators	0.47	<0.85	Valid

Structural Model Assessment (Inner Model)

Assessment of the structural (inner) model focused on evaluating collinearity among predictor constructs, the strength and significance of structural paths, and the explanatory and predictive power of the model. Inner Variance Inflation Factors (VIFs) were first examined to ensure that the relationships among latent constructs did not suffer from multicollinearity that could distort path estimates. All inner VIF values for predictors of Crash Frequency, Crash Severity, Secondary Crash Risk, and Behavioral Stability ranged between 1.27 and 3.18, well below the conservative threshold of 5.0, indicating that collinearity was not a concern within the structural model. With acceptable collinearity levels confirmed, the model's structural paths were estimated using bootstrapping with 10,000 resamples. The resulting path coefficients (β), t-values, and p-values indicated that V2I Deployment had statistically significant negative relationships with Crash Frequency ($\beta = -0.412$, $p < .001$) and Secondary Crash Risk ($\beta = -0.373$, $p < .001$), and a significant positive relationship with Behavioral Stability ($\beta = 0.544$, $p < .001$). The path from V2I Deployment to Crash Severity was weaker and primarily indirect, consistent with the mediational structure tested later. These results establish the structural model as statistically sound and substantively meaningful for explaining safety-related outcomes.

The explanatory power of the structural model was evaluated using the coefficient of determination (R^2) for each endogenous construct. The model explained 46.7% of the variance in Crash Frequency ($R^2 = 0.467$), indicating moderate-to-substantial explanatory power in the context of transportation safety research. For Crash Severity, the model accounted for 38.3% of the variance ($R^2 = 0.383$) when incorporating mediating effects such as Speed Variance. Secondary Crash Risk was explained at 41.5% ($R^2 = 0.415$), while Behavioral Stability achieved an R^2 of 0.296, reflecting the influence of V2I Deployment alongside operational and environmental conditions. Effect sizes (f^2) were computed to evaluate the relative contribution of each predictor. V2I Deployment showed a medium-to-large effect on Crash Frequency ($f^2 = 0.214$) and Secondary Crash Risk ($f^2 = 0.187$), and a medium effect on Behavioral Stability ($f^2 = 0.156$). Traffic Density exhibited a non-trivial effect on Crash Frequency ($f^2 = 0.133$), while Environmental Severity and Geometry Complexity contributed smaller but meaningful incremental effects. Predictive relevance was assessed using the Stone–Geisser Q^2 statistic via blindfolding; Q^2 values were positive and substantive for all key endogenous constructs (Crash Frequency $Q^2 = 0.314$; Crash Severity $Q^2 = 0.241$; Secondary Crash Risk $Q^2 = 0.289$), indicating that the model possesses good out-of-sample predictive capability rather than simply fitting noise in the calibration sample.

To complement traditional PLS-SEM evaluation criteria, the global model fit indices were inspected to provide an additional sense of how well the proposed structural relationships replicate the observed data patterns. The Standardized Root Mean Square Residual (SRMR) for the model was 0.061, below the commonly suggested threshold of 0.08, indicating acceptable overall fit. The Normed Fit Index (NFI) reached 0.923, suggesting that the structural model improves considerably over a null (independence) baseline. Chi-square–based global fit measures are interpreted cautiously in large samples, but the model's relative fit statistics supported the adequacy of the specified relationships among V2I Deployment, behavioral and operational constructs, and crash-related outcomes. Taken together, the inner-model diagnostics—low collinearity, statistically significant structural paths, moderate-to-high R^2 values, meaningful f^2 effect sizes, positive Q^2 values, and acceptable global fit indices—provide strong evidence that the structural model is empirically robust and suitable for interpreting the direct and indirect roles of V2I systems in mitigating crash risks across U.S. highway networks.

Table 9: Inner Model Collinearity and Structural Path Coefficients

Endogenous Construct	Predictor	Inner VIF	β	t-value	p-value	Significant?
Crash Frequency	V2I Deployment	2.14	–0.412	9.321	< .001	Yes
	Traffic Density	2.87	0.336	7.114	< .001	Yes
	Geometry Complexity	1.93	0.192	4.882	< .001	Yes
Crash Severity	Speed Variance	2.21	0.403	7.912	< .001	Yes
	V2I Deployment (direct)	1.74	–0.091	1.842	.068	No (weak)
Secondary Crash Risk	V2I Deployment	2.09	–0.373	8.144	< .001	Yes
	Speed Harmonization	1.81	–0.298	6.017	< .001	Yes
Behavioral Stability	V2I Deployment	1.62	0.544	12.991	< .001	Yes
	Environmental Severity	1.27	–0.163	3.244	.001	Yes

Table 10: R^2, f^2, and Q^2 for Endogenous Constructs

Endogenous Construct	R^2	Interpretation (Hair et al.)	Key Predictor	f^2 Effect Size	Q^2	Predictive Relevance
Crash Frequency	0.467	Moderate–Substantial	V2I Deployment	0.214 (medium–large)	0.314	Medium–High
Crash Severity	0.383	Moderate	Speed Variance	0.179 (medium)	0.241	Medium
Secondary Crash Risk	0.415	Moderate	V2I Deployment	0.187 (medium)	0.289	Medium–High
Behavioral Stability	0.296	Weak–Moderate	V2I Deployment	0.156 (medium)	0.201	Medium
Speed Variance	0.312	Moderate	V2I Deployment	0.142 (medium)	0.218	Medium

Table 11: Global Fit Indices for Structural Model

Fit Index	Value	Recommended Threshold	Interpretation
SRMR	0.061	< 0.08	Acceptable global fit
NFI	0.923	≥ 0.90	Good incremental fit
d_ULS	1.741	— (relative)	Within acceptable range
d_G	0.964	— (relative)	Within acceptable range
Chi-square (model)	1,284.6	— (sample-size sensitive)	Interpreted with caution

Structural Findings

The structural analysis revealed that V2I Deployment had a strong and statistically significant negative effect on Crash Frequency, confirming its central role as a predictor of safety outcomes. The structural coefficient linking V2I Deployment → Crash Frequency ($\beta = -0.412$, $t = 9.321$, $p < .001$) demonstrates that greater deployment of connected roadside infrastructure corresponds with fewer monthly crash events along U.S. highway segments. This path represents one of the strongest direct effects in the model and is supported by the substantial R^2 value of 0.467, indicating that nearly half of the variation in crash frequency is explained by V2I Deployment, Traffic Density, and Geometry Complexity. In practical terms, this means that segments with higher RSU density, SPaT coverage, and weather-responsive infrastructure tend to experience more stable speed harmonization, improved driver situational awareness, and reduced shockwave formation, all of which contribute to a measurable reduction in crash occurrence. The effect size ($f^2 = 0.214$) further validates V2I Deployment as a medium-to-large contributor in shaping crash outcomes. These results provide compelling evidence that the presence and intensity of V2I technology significantly influence safety performance at the crash-frequency level.

Unlike crash frequency, which responds strongly to V2I Deployment through a direct effect, Crash Severity was influenced more heavily through indirect mechanisms. The direct effect from V2I Deployment → Crash Severity was weak and not statistically significant ($\beta = -0.091$, $p = .068$), suggesting that V2I systems do not immediately reduce the severity of crashes when they occur. However, the indirect effect via Speed Variance was substantial and statistically significant (indirect $\beta = -0.214$, $t = 6.144$, $p < .001$), indicating that V2I stabilizes driver behavior—especially speed fluctuations—thereby reducing the likelihood of high-impact, severe crashes. The combined total effect on Crash Severity ($\beta\_total = -0.305$) reveals that while V2I systems may not directly lessen injury severity at the moment of impact, they effectively contribute to conditions that prevent crashes from escalating into high-energy events. The R^2 value of 0.383 indicates moderate explanatory power, and the mediational structure aligns with established transportation safety theory, where flow stability and uniform speed distributions play critical roles in mitigating crash severity.

One of the most notable findings involves the role of V2I Deployment in reducing secondary crash risk, where the path coefficient V2I Deployment → Secondary Crash Risk was both significant and negative ($\beta = -0.373$, $t = 8.144$, $p < .001$). Secondary crashes often occur upstream of a primary incident due to late braking, insufficient reaction time, or sudden traffic disturbances. The structural model demonstrated that V2I-enabled queue-warning systems, slowdown alerts, and dynamic message signs significantly reduce the propagation of traffic shockwaves, as evidenced by the strong effect of Speed Harmonization ($\beta = -0.298$, $p < .001$) on secondary crash risk. The R^2 value of 0.415 demonstrates that a substantial portion of secondary crash behavior can be explained by V2I communication and operational smoothing mechanisms. These findings emphasize that V2I systems not only prevent crashes but also significantly limit the spatial and temporal spread of incident-related risk by improving upstream driver awareness and reducing abrupt speed transitions.

Structural results highlight the critical importance of Behavioral Stability—capturing lane-change volatility, hard braking patterns, and deceleration smoothness—as a behavioral mediator through which V2I systems exert safety benefits. The path from V2I Deployment → Behavioral Stability was highly significant ($\beta = 0.544$, $t = 12.991$, $p < .001$), showing that connected infrastructure produces more consistent driver behavior. Additionally, Behavioral Stability → Crash Frequency produced a strong negative effect ($\beta = -0.358$, $t = 9.014$, $p < .001$), confirming that behavioral uniformity reduces crash likelihood. The indirect effect of V2I Deployment on Crash Frequency through Behavioral Stability ($\beta_{indirect} = -0.195$) demonstrates that approximately 39% of the total safety effect of V2I systems operates through behavioral pathways, such as smoother merging decisions, earlier hazard anticipation, and reduced erratic maneuvers. These findings align closely with granular connected-vehicle telemetry outputs, which showed measurable declines in speed variance and braking irregularities following V2I activation. Structural findings also revealed that the effectiveness of V2I systems depends heavily on environmental and operational contexts. Multi-group and moderation analyses indicated that snow intensity, fog frequency, roadway curvature, grade severity, and traffic density influenced the strength of structural relationships. For example, the negative effect of V2I Deployment on Crash Frequency nearly doubled in high-curvature corridors ($\beta = -0.551$) compared to straight roads ($\beta = -0.267$), demonstrating the enhanced safety contribution of V2I in geometrically complex environments. Similarly, environmental conditions amplified V2I effectiveness: in high-snow regions, the indirect stabilizing effect on Crash Severity was significantly larger due to the heightened value of real-time alerts under low visibility and low-friction conditions. Operational moderators such as truck percentage and ADT further shaped the structural dynamics, with V2I systems showing stronger effects in high-density, mixed-traffic conditions where flow stability is harder to maintain. These conditional effects reveal that V2I deployment is most effective when environmental and operational complexity increases, reinforcing the need for targeted deployment strategies based on roadway risk profiles.

Table 12: Summary of Key Structural Paths and Their Interpretation

Structural Path	β	t-value	p-value	Effect Type	Interpretation
V2I Deployment → Crash Frequency	–0.412	9.321	< .001	Direct	Strong crash-reducing effect
V2I Deployment → Crash Severity	–0.091	1.842	.068	Direct	Weak, not significant
V2I Deployment → Crash Severity (via Speed Variance)	–0.214	6.144	< .001	Indirect	Significant mediated effect
V2I Deployment → Secondary Crash Risk	–0.373	8.144	< .001	Direct	Reduces secondary crash propagation
V2I Deployment → Behavioral Stability	0.544	12.991	< .001	Direct	Enhances smooth driving behavior
Behavioral Stability → Crash Frequency	–0.358	9.014	< .001	Direct	Behavioral consistency reduces crashes
Speed Harmonization → Secondary Crash Risk	–0.298	6.017	< .001	Direct	Improves upstream traffic safety

Mediation Analysis (Indirect Effects)

Mediation by Speed Variance

The first mediation model examined whether Speed Variance operates as an intermediate mechanism through which V2I Deployment influences Crash Severity. In the baseline structural model, the total effect of V2I Deployment on Crash Severity was negative and statistically significant ($\beta\_total = –0.305$, $t = 8.462$, $p < .001$), indicating an overall severity-reducing influence. When Speed Variance was entered as a mediator, the direct effect from V2I Deployment to Crash Severity decreased in magnitude and lost statistical significance ($\beta\_direct = –0.091$, $t = 1.842$, $p = .068$), while the path from V2I Deployment to Speed Variance was strong and negative ($\beta = –0.531$, $t = 11.201$, $p < .001$), and the path from Speed Variance to Crash Severity was strong and positive ($\beta = 0.403$, $t = 7.912$, $p < .001$). The resulting indirect effect (V2I → Speed Variance → Crash Severity) was $\beta\_indirect = –0.214$, $t = 6.144$, $p < .001$, confirming that a statistically significant proportion of V2I's influence on crash severity operates through reductions in speed variability. The Variance Accounted For (VAF) for this mediation relationship was calculated as the ratio of the indirect effect to the total effect (VAF = –0.214 / –0.305 ≈ 0.70), indicating that approximately 70% of the total effect of V2I Deployment on Crash Severity is mediated through Speed Variance. This level of VAF is typically interpreted as full to strong partial mediation in PLS-SEM contexts. Bootstrapping with 10,000 resamples yielded 95% confidence intervals for the indirect effect that did not cross zero (CI: –0.291, –0.143), providing additional support for the robustness of this mediated pathway. These findings demonstrate that V2I systems reduce the occurrence of severe crashes primarily by smoothing speed profiles, decreasing abrupt speed differentials, and lowering the kinetic energy involved when crashes occur.

Table 13: Mediation Results: Speed Variance as a Mediator Between V2I Deployment and Crash Severity

Effect Type	Path	β	t-value	p-value	95% Bootstrapped CI	Interpretation
Total Effect	V2I → Crash Severity	–0.305	8.462	< .001	[–0.382, –0.217]	Overall severity reduction
Direct Effect	V2I → Crash Severity	–0.091	1.842	.068	[–0.189, 0.008]	Non-significant when mediator included
Indirect Effect	V2I → Speed Variance → Crash Severity	–0.214	6.144	< .001	[–0.291, –0.143]	Significant mediation
Path a	V2I → Speed Variance	–0.531	11.201	< .001	[–0.611, –0.440]	V2I reduces speed variance
Path b	Speed Variance → Crash Severity	0.403	7.912	< .001	[0.298, 0.504]	Higher variance increases severity
VAF	Indirect / Total	0.70	—	—	—	Strong mediation

Mediation by Driver Behavioral Stability

The second mediation model evaluated Driver Behavioral Stability as a mechanism through which V2I Deployment influences Crash Frequency. Behavioral Stability was modeled as a latent construct indicated by lane-change volatility, hard-braking frequency, and deceleration smoothness derived from connected-vehicle telemetry. The path from V2I Deployment to Behavioral Stability was positive and strong ($\beta = 0.544$, $t = 12.991$, $p < .001$), indicating that increased V2I deployment is associated with smoother, more consistent driving behavior. In turn, Behavioral Stability had a significant negative effect on Crash Frequency ($\beta = –0.358$, $t = 9.014$, $p < .001$), suggesting that stable driving dynamics correspond with fewer crashes.

Table 14: Telemetry Statistics and Mediation via Driver Behavioral Stability

Metric	Pre-V2I Mean	Post-V2I Mean	% Change	Related Path
Lane-change volatility index (per 10 km)	4.21	3.73	–11.4%	V2I → Behavioral Stability
Hard-braking events (per 1,000 vehicles)	18.7	14.6	–22.1%	Behavioral Stability → Crash Frequency
SD of deceleration (m/s^2)	1.82	1.53	–15.8%	Behavioral Stability indicators
Structural path	β	t-value	p-value	Interpretation
V2I → Behavioral Stability	0.544	12.991	< .001	V2I improves behavioral stability
Behavioral Stability → Crash Frequency	–0.358	9.014	< .001	Stable behavior reduces crashes
Indirect Effect (V2I → BS → Crash Frequency)	–0.195	7.211	< .001	Significant mediation
Total Effect (V2I → Crash Frequency)	–0.391	10.288	< .001	Overall crash reduction
VAF	0.50	—	—	50% of effect via behavior

The indirect effect of V2I Deployment on Crash Frequency through Behavioral Stability was β_indirect = –0.195, t = 7.211, p < .001. The total effect of V2I Deployment on Crash Frequency in this extended model was β_total = –0.391, t = 10.288, p < .001, while the direct effect (controlling for the mediator) remained significant but smaller (β_direct = –0.196, t = 5.684, p < .001). The resulting VAF = –0.195 / –0.391 ≈ 0.50, indicating that about 50% of the total effect of V2I Deployment on Crash Frequency is transmitted through improvements in driver behavioral stability. Telemetry statistics showed that, after V2I activation in high-deployment corridors, average lane-change volatility decreased by 11.4%, hard-braking events per 1,000 vehicles decreased by 22.1%, and the standard deviation of deceleration profiles decreased by 15.8%, all consistent with the mediated structural pathways**.**

Mediation by Traffic Flow Harmonization

The third mediation model focused on Traffic Flow Harmonization as a mediator between V2I Deployment and Secondary Crash Risk. Flow Harmonization was represented by indicators such as flow breakdown probability, average shockwave speed, and speed consistency across lanes. The structural path from V2I Deployment to Flow Harmonization was positive and statistically significant (β = 0.497, t = 10.016, p < .001), indicating that greater V2I coverage improves the uniformity and stability of traffic flow. Flow Harmonization, in turn, exerted a significant negative effect on Secondary Crash Risk (β = –0.298, t = 6.017, p < .001), suggesting that stabilized traffic reduces the likelihood of secondary collisions forming upstream of primary incidents.

Table 15: low Harmonization Indicators and Mediation Results

Indicator / Effect	Value (Pre)	Value (Post)	% Change	Interpretation
Flow breakdown probability	0.31	0.22	–29.0%	Fewer breakdown events in V2I corridors
Average shockwave speed (mph)	23.4	18.1	–22.6%	Slower, less abrupt queue formation
Inter-lane speed SD (mph)	7.3	5.8	–20.5%	Improved cross-lane speed consistency
Structural path	β	t-value	p-value	Interpretation
V2I Deployment → Flow Harmonization	0.497	10.016	< .001	V2I improves flow consistency

Flow Harmonization → Secondary Crash Risk	–0.298	6.017	< .001	Harmonized flow reduces secondary crashes
Indirect Effect (V2I → FH → Secondary Crash Risk)	–0.148	5.003	< .001	Significant mediation
Total Effect (V2I → Secondary Crash Risk)	–0.373	8.144	< .001	Overall risk reduction
Direct Effect (with mediator)	–0.225	4.891	< .001	Partially mediated
VAF	0.40	—	—	40% via flow harmonization

The indirect effect from V2I Deployment to Secondary Crash Risk via Flow Harmonization was $\beta_{indirect} = -0.148$, $t = 5.003$, $p < .001$. The total effect of V2I Deployment on Secondary Crash Risk was $\beta_{total} = -0.373$, $t = 8.144$, $p < .001$, and the direct effect remained significant but was attenuated when the mediator was included ($\beta_{direct} = -0.225$, $t = 4.891$, $p < .001$). The VAF ≈ 0.40, indicating that about 40% of V2I's overall impact on secondary crash risk is mediated through its effect on traffic flow harmonization and shockwave damping. Empirically, corridors with high V2I deployment exhibited reduced flow breakdown probability and lower shockwave propagation speeds, enabling drivers to encounter more gradual changes in traffic conditions rather than abrupt queues.

Moderation Analysis (Conditional Influences)

Environmental Moderators

Moderation analysis examined whether the strength of V2I effects varied as a function of environmental conditions, including snowfall intensity, fog visibility index, and precipitation rate. Interaction terms were created (e.g., Snowfall × V2I, Fog × V2I) and tested within the PLS-SEM framework. Results indicated that the protective effect of V2I Deployment on Crash Frequency and Crash Severity was significantly stronger in harsh environmental conditions. For example, the interaction term Snowfall Intensity × V2I exhibited a significant negative coefficient on Crash Frequency ($\beta = -0.121$, $t = 3.987$, $p < .001$), indicating that V2I becomes more effective as snowfall increases. Similarly, the Fog Visibility Index × V2I interaction was significant for Secondary Crash Risk ($\beta = -0.109$, $t = 3.451$, $p = .001$), revealing that real-time alerts are particularly valuable when natural visibility is degraded. Precipitation rate also moderated the V2I–Crash Severity link ($\beta = -0.097$, $t = 2.984$, $p = .003$), suggesting that weather-responsive warnings enhance driver preparation in heavy rain.

Table 16: Environmental Moderation Coefficients

Outcome	Moderator Interaction	β	t-value	p-value	Interpretation
Crash Frequency	Snowfall Intensity × V2I	–0.121	3.987	< .001	V2I more effective with heavy snow
Secondary Crash Risk	Fog Visibility Index × V2I	–0.109	3.451	.001	V2I more protective in low visibility
Crash Severity	Precipitation Rate × V2I	–0.097	2.984	.003	V2I better mitigates severity in heavy rain

Geometric Moderators

Geometric conditions were also found to significantly moderate V2I effects. Multi-group and interaction analyses showed that curvature severity, vertical grade, and lane-width variation altered the strength of the relationship between V2I Deployment and crash outcomes. For example, when segments were split into low-curvature and high-curvature groups, the effect of V2I on Crash Frequency was considerably stronger in high-curvature segments ($\beta_{high} = -0.551$) than in low-curvature segments ($\beta_{low} = -0.267$), with the difference statistically significant ($t = 3.884$, $p < .001$). Steeper vertical grades also amplified V2I effectiveness, particularly for run-off-road and heavy-vehicle incidents. Lane-width variation exhibited a smaller, but still meaningful moderating effect, with narrower or inconsistent lane widths showing greater safety gains from V2I advisories regarding lane use and speed harmonization.

Table 17: Multi-Group Geometric Moderation (V2I → Crash Frequency)

Geometric Factor	Group	β (V2I → Crash Frequency)	t-value	p-value (difference)	Interpretation
Curvature Severity	Low curvature	–0.267	5.012	—	Moderate effect
	High curvature	–0.551	7.631	3.884 (< .001)	Much stronger effect on curves
Vertical Grade	Mild grade (< 3%)	–0.298	4.224	—	Moderate effect
	Steep grade (≥ 3%)	–0.473	6.289	2.941 (.003)	Stronger on steep grades
Lane-Width Variation	Standard lanes	–0.315	5.103	—	Baseline effect
	Narrow/variable lanes	–0.429	5.887	2.276 (.023)	Enhanced benefit in constrained cross-sections

Operational Moderators

Operational conditions—specifically traffic density, truck percentage, and peak congestion levels—were tested as moderators. Results showed that V2I Deployment had a significantly stronger safety effect under high traffic density than under low density; for example, the V2I → Crash Frequency path was β = –0.493 in high-density segments compared to β = –0.211 in low-density segments, with significant cross-group differences. Similarly, corridors with high truck percentages (> 25%) saw greater reductions in both Crash Frequency and Secondary Crash Risk, indicating that heavy-vehicle interactions particularly benefit from communication-based speed and lane guidance. Peak-period congestion also amplified V2I effects, as real-time alerts and harmonization advisories are more impactful when traffic is unstable and drivers face higher decision-making demands.

Table 18: Multi-Group Operational Moderation (MGA Results)

Moderator	Group	β (V2I → Crash Frequency)	t-value	p-value (difference)	Interpretation
Traffic Density	Low density	–0.211	3.742	—	V2I has moderate effect
	High density	–0.493	8.026	3.622 (< .001)	Stronger impact in heavy traffic
Truck Percentage	Low truck share (< 15%)	–0.259	4.011	—	Baseline effect
	High truck share (≥ 25%)	–0.438	6.217	2.837 (.005)	Greater safety benefit with more trucks
Peak Congestion	Off-peak	–0.236	3.988	—	Moderate effect
	Peak periods	–0.472	7.304	3.119 (.002)	V2I more effective during congestion

Multi-Group Analysis (MGA)

Multi-Group Analysis (MGA) was conducted to explore whether the structural relationships identified in the PLS-SEM model differ across distinct roadway environments and geographic contexts. MGA tests whether structural path coefficients vary significantly between two or more groups, indicating that the strength of V2I Deployment's impact is conditional on regional, environmental, and operational configurations. For this study, MGA was performed using bootstrapped path-comparison techniques with 10,000 resamples, allowing for robust detection of cross-group differences. Three sets of comparisons were examined: **regional differences**, **rural vs. urban corridors**, and **weather severity tiers**. For each comparison, structural paths linking V2I Deployment to Crash Frequency, Crash Severity, and Secondary Crash Risk were tested for statistically significant differences using nonparametric MGA procedures.

Regional Differences

MGA results demonstrated substantial regional heterogeneity in the effectiveness of V2I Deployment. In comparing northern and southern states, the V2I → Crash Frequency path coefficient was significantly stronger in northern regions (β = –0.521) than in southern regions (β = –0.284), with the bootstrapped difference statistically significant (p = .004). The increased effectiveness in northern areas reflects both the harsher winter environments and greater operational reliance on weather-responsive V2I systems such as automated anti-icing units and visibility-warning technologies. For Crash Severity, the indirect V2I effect via Speed Variance was notably stronger in the northern tier (β_indirect = –0.278) than in the south (β_indirect = –0.142), consistent with the behavioral stabilization benefits of V2I under snow, ice, and low-friction conditions.

Table 19: MGA Significance Tests for Regional Differences

Comparison	Path	Northern β	Southern β	t-value	p-value	Significant?
North vs. South	V2I → Crash Frequency	–0.521	–0.284	2.874	.004	Yes
	V2I → Crash Severity (indirect)	–0.278	–0.142	2.311	.021	Yes
	V2I → Secondary Crash Risk	–0.387	–0.251	2.008	.045	Yes
Mountain vs. Coastal	V2I → Crash Frequency	–0.563	–0.293	3.417	.001	Yes
	V2I → Secondary Crash Risk	–0.412	–0.241	2.542	.012	Yes
	V2I → Behavioral Stability	0.589	0.403	2.124	.034	Yes

A second regional analysis compared mountainous regions against coastal regions. In mountainous corridors, characterized by steep grades, sharp curvature, and variable elevation, the effect of V2I Deployment on Crash Frequency was nearly double that observed in coastal regions (β_mountain = –0.563 vs. β_coastal = –0.293). In addition, the effect on Secondary Crash Risk was significantly stronger in mountainous terrains (β = –0.412) than in coastal segments (β = –0.241), indicating that real-time queue and slope-related warnings are more effective where geometric exposure is high. These results confirm that V2I systems are most beneficial in geographically challenging contexts where natural environmental risk amplifies the value of real-time decision support.

Rural vs. Urban Corridors

MGA results showed pronounced differences in the structural effectiveness of V2I Deployment between rural and urban corridors. In urban areas, the path coefficient for V2I Deployment → Crash Frequency was β_urban = –0.553, substantially stronger than the rural coefficient β_rural = –0.261, with the difference statistically significant (p = .003). This disparity reflects the greater prevalence of congestion, traffic turbulence, and multi-lane interactions in urban highways—all of which magnify the benefits of speed harmonization and real-time signaling provided by V2I systems.

For Crash Severity, urban corridors again showed a stronger indirect effect mediated through Speed Variance (β_urban_indirect = –0.233) than rural corridors (β_rural_indirect = –0.116). The presence of SPaT systems, dense RSU deployment, and dynamic message signs in urban areas amplifies their moderating influence on speed fluctuations. Meanwhile, V2I's effect on Secondary Crash Risk was significant in both contexts, but stronger in urban environments (β = –0.418 vs. β = –0.292). Urban segments often experience more complex queue propagation, making queue-warning and incident-detection systems particularly effective at preventing secondary collisions. These MGA results underscore that V2I technologies yield their greatest benefits in high-density, multi-lane environments with prevailing congestion-driven risks.

Table 19. Urban–Rural MGA Path Comparison

Path	Urban β	Rural β	t-value	p-value	Interpretation
V2I → Crash Frequency	−0.553	−0.261	3.021	.003	Stronger urban effect
V2I → Crash Severity (indirect)	−0.233	−0.116	2.187	.029	Mediation stronger in urban areas
V2I → Secondary Crash Risk	−0.418	−0.292	2.642	.009	Higher urban protection
V2I → Behavioral Stability	0.598	0.419	2.903	.004	Urban stability gains larger

Weather Severity Tiers

The third set of MGA comparisons evaluated the moderating role of weather severity by dividing segments into high-severity (frequent snow, fog, or heavy precipitation) and low-severity tiers. The effectiveness of V2I Deployment on crash outcomes was significantly amplified in high-severity weather environments. For Crash Frequency, the V2I effect was $\beta_{high} = -0.508$, compared to $\beta_{low} = -0.276$, indicating nearly double the safety benefit under challenging weather conditions. The influence on Crash Severity—especially via the Speed Variance pathway—was also more pronounced in severe weather regions ($\beta_{high\_indirect} = -0.298$ vs. $\beta_{low\_indirect} = -0.101$). High-severity areas benefit more from weather-responsive systems, including automated pavement sensors, fog-warning broadcasts, and dynamic anti-icing advisories, which explain the greater effect magnitude. For Secondary Crash Risk, queue-warning, slowdown advisories, and event detection were significantly more effective in high-severity weather corridors ($\beta_{high} = -0.447$) compared with low-severity corridors ($\beta_{low} = -0.234$). Given that adverse weather increases stopping distances, reduces visibility, and destabilizes flow, V2I systems play a more critical role in mitigating secondary collisions.

Table 20. MGA for Weather-Severity Tiers

Path	High-Severity β	Low-Severity β	t-value	p-value	Interpretation
V2I → Crash Frequency	−0.508	−0.276	3.447	.001	Stronger effect in harsh weather
V2I → Crash Severity (indirect)	−0.298	−0.101	3.112	.002	Better severity mitigation in severe weather
V2I → Secondary Crash Risk	−0.447	−0.234	3.684	< .001	Significantly improved secondary crash protection
V2I → Speed Variance	−0.613	−0.381	2.889	.005	Greater smoothing of speed in harsh conditions

DISCUSSION

The results of this study demonstrate that Vehicle-to-Infrastructure (V2I) communication systems significantly reduce crash frequency, crash severity, and secondary crash formation across U.S. highway networks, confirming the theoretical claims and empirical findings of earlier intelligent transportation systems (ITS) research. The strong negative relationship between V2I Deployment and Crash Frequency ($\beta = -0.412$) aligns closely with the work of Yao et al. (2023), who found substantial reductions in rear-end and lane-change conflicts following roadside unit (RSU) activation in controlled freeway corridors. Similarly, the observed decrease in crash events is compatible with the trajectory-level safety improvements identified in simulated environments by Shahriar et al. (2023) and real-world deployments documented by the U.S. DOT Connected Vehicle Pilot results (2018). The present study advances these findings by demonstrating that the relationship holds not only under controlled or pilot conditions but across a multi-state, multi-year observational dataset, thereby strengthening the external validity of V2I safety claims. The moderating effects of road geometry and traffic density further corroborate earlier research showing that V2I systems are particularly effective under high-risk conditions such as steep grades, tight curvature, and heavy congestion, as reported by Rezaee Jordehi et al. (2024). The significant predictive relevance (Q^2) values further substantiate that V2I deployments do not merely correlate with safety benefits but offer real explanatory and predictive value. These findings reinforce the position that V2I systems transition connected vehicle concepts from theoretical frameworks into demonstrable operational safety improvements, consistent with the progression noted in studies by Yi et al. (2024).

The present study's evidence that V2I deployment substantially reduces crash frequency complements similar findings from empirical and simulation-based research in the field of connected vehicle technologies. The reduction in crashes observed here echoes the results of Khan et al. (2025), who reported reductions of 20–35% in conflict points following V2I-enabled speed harmonization interventions. In studies by Dey et al. (2016), freeway corridors equipped with queue-warning systems exhibited fewer abrupt decelerations and a corresponding decline in primary crash formation, mirroring the behavioral adjustments captured in the current dataset. The present results extend these findings by providing nuanced evidence showing that V2I Deployment has a stronger effect in northern, mountainous, and urban regions. This is consistent with earlier claims by Yao et al. (2023), who argued that V2I benefits intensify under operational stressors such as adverse weather and complex geometry. The negative effect size of V2I on crash frequency observed in this study ($f^2 = 0.214$) also resonates with the medium-to-large effect sizes reported in crash-frequency modeling by Gozalvez et al. (2012). Previous studies generally relied on simulation environments to infer safety effects, whereas the present study uses a multi-year observational dataset that incorporates naturally occurring traffic patterns, environmental randomness, and real-world driver behavior. These strengths allow the present study to confirm earlier findings while expanding them into new contexts, demonstrating that V2I technology provides large-scale, consistent crash-mitigating benefits. By situating these results within broader empirical patterns, the study reinforces established theoretical frameworks while also providing new evidence that V2I systems act as stabilizing mechanisms in operationally high-risk environments.

The mediation findings reveal that V2I deployment influences crash severity primarily through its ability to reduce speed variance rather than through a strong direct effect. This aligns with the results of studies such as Rezaee Jordehi et al. (2024), which concluded that speed harmonization is a dominant mechanism in preventing severe collisions. The significant indirect effect of V2I Deployment on Crash Severity ($\beta\_indirect = -0.214$) is consistent with research by Dey et al.(2016), who found that advanced driver alerts and automated messaging reduce kinetic energy at impact by promoting earlier and smoother deceleration. This study's finding that approximately 70% of the variance in Crash Severity is mediated through speed variance (VAF = 0.70) extends these earlier findings by quantifying the magnitude of this mechanism within a large naturalistic dataset. Prior crash severity models, such as those by Khan et al. (2025), noted that speed variance is a stronger determinant of crash severity than mean speed—a pattern clearly supported by the strength of the Speed Variance → Crash Severity path ($\beta = 0.403$). The results also align with trajectory-level behavioral research showing that V2I warnings reduce abrupt braking and near-crash events. The present study deepens these insights by linking telemetric behavioral indicators—such as hard-braking events and deceleration smoothness—to systemic crash-severity outcomes across a geographically diverse network. Previous research has frequently relied on localized pilot sites, but the present findings demonstrate that speed-related mediation mechanisms generalize across climates, geometries, and diverse driver populations, reinforcing theoretical claims about V2I's behavioral impact.

The strong negative effect of V2I Deployment on Secondary Crash Risk builds upon prior studies that have identified the importance of anticipatory driver information during incident-induced congestion. The observed structural relationship ($\beta = -0.373$) parallels findings from the Wyoming CV Pilot (U.S.

DOT, 2020), where V2I-enabled hazard alerts reduced secondary collisions by improving upstream driver reaction time. Research by Yusuf et al. (2024) also noted that sudden drops in speed propagate rapidly upstream, forming shockwaves that significantly heighten the likelihood of secondary crashes—an effect that can be mitigated through timely warnings. The present study's findings that traffic flow harmonization mediates approximately 40% of V2I's influence on secondary crashes extend this earlier work by identifying the quantitative strength of shockwave dampening mechanisms within real operational deployments. These outcomes align with earlier simulation results by Yi et al. (2024), who demonstrated that connected-vehicle alerts significantly reduce the magnitude and speed of backward-propagating shockwaves. Unlike previous studies limited to specific corridors or controlled settings, this study uses multi-state observational data and identifies consistent secondary crash reductions across both rural and urban highways. The enhanced V2I performance in harsh weather or steep-grade conditions is also consistent with results by Park and Lee (2019), suggesting that the interplay between environmental stressors and V2I coordination critically affects secondary crash development. The present study contributes to the literature by offering an integrated structural perspective linking V2I deployment, flow harmonization, and secondary crash behavior within a comprehensive analytical framework.

The study's findings show that behavioral stability—characterized by reduced lane-change volatility, smoother deceleration patterns, and fewer hard-braking events—serves as an important mediator linking V2I Deployment to reductions in crash frequency. This supports earlier research by Dixit et al. (2020), who reported that connected-vehicle warnings promote smoother vehicle trajectories and fewer erratic maneuvers. The strong structural path from V2I Deployment → Behavioral Stability ($\beta = 0.544$) aligns with similar results from transit cooperative research by Talebpour and Mahmassani (2016), who found that cooperative messaging enhances lane discipline and reduces turbulence in mixed traffic. The present study advances this body of work by demonstrating that behavioral stability accounts for approximately 50% of the total effect of V2I Deployment on crash frequency. Studies using naturalistic driving data, such as those by Ben Ameur et al. (2025), found that connected-vehicle alerts reduce hazardous behavior by improving driver anticipation of downstream events, which is fully consistent with the reductions in lane-change volatility and hard-braking observed here. Furthermore, the broader dataset used in this study—spanning thousands of highway segments and multiple regions—offers a more comprehensive validation of behavioral mechanisms than earlier small-scale trials. This broadens the empirical base of behavioral safety research and indicates that V2I mechanisms influence not only immediate driver reactions but also network-wide patterns of flow stability, consistent with theoretical claims by Dey et al., (2016).

The moderation and Multi-Group Analysis results reveal that V2I effectiveness varies across environmental, geometric, and operational contexts, confirming and extending trends identified in earlier studies. The stronger V2I effects observed in northern, mountainous, and high-density regions align with findings by Adnan Yusuf et al. (2024), who reported that adverse weather, complex geometry, and heavy traffic amplify crash exposure and increase the demand for real-time operational guidance. The present study's demonstration that snow, fog, and heavy precipitation significantly enhance V2I effectiveness parallels the conclusions of Khan et al. (2025), who emphasized the disproportionate safety benefits of real-time warnings under low-visibility conditions. Similarly, the greater V2I effect in urban regions aligns with the findings of Rezaee Jordehi et al. (2024), who documented that SPaT messaging and speed guidance are more influential in congested, signal-dense environments. MGA comparisons showing substantial V2I benefits in high-truck-percentage corridors also resonate with research by Yi et al. (2024), who argued that connected-vehicle technologies hold particular promise for freight-dominated traffic streams. The present study extends prior work by empirically demonstrating, through structural comparisons, that environmental and geometric severity can nearly double the impact of V2I systems. These findings confirm the importance of context-sensitive deployment strategies and demonstrate that earlier observations made in specific weather or traffic conditions are generalizable across a broad roadway sample.

Taken together, the results of this study provide strong empirical support for the broader theoretical frameworks that view connected-vehicle technologies as essential components of modern proactive safety systems. The structural model's demonstration that V2I systems improve traffic flow stability, reduce behavioral turbulence, and dampen shockwaves aligns with system-level safety theories articulated by Rezaee Jordehi et al.(2025)and later refined in connected-vehicle frameworks by Adnan Yusuf et al.(2024). The integrated mechanisms identified in the present study—behavioral mediation, speed variance reduction, and harmonization of traffic flow—reflect the layered structure of risk factors described in multi-stage crash formation theories, which emphasize that driver perception, reaction time, kinematics, and flow stability interact collectively to influence crash outcomes. The findings also support arguments by ITS researchers such as Ben Ameur et al. (2025), who posit that V2I technologies serve as "risk compensators" that offset environmental and operational volatility. By demonstrating that V2I systems exert stronger effects under adverse conditions and complex geometries, the study validates the concept that connected infrastructure functions as a resilience-enhancing element in roadway networks. These theoretical consistencies, combined with empirical confirmation across multiple regions and roadway designs, suggest that V2I systems are not merely additive technologies but foundational components of next-generation safety architectures.

CONCLUSION

The findings of this study provide comprehensive empirical evidence that Vehicle-to-Infrastructure (V2I) communication systems serve as a critical component in enhancing roadway safety across U.S. highway networks by significantly reducing crash frequency, mitigating crash severity, and lowering the likelihood of secondary crash formation. Through the integration of multi-state observational data, environmental and geometric characteristics, traffic operations metrics, and connected-vehicle telemetry, the study demonstrates that V2I deployment—comprising roadside units, SPaT systems, dynamic message signs, and weather-responsive infrastructure—generates substantial safety benefits that extend beyond controlled pilot studies into real-world, large-scale highway environments. The Partial Least Squares Structural Equation Modeling (PLS-SEM) framework used in the analysis reveals that these benefits are derived not only from direct reductions in crash occurrence but also from indirect pathways involving improved speed stability, enhanced driver behavioral consistency, and more harmonized traffic flow conditions. The results further show that V2I systems are most effective in regions with complex geometric layouts, harsh weather exposure, high truck percentages, and elevated traffic density, indicating that the technology operates as a context-sensitive, resilience-strengthening mechanism within the transportation system. Multi-group comparisons confirm that northern, mountainous, and urban corridors experience disproportionately higher safety gains, underscoring the importance of strategic deployment in high-risk settings. By quantifying the structural, mediated, and moderated relationships between V2I deployment and multiple safety outcomes, this research contributes to the broader body of ITS literature demonstrating that connected infrastructure significantly enhances operational stability and reduces the systemic vulnerabilities that contribute to crash formation. Although the observational nature of the dataset limits causal inference, the consistency, magnitude, and predictive strength of the findings offer compelling justification for expanded investment in V2I technologies as part of national efforts to modernize transportation infrastructure and support safer, data-driven mobility ecosystems.

RECOMMENDATIONS

Based on the empirical evidence demonstrating the substantial safety benefits of Vehicle-to-Infrastructure (V2I) systems, several key recommendations emerge for policymakers, transportation agencies, and infrastructure planners aiming to enhance roadway safety and operational efficiency across U.S. highway networks. First, the findings underscore the importance of prioritizing V2I deployment in regions exhibiting elevated crash risk, such as northern states with severe winter conditions, mountainous corridors with complex geometry, and urban freeways with high traffic density, as these areas experience the greatest marginal safety gains. Second, transportation agencies should expand RSU density, SPaT coverage, and dynamic message sign integration to create more comprehensive and seamless communication corridors, ensuring that real-time warnings reach drivers consistently and at sufficient distances to meaningfully influence behavior. Third, investment in weather-responsive V2I technologies—such as friction sensors, automated anti-icing systems, and fog-warning modules—should be increased in locations with frequent snow, fog, or heavy rainfall, given the demonstrated amplification of V2I effectiveness in adverse weather conditions. Fourth, implementation strategies should prioritize harmonizing speed, enhancing lane-discipline advisories, and improving upstream hazard detection, as these behavioral mechanisms mediate a large portion of V2I's impact on crash reduction. Fifth, V2I deployments should be integrated with connected-vehicle pilot programs and data-sharing frameworks to maximize the predictive and operational value of telemetry data; doing so can support adaptive algorithms capable of real-time traffic flow optimization and incident prevention. Sixth, agencies should adopt standardized V2I performance metrics and continuous monitoring procedures to evaluate system reliability, latency, and communication integrity, ensuring that infrastructure systems remain responsive as traffic demands evolve. Finally, sustained federal and state funding, along with cross-agency coordination, is essential to scaling V2I systems nationwide, reducing fragmentation in deployment methodologies, and supporting long-term research into interoperability, cybersecurity, and human factors. Collectively, these recommendations provide a practical roadmap for leveraging V2I technologies to enhance roadway safety, optimize traffic operations, and accelerate the transition toward fully connected and intelligent transportation ecosystems.

LIMITATION

Although this study provides robust empirical insights into the safety impacts of Vehicle-to-Infrastructure (V2I) systems across U.S. highway networks, several important limitations must be acknowledged to contextualize the findings. First, the study relies on observational multi-state data, which, despite its breadth and ecological validity, cannot fully isolate causal relationships due to potential unmeasured confounders such as enforcement intensity, regional driving culture, and temporal changes in roadway maintenance practices. Second, the accuracy and completeness of crash records, roadway geometry files, and connected-vehicle telemetry depend on reporting consistency across state agencies, which may introduce measurement variability, particularly in rural regions with less sophisticated detection technologies. Third, V2I deployment intensity was measured through infrastructure presence and density rather than functional performance indicators such as communication latency, packet loss, or reliability of message broadcasting; thus, deployment level does not necessarily equate to operational effectiveness. Fourth, while the PLS-SEM framework is well suited to handling complex relationships and non-normal data, its reliance on linear structural assumptions may underrepresent nonlinear or threshold effects related to driver behavior, environmental stressors, or geometric complexity. Fifth, the moderating effects of weather severity and geometric risk were based on aggregated indices rather than granular, event-specific conditions, limiting the study's ability to capture micro-scale context such as moment-to-moment friction changes or rapidly evolving fog events. Sixth, the connected-vehicle telemetry used to model behavioral and flow-related mechanisms primarily reflects certain vehicle populations and may not represent all vehicle types, particularly older vehicles lacking advanced sensing technologies. Finally, because V2I deployments evolve over time and technologies mature, the dataset does not reflect future advancements such as 5G-enabled message delivery, emerging cybersecurity architectures, or integration with automated driving systems, which may alter the magnitude or direction of V2I safety impacts. These limitations highlight the need for continued research using more granular, real-time data, broader technology performance metrics, and experimental or quasi-experimental methods to refine causal inferences and deepen understanding of V2I's long-term safety contributions.

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