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Connected and Automated Vehicles and Safety of Vulnerable Road Users: A Systems Approach

November 2018

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16. Abstract
Connected and automated vehicle (CAV) technologies can dramatically improve safety by reducing human errors, which contribute substantially (an estimated 94 percent) to roadway crashes. CAVs can eventually operate effectively on roadways without experiencing decreased performance due to distraction or fatigue. However, technological advances will not uniformly decrease crash risks. Some environments, crash types, and user groups will continue to experience elevated risks, particularly vulnerable road users such as pedestrians. This project addresses these critical safety issues by: 1) Assessing the current and future landscape of pedestrian and vehicle conflicts; 2) Identifying how vehicle technology, planning policies, and data analytics can provide systemic solutions to pedestrian-vehicle conflicts; and 3) Using data analytics to identify dangerous pre-crash behaviors. This trans-disciplinary and multimodal approach is critical because solutions require insights from multiple fields. The information presented includes literature reviews on current patterns of pedestrian-vehicle conflicts, assessment of how planning and physical design strategies can reduce pedestrian-CAV conflicts. Furthermore, risk analysis was conducted based on Fatality Accident Reporting System (FARS) data, and SHRP2 Naturalistic Driving Study data. An assessment of how automated vehicle technology will impact crash risk and how future countermeasures may change with the adoption of emerging technologies is provided. The team has analyzed safety data from diverse sources and propose a framework to link automation technology to human error/crash typologies. Overall, the study applies innovative statistical, artificial intelligence, and visualization tools to extract valuable information from studies and data, with the purpose of improving safety across modes, especially for vulnerable road users.

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Overview

Connected and automated vehicle (CAV) technologies can dramatically improve safety by reducing human errors, which contribute substantially (an estimated 94 percent) to roadway crashes. CAVs can eventually operate effectively on roadways without experiencing decreased performance due to distraction or fatigue. However, technological advances will not uniformly decrease crash risks. Some environments, crash types, and user groups will continue to experience elevated risks, particularly vulnerable road users such as pedestrians. This project addresses these critical safety issues by:

- Assessing the current and future landscape of pedestrian and vehicle conflicts.
- Identifying how vehicle technology, planning policies, and data analytics can provide systemic solutions to pedestrian-vehicle conflicts.
- Using data analytics to identify dangerous pre-crash behaviors.

This trans-disciplinary and multimodal approach is critical because solutions require insights from multiple fields. For example, data science provides ideas on how to use data from CAVs to manage the system and identify conflict situations; travel behavior provides insights into how travel patterns will change in the future and how this will affect risk profiles; and planning offers lessons about how to design transportation infrastructure to reduce risks that technology alone cannot ameliorate.

The specific tasks include literature reviews on current patterns of pedestrian-vehicle conflicts, assessment of how planning and physical design strategies can reduce pedestrian-CAV conflicts. Furthermore, risk analysis was conducted based on Fatality Accident Reporting System (FARS) data, and SHRP2 Naturalistic Driving Study data. An assessment of how automated vehicle technology will impact crash risk and how future countermeasures may change with the adoption of emerging technologies is provided. The team has analyzed safety data from diverse sources and propose a framework to link automation technology to human error/crash typologies. Overall, the study applies innovative statistical, artificial intelligence, and visualization tools to extract valuable information from studies and data, with the purpose of improving safety across modes, especially for vulnerable road users.

Research questions

This project investigates how to improve road safety outcomes for vulnerable road users in an era of connected and automated vehicles. To do this we address five related research questions:

1. What are the research issues related to walkability in the CAV era?
2. What are the current types of fatal vehicle-pedestrian crashes?
3. How can we establish limits on reductions in pedestrian fatalities if all vehicles on the road today were replaced by CAVs?
4. What strategies can reduce pedestrian-vehicle conflicts in an era of CAVs?
5. What emerging naturalistic driving data can be harvested to identify risky behaviors prior to unsafe outcomes in pedestrian and bicycle crashes and near misses?

Multi-pronged approach

This report describes work performed in several distinct efforts under this overall project. Each effort is listed under its own chapter heading, as follows:

Chapter 2. “Walkability in the Connected and Automated Vehicle Era: A U.S. Perspective on Research Needs” considers the concept of walkability in light of the approaching transition to connected and automated vehicles, considering literature in engineering, information technology, built environment, land use, and public health, to support a discussion on research needs. Text analytics were used to identify major themes. The paper discusses research issues related to walkability in the CAV era.

Chapter 3. “Automated vehicles and pedestrian safety: exploring the promise and limits of pedestrian detection” presents the results of an analysis using FARS data to estimate theoretical best case scenario reductions in pedestrian fatalities if all vehicles on the road today were replaced by fully automated versions using current state-of-the-art pedestrian detection technology. This research effort establishes an upper limit on expectations for the ability of automated vehicles to reduce loss of life for vulnerable road users. The paper explores how we can establish limits on reductions in pedestrian fatalities if all vehicles on the road today were replaced by CAVs?

Chapter 4. “Analysis of Crashes Involving Pedestrians across the United States: Implications for Connected and Automated Vehicles” also uses FARS data to explore how pedestrians can be better protected as connected and automated vehicles diffuse through the transportation system using Vehicle-to-pedestrian (V2P) connectivity. The paper discusses the types of fatal vehicle-pedestrian crashes and what strategies can reduce pedestrian-vehicle conflicts?

Chapter 5. “Exploring injury severity correlates of vulnerable roadway users involved crashes” further explores the potential role for V2P applications to reduce injury severities of pedestrian- and bicyclist-involved crashes.

Chapter 6. “Using Driving Volatility as a Leading Predictor of Unsafe Events Involving Vulnerable Road Users - A Naturalistic Driving Environment Study” uses the SHRP2 Naturalistic Driving Study data to explore how intentional driving volatility well before a crash or near-crash can serve as a leading indicator of pedestrian and bicycle crashes. Such information can be used to alert and warn in advance drivers of connected and automated vehicles about the potential pedestrian crashes. The study harvests naturalistic driving data to identify risky behaviors prior to unsafe outcomes in pedestrian and bicycle crashes and near misses.

Collectively, these studies contribute to a better understanding of research issues related to pedestrian safety and walkability in the future and typologies of crashes among vehicles and vulnerable road users. They shed light on the ways in which current and future technologies might be deployed to detect vulnerable road users. They also provide guidance on how new V2P technologies might be tested and what their limits are in terms of addressing pedestrian-involved collisions.

Research outputs

Publications

Shay E., Khattak A., & Wali, B. Walkability in the connected and automated vehicle era: A U.S. perspective on research needs, *Transportation Research Record: Journal of the Transportation Research Board,* Vol 2672, Issue 35, https://doi.org/10.1177/0361198118787630, 2018.

Combs, T.S., Sandt, L., Clamann, M., McDonald, N.C., Automated vehicles and pedestrian safety: exploring the promise and limits of pedestrian detection. American Journal of Preventive Medicine. DOI: https://doi.org/10.1016/j.amepre.2018.06.024, 2018.

Presentations

Zhang M., A. Khattak, & E. Shay, Analysis of Crashes Involving Pedestrians across the United States: Implications for Connected and Automated Vehicles, 18-04721, Presented at *Transportation Research Board annual meeting,* National Academies, Washington, D.C., 2018.

Combs, T.S., Sandt, L., McDonald, N.C., Clamann, M., Limitations in Detection Technologies for Automated Driving Systems and Implications for Pedestrian Safety. Presented at the Transportation Research Board Annual Meeting, Washington D. C., United States, 2018.

Combs, T.S. Hidden equity challenges of an AV-dominant transport system: tradeoffs between access to opportunity and safety for vulnerable pedestrians. Breakout session at the Automated Vehicles Symposium, San Francisco CA, 2018.

Lester, T.W.; Combs, T.S.; Zhang, W. How can planning theory inform the challenges of planning for automated vehicles? Roundtable discussion at the Association of Collegiate Schools of Planning (ACSP) Conference, Buffalo NY, 2018.

Mussah, AR., Khattak, A., Wali, B., Using Driving Volatility as a Leading Predictor of Unsafe Events Involving Vulnerable Road Users - A Naturalistic Driving Environment Study, TRB Paper 19-02947, Presented at the Transportation Research Board Annual Meeting, Washington D. C., United States, 2019.

Thesis

Mussah, A.R., What Effect Does Driver Maneuvers Have on The Safety of Pedestrians and Cyclists? An In-Depth Descriptive Analysis of Vulnerable User Crashes and Near-Misses, MS Thesis, The University of Tennessee, December 2017.

Walkability in the Connected and Automated Vehicle Era: A U.S. Perspective on Research Needs

Authors

Elizabeth Shay[1], Asad J. Khattak[2], Behram Wali[2]

This chapter presents an extended abstract of CSCRS-sponsored research, based on a paper with the same title presented at the 97th Annual Meeting of Transportation Research Board. The paper is published in *Transportation Research Record*, Journal of the Transportation Research Board, National Academies, Washington, D.C. and it is available online. DOI: https://doi.org/10.1177/0361198118787630

Walkability and walking activity are of interest to planners, engineers and health practitioners for their potential to improve safety, promote environmental and public health, and increase social equity. Connected and automated vehicles (CAVs) will reshape the built environment, mobility, and safety in ways we cannot know with certainty—but which we may anticipate will change the meaning of 'walkability.' The CAV era may provide economic, environmental and social benefits, while potentially disrupting the *status quo*. This paper considers the concept of walkability in light of the approaching transition to CAVs, considering literature in engineering, information technology, built environment, land use, and public health, to support a discussion on research needs. Text analytics were used to identify major themes.

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Introduction

Walking and walkability are key elements of communities that are active, accessible, livable, efficient, safe and just. In the US, a recent surge of interest in walking represents a paradigm shift—a re-examination of a mode once undervalued, now promising to support human and environmental health, promote economic prosperity, and advance social equity. After decades advocating for walkability, planners are buoyed by renewed demand for walkable environments, as individuals, governments, and businesses increasingly recognize the potential benefits for physical and mental health, economic development, and efficient use of land (Litman, 2017).

At the same time, several early-21st-century trends coexist in some degree of tension: walkable urbanism as an explicit goal for planning and economic development; the emergence of a sharing economy that alters travel choice sets and behaviors; and rapid technological advances that promise a transition to driverless vehicles and networked systems—sooner rather than later.

Recent literature on walkability was considered within the context of a rapidly changing transportation landscape where CAVs will mix with—and eventually largely supplant—manually driven vehicles. This supports ongoing inquiry into the most promising technology, designs and policies to reduce risk to vulnerable road users, better understand and influence behavior of drivers and walkers, and identify moral dilemmas and grey areas that may arise in the CAV era.

This paper reviewed literature on walkability and urban form, travel behavior, traffic safety, public health, information technology, and engineering, searching on a controlled list of 14 terms in four knowledge bases (TRID, ScienceDirect, Web of Science, Google Scholar). Of several hundred empirical papers, technical reports, book chapters and reviews scanned, a subset relating to walkability and CAVs were inventoried and subjected to text analysis. The rapidly changing transportation landscape, where emerging CAV technology intertwines with a push for walkable communities and mobility equity, motivated our examination of literature from diverse fields in order to illuminate points of intersection and gaps in knowledge. The resulting network visualization and frequency counts support a discussion of the state of knowledge about technology and vulnerable road users and inform a research agenda.

Methods

A cost/benefit framework (Figure 0-1), listing automation mechanisms on the right, shows pedestrian and bicycle safety impacts of CAVs as potential reductions in harm costs (sum of crash costs in a year) for a region. Notably, crash avoidance technology (vehicle-pedestrian communication) may lower crash risks and costs (blue bars). However, potential VMT increases in CAVs may offset these gains and increase the risk and cost of collisions with pedestrians and bicyclists (red bars). Rough estimates of safety costs range from a 50% decrease to a 30% increase. This highlights uncertain-ties about whether net CAV impacts on pedestrian and bicycle safety will be positive or negative, and the need to identify mechanisms for enhancing safety for all these modes.

To probe views on walkability and CAVs, we performed statistical pattern learning analysis on 70 research and technical papers. This involved extracting key topics and graphically representing them based on proximity/conception distances among them. Frequency analysis identified common keywords, from which an inclusion dictionary was manually constructed to define categories and group similar words together. To refine that dictionary, a combination of natural language processing and statistical (factor analysis) techniques was applied on the otherwise random textual data in the collection (Joliffe, 1986).

Table 0-1 presents the results of topic extraction, in broad categories: vehicle-related, energy consumption, technology and applications, safety, built-environment, walking, government assistance/subsidy, outreach.

Appearing 5762 times in 66 articles (94% of the collection), the factor ‘automated vehicles; driving’ has the highest Eigen-value at 6.15, and explains 1.85% of the variance in the collection. Next most frequent is ‘vibrant suburban,’ with an Eigen-value of 4.23, explaining 1.40% of the variance, and appearing in 47% of the articles. All key topics shown in Table 0-1 have an Eigen-value greater than 1, indicating the topics are worth analyzing (Provalis, 2015). Interestingly, ‘liability, security, and privacy’ and ‘moral and ethics’ also appeared prominently. However, cyber-security, insurance, and attitudes toward automation, encouragement and enforcement fell beyond this paper’s scope.

Concept maps to visualize the co-presence of keywords were constructed with proximity values computed on all key topics in Table 0-1, using constrained multi-dimensional scaling (Breiger et al., 1975). Topics that plot closer tend to occur together in text. The network visualization (Figure 0-2Figure 0-2) shows clustering of words that are significantly connected. Broader concepts are written next to the clusters. Technology-related key-words and topics cluster to the right, while planning-related keywords cluster to the left.

Some keywords serve as bridges in the visual network, e.g., the broader concept of ‘wireless communications’ appears between ‘automation’ and ‘collision avoidance systems; adaptive cruise control,’ suggesting that ideas related to wireless communications are discussed in close proximity to automation or collision avoidance systems. Shared automated vehicles and market penetration, adoption, and scenario development appear near the concept of automation. Finally, planning concepts, i.e., built environment, walkability and government subsidies, cluster together. Concept maps are useful for revealing how key topics are connected through their keyword distribution and relate to walkability and CAVs. Note that the output reflects the selection of documents analyzed; results are illustrative, not determinative.

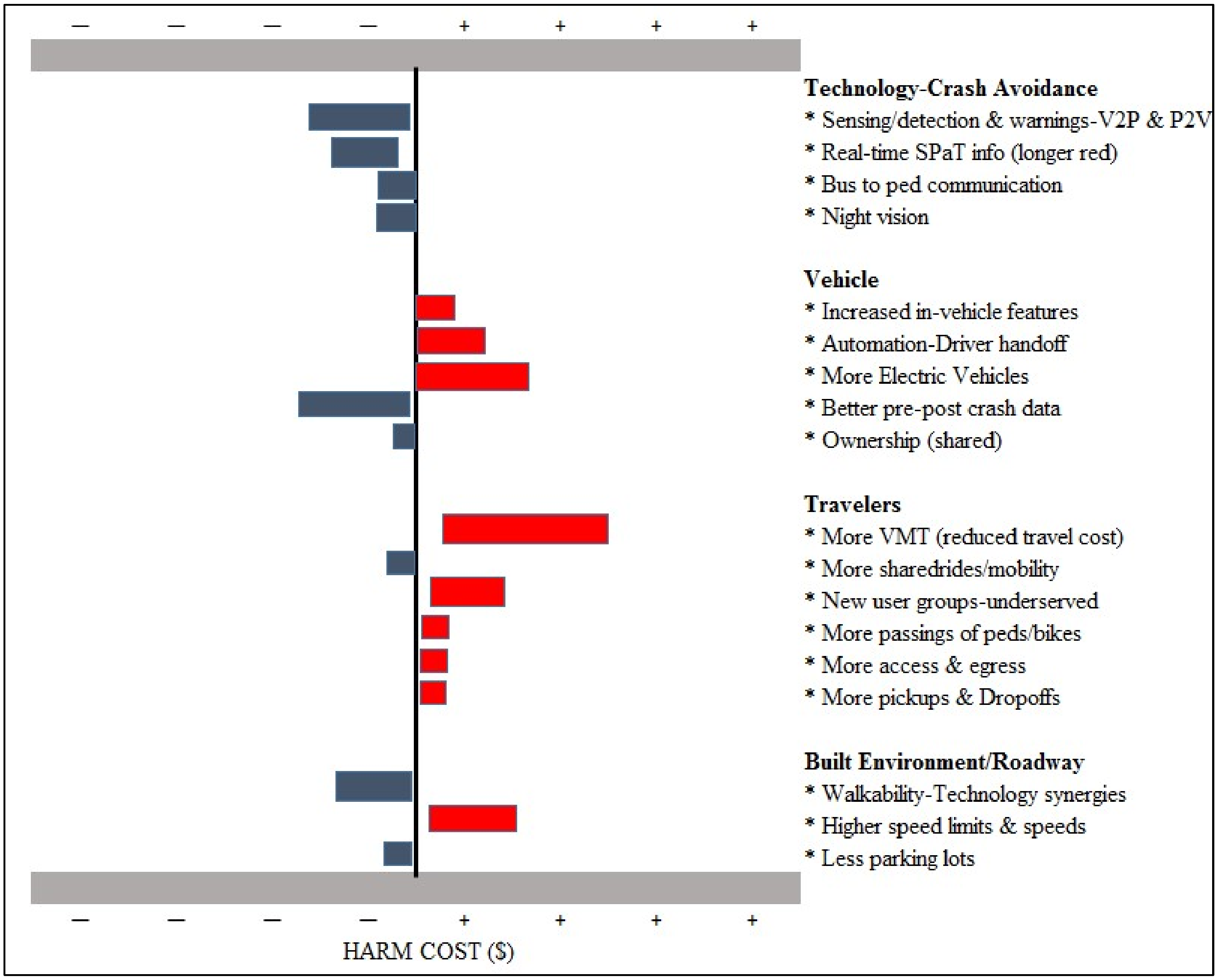

Figure 0-1. Framework for technology and mechanisms that can affect harm cost

Table 0-1. Results of Text Mining via Factor Analysis Procedure for Topics Extraction

Broader Category	Topic	Keywords	Eigen-value	% Variance	Frequency	Cases	% Cases
Vehicle-related	Automated Vehicles; Driving	Driving; Automation; Driver; Vehicle; Human; Vehicles; Task; Systems; Society of Automotive Engineers; Automotive; Control	6.15	1.85	5762	66	94.29
	Shared Automated Vehicles	AV; Shared Automated Vehicles; Scenarios; Adoption; Shared; Scenario; Penetration.	2.90	1.59	571	24	34.29
	Liability, Security, & Privacy	Liability; Privacy; Legal; Security; Law; Insurance	1.55	1.08	1674	59	84.29
	Moral & Ethics	Moral; Ethics; Ethical; Machine; Algorithms	1.54	1.01	1628	52	74.29
Energy Consumption	Truck Platooning & Fuel Consumption	Platoon; Trucks; Platooning Consumption; Energy; Emissions; Fuel	2.17	1.19	0	0	0.00
	Electric Power & Oil	Electric; Electric Vehicles; Power; Cars; Oil; Driverless	1.65	0.99	2974	63	90.00
Technology & Applications	Wireless Communications; Mobile Applications	Applications; Communications; Wireless; Mobile; Connected; Dedicated Short Range Communication; Smart	2.01	1.21	878	47	67.14
	Adaptive Cruise Control; Controls	Cruise; Adaptive; Adaptive Cruise Control; Control; Lane	1.89	1.41	1627	59	84.29
	Collision Avoidance Systems	Collision; Avoidance; Warning; Collisions	1.80	1.23	2868	63	90.00
Safety	Pedestrian Injuries; Bumper	Bumper; Injuries; Hood; Injury; Crashes; Pedestrian	2.27	1.24	1363	57	81.43
	Safety	Pedestrians; Users; Traffic; Drivers; Safety	1.38	1.06	467	26	0.371
Built-Environment	Built Environment & Physical Activity	Environment; Physical; Built; Activity; Walking; Cycling; Health; Active	2.46	1.25	11913	65	92.86
	African Americans, Submarkets	African; Americans; Town; City; Suburbs; Family Submarket; Sub-markets; Central Business District; Costar; Markets; Downtown; Office	1.42	0.93	896	48	68.57
	Parking Space, Shared	Space; Parking; Shared; Sharing; Ownership	1.35	0.93	490	47	67.14
Walking	Walkable Urban Metros	Metros; Walkups; Metro; Rental; Drivable; Urbanism; Walkup; Family; Walkable	2.65	1.60	1294	56	80.00
	Vibrant Suburban	Vibrant; Centers; Suburban; Center; Town	4.23	1.40	698	33	47.14
	Walking Trips	Trips; Trip; Mode; Transit; Travel; Vehicle Miles Travelled; Walking; Distance; Station	2.12	1.36	623	29	41.43
	Walkability Score	Score; Walk; Properties; Retail; Property; Office Neighborhood; Walkable; Neighborhoods; Walkability; Social; Capital; Residents	1.77	1.07	3427	62	0.886
	Exercise & Motivation	Intrinsic; Motivation; Motives; Exercise Med; Activity; Physical	1.52	0.89	423	26	37.14

Government Assistance	Government Programs	Low-Income Housing Tax Credit (LIHTC); Subsidized; Households; Voucher	1.73	1.29	1309	56	80.00
	Project-Based Rental Assistance; Housing Units	Project-Based Rental Assistance (PBRA); Units; Poverty; Tenants; Housing; Voucher; Rental	3.40	1.39	1749	45	64.29
Outreach	International Conferences	Conference; IEEE; International; Intelligent; Systems; Journal	1.76	1.03	872	38	0.543

Notes: % variance shows the percentage of variance explained by each topic. Note that the smaller the text phrases in each topic, the lower the percentage of variance explained, at least theoretically; Eigen-value are calculated and used in deciding how many "text phrases" to extract for a specific topic. In factor analysis, "the topic" with largest Eigen value has the most variance, and topics with Eigen-values greater than 1.00 are traditionally considered worth analyzing.

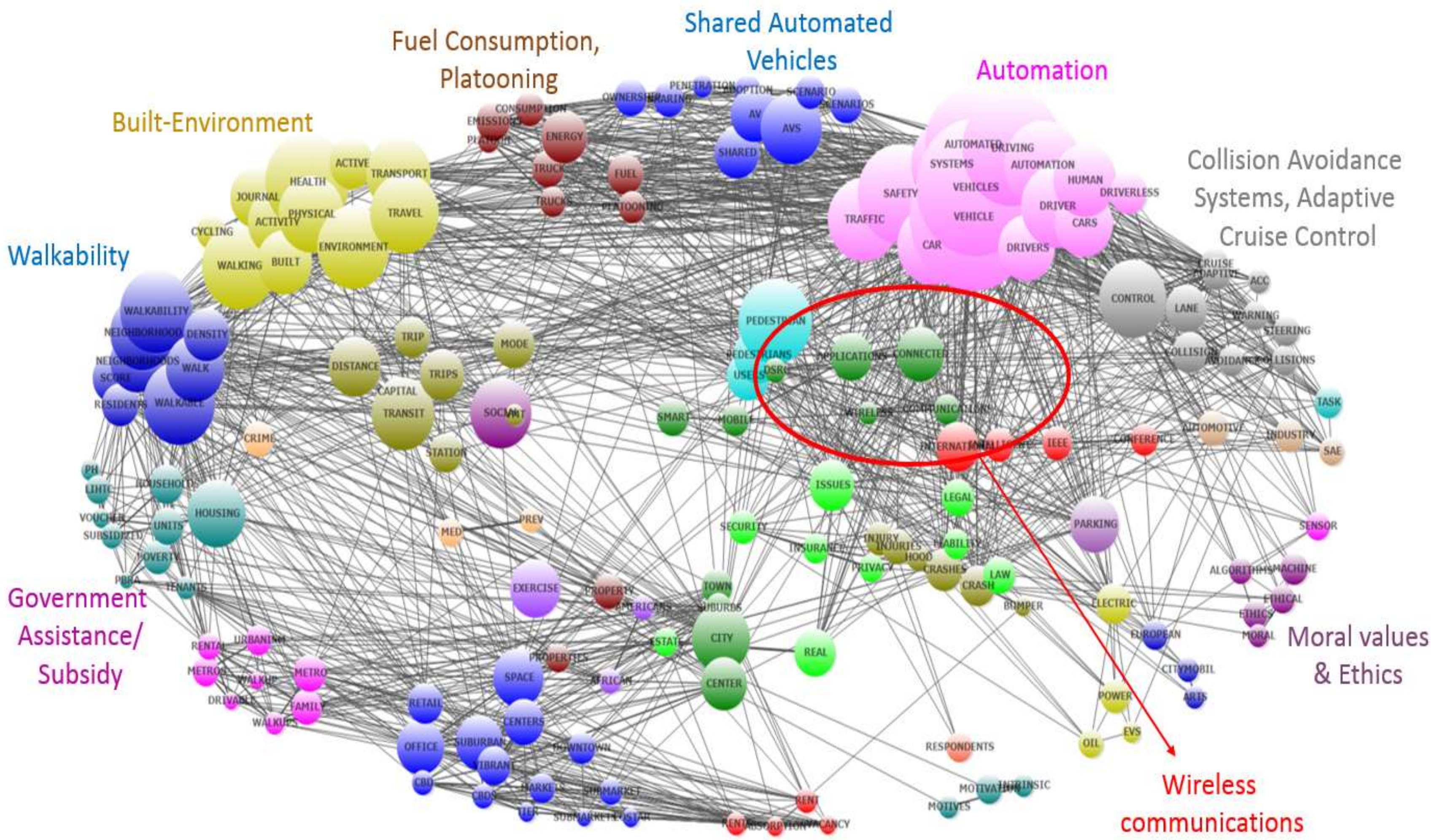

Figure 0-2. Co-Presence Structure of Words Across Key Topics

Findings

The review of CAVs and walkability was grounded in the broad call for more walkable communities, in part to address congestion and mobile-source pollution. Planners and health professionals increasingly view the physical environment as an intervention opportunity in the U.S., where over three-quarters of adults are obese or overweight (NCHS, 2017) and only 20% of adults meet physical activity guidelines (CDC, 2015). This review considered technology that may impact walkability and walking, and describes how walkability discourse is changing on the cusp of a transition to CAVs.

In practice and research, the term walkability applies to a variety of settings displaying a range of features, particularly relating to accessibility, connectivity, safety, aesthetics, and comfort. The walkability literature deals largely with networks (paths, sidewalks, crossings), connectivity (connections, directness), security, density, and access. Tools such as inventories, checklists and audits are used by planners, engineers, advocates, consultants, and citizens to assess whether an environment promotes efficient, safe, comfortable, and pleasant walking. Beyond the economic, public health and equity arguments, walkability has interconnections with engineering and planning, as well as also economics, housing and design.

An array of emerging technologies that suffuse the travel landscape range from personal devices to retrieve information and support decision-making, to IT systems like incident management, to in-vehicle technology—from simple driver assists through full automation. Smart travel technology may reduce cost, time and emissions; it also may introduce additional risks—for both drivers and walkers—of distracted travelers (Siuhi and Mwakalonge, 2016). While increased safety is a primary claim of CAV advocates, understudied potential negative safety impacts merit scrutiny (Cavoli et al., 2017).

Travel safety is deeply personal—but increasingly impacted by forces beyond the control of the individual traveler. That the looming CAV era will challenge pedestrian safety is nearly certain—but murky in the details. Moreover, the rising profile of walkability—in research and practice, as well as in public discourse—exists in apparent tension with growing acceptance and penetration of CAVs.

The CAV era may rewrite established relationships among congestion, VMT, travel time, and auto ownership, changing fuel consumption and emissions, and uncertain impacts on land use, safety, health and equity. The technical challenges of designing, operating and controlling CAV systems raise human factor and socioeconomic questions that demand attention if CAVs are to deliver the safety, equity, and efficiency gains they promise (Schwartz et al., 2013).

With several decades of research and practice in walkable environments and active travel yielding evidence of effective design, the paradigm of walkable, livable, efficient and equitable urban form faces uncertain threats from the CAV transition, with thorny questions about the walking/CAV relationship. Questions include:

Vehicles—owned, rented, shared

If vehicle ownership fades in favor of access, will shared mobility delivered through CAVs make walkability less or more valued? Will stratified ownership models (private, shared, mixed) change propensity to walk?

Built environment

How will CAV infrastructure impact pedestrian comfort and safety? The promised space-efficiency of CAV fleets may alter parking demand and amount of driving *and* walking. Excess infrastructure could be reclaimed for other uses, but who would design, site, and control that process? Will the advent of CAVs dampen, reverse, or change the trend toward compact active walkable cities?

Trip-making

How might CAVs change the mix and character of trips for utilitarian and recreational purposes? Will general and special (underserved) populations increase walking to access CAVs—or demand door-to-door service that dampens walking?

Safety

What safety gains do CAVs offer—for drivers and pedestrians? Safety claims rest on deep penetration of IT to support communications among vehicles, infrastructure and non-drivers. Will walkers be required to be connected to a network? Will walking become criminalized in some environments? What data should be collected—by and from whom, and for whose consumption and action? How have causes of crashes changed over time—and what role do distraction and technology failure play?

Engineering

The CAV transition requires a foundation of sophisticated technology. How will it account for human behavior, and support safe convenient mobility and equitable accessibility to travelers of multiple modes? How might expectations for communication among vehicles, environment and pedestrians affect walkability?

Conclusion

Many planning, engineering, and public health professionals value walkability that promotes safe mobility. While evidence shows that walkability increases walking, it is not a complete response to safety threats, congestion, physical inactivity, and other economic, environmental and social problems in highly motorized societies. Local context and shared goals should guide planning, with solutions found in technology, markets, and behavior. The literature for walkability and walking is necessarily broad, given the complex interactions between human behavior and richly diverse environments. Future research should continue to build links among engineering, planning, policy, public health, and other fields, and account for the emergence and penetration of CAVs. Open questions include how human-driven vehicles will interact with AVs; how CAV penetration will influence walking behavior; and how CAVs will respond to pedestrians' changing behavior as they challenge CAVs in dynamic environments.

Given the high cost of mobility—in dollars as well as lives and health, the nation should prioritize safety and accessibility for all modes, with strategically selected technology. In particular, research is needed on new connected and automated technologies that can avoid crashes and meet the mobility needs of diverse users and stakeholders. Crosscutting safety and technology-oriented research, development and deployment efforts should encompass CAVs and infrastructure, and safety technologies and strategies to promote safe and smart communities. A comprehensive research agenda should use partnerships among academia, public sector agencies, and leaders in the private sector, to identify innovative life-saving and community-strengthening models for safe and walkable environments.

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Automated vehicles and pedestrian safety: exploring the promise and limits of pedestrian detection

Authors

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This chapter presents an extended abstract of CSCRS-sponsored research, based on a presentation titled *Limitations in detection technologies for automated driving systems and implications for pedestrian safety* presented at the 97th Annual Meeting of Transportation Research Board, and on a peer-reviewed paper published in the American Journal of Preventive Medicine. The paper is published as open-access and is available here: https://www.sciencedirect.com/science/article/pii/S0749379718320932.

Abstract

U.S. pedestrian fatalities have risen in recent years, even as vehicles are equipped with increasingly sophisticated safety and crash avoidance technology. Many assert that advances in automated vehicle (AV) technology can reduce fatalities, including pedestrian fatalities, by eliminating the estimated 94 percent of traffic fatalities caused by human error. This paper explores this assertion by analyzing nearly 5,000 pedestrian fatalities recorded in 2015 in the Fatality Analysis Reporting System (FARS) under a hypothetical scenario in which the involved vehicles were replaced with automated vehicles equipped with state-of-the-art detection technology.

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Introduction

Many proponents of self-driving vehicles laud the safety potential of such vehicles, claiming that replacing fallible human drivers with autonomous driving system will lead to substantial reductions in traffic fatalities, including pedestrian fatalities. With pedestrian fatalities on the rise in recent years, the promise of dramatic improvements in pedestrian safety is a tantalizing aspect of automation (McCauley, 2017; Thune et al., 2017). However, some experts have pointed to shortcomings in current technology for pedestrian detection as an unexamined weak link in autonomous driving systems with respect to pedestrian safety (Barnard, 2016; Dollar et al., 2012; Zhang et al., 2017). In this paper, we evaluate state-of-the-art pedestrian detection technology, virtually testing whether or not the technology would have been capable of detecting pedestrians in real life crashes. The result of the analysis is an estimated maximum percentage of transportation-related pedestrian fatalities in 2015 that potentially could have been avoided had the striking motor vehicle been replaced with a fully-automated vehicle equipped with state-of-the-art pedestrian detection technology.

Methods

We use data from the Fatality Analysis Reporting System (FARS) for 2015. This publicly-available dataset is administered by the National Highway Traffic Safety Administration and provides detailed information about every reported vehicle-related fatality in the United States. In our analysis, we crosscheck the conditions of each fatality with known functional limitations of each of the three most common types of pedestrian detection technology, visible light cameras, Lidar, and radar. Based on reports from manufacturers and independent laboratories, even the most advanced versions of each of these technologies have limitations that render them ineffective under certain circumstances. Specifically, cameras function poorly in low-light situations and during adverse weather conditions such as heavy rain, snow, or fog (Barnard, 2016; Sandt and Owens, 2017). Lidar also functions poorly in adverse weather, and often fails to detect objects at very close range. Radar has difficulty detecting small or partially-occluded pedestrians and cannot detect stationary objects (Manston, 2011; Turnbull et al., 2017). Crashes that take place under these conditions are considered outside of the respective technology's functional range.

We estimate the maximum potentially pedestrian fatalities that could have been avoided by fully-autonomous vehicles equipped with the three technologies individually and in combination via a fairly straightforward process in which we apply increasingly restrictive filters to the data. All filters were created using data included in the FARS dataset.

First, we remove all crashes that do not directly result in a pedestrian fatality as part of the crash's first harmful event, as well as those pedestrian fatalities that occurred during non-transportation-related crashes, such as domestic disputes, disabled or unoccupied vehicles, and other "unusual circumstances" as categorized by the FARS dataset. Second, we filter out fatalities resulting from crash situations that are likely to be unavoidable, no matter how advanced the detection or self-driving technology. We include in this category fatalities associated with crashes occurring on impaired or slick road surfaces and those due to obscured pedestrians darting out into traffic ("dart-outs"). In these sorts of situations, appropriate evasive action is assumed to be beyond vehicles' physical limits. Finally, we remove fatalities arising from conditions unlikely to be present with autonomously operated vehicles: distracted/impaired drivers and police pursuits. After filtering out the unavoidable and obsolete fatalities, all remaining fatalities should—in theory—be able to be addressed through autonomous vehicle technology. These are the fatalities considered candidates for avoidance.

The next step is to identify the crash conditions under which each detection technology is expected to function effectively (based on the known limitations described above) and create filters that allow us to distinguish between fatalities resulting from crashes occurring within each technology's functional range and those resulting from crashes occurring outside those conditions. We apply filters for each technology independently, as well as for camera + Lidar and camera + Lidar + radar combinations, to all candidate fatalities. The fatalities caught by each technology's or technology combinations' filters are presumed to be detectable, and thus preventable. Fatalities not caught by a technology's or technology combination's filter are undetected (they occurred outside the technology's or technology combination's functional range, so the technology was incapable of detecting the pedestrian and sending appropriate signals to the vehicle to take evasive action) and are therefore unavoidable.

Using information provided in the FARS data, we create filters for low-light conditions (dusk-to-dawn), adverse weather (fog or precipitation), wet or reflective road surfaces, pedestrians becoming visible only just before impact (as is often the case when vehicles are emerging from driveways), and stationary pedestrians (such as those waiting to enter an intersection). These filters are used to determine effective limits for each detection technology evaluated.

In theory, all fatalities that make it through a technology's effective limits filter are detectable, making them potentially avoidable by an ideal, fully-autonomous driving system. Note that, as we are only evaluating pedestrian detection technology, and not follow-on crash avoidance technology, the fatalities making it through these filters represent the maximum number of fatalities that could be avoided through the use of state-of-the-art pedestrian detection technology.

Finally, we divide the number of each detection technology's potential successes (i.e., candidate fatalities falling within the technology's effective limits) by the total number of transportation-related pedestrian fatalities. This gives us a score representing the maximum percentage of total relevant fatalities potentially avoided by each technology or combination of technologies.

We further break fatalities down according to other crash conditions of interest, such as whether the crash occurred in urban or rural settings, at intersections or crosswalks (vs. neither), or on limited access freeways or unrestricted surface streets, and according to whether the driver was distracted or impaired and whether the victim was a minor or an adult.

Findings

FARS data include 5,261 recorded pedestrian fatalities in 2015. Of those, 4,241 were transportation-relevant and had complete data on the variables used to create our filters. After filtering out crashes that were either unavoidable or the result of conditions unlikely to be exist when vehicles are operated autonomously, we were left with 3,386 theoretically preventable pedestrian fatalities.

Overall, 77% of candidate pedestrian fatalities occurred between dusk and dawn. Adverse weather was a factor in 10% of pedestrian fatalities; reflective surfaces in 14%. Just under 10% of pedestrian fatalities involved 'close-range' pedestrians, and in 6% of candidate fatalities, pedestrians were stationary.

When we examine fatalities according to other crash conditions, we find that fatality rates for various conditions are similar to overall rates, with the exception of fatalities involving minors. Pedestrians under the age of 18 were killed much less frequently in the dusk-to-dawn hours, during adverse weather, and when road surfaces were slick than were adults. However, minors were over-represented among close-range fatalities—approximately one quarter of minors killed were killed in close-range situations.

Unsurprisingly, visible light cameras perform poorly overall and for nearly all specific crash conditions: fewer than 30% of transportation-relevant fatalities could potentially have been avoided if the striking vehicles had been replaced by fully autonomous versions equipped with 360-degree state-of-the-art optical camera pedestrian detection technology. Lidar and the camera + Lidar combination offer dramatic improvement over cameras, with between 70% and 89% of fatalities potentially avoided for all conditions except fatalities involving minors (in which fatalities avoided for Lidar alone drops down to the 50%-69% range). The camera + Lidar + radar combination is by far the most effective, with 90% or more fatalities potentially avoided in all cases.

Conclusion

Our study finds that the proportion of pedestrian fatalities that are theoretically avoidable varies widely among the detection technologies examined. At first glance, radar appears to offer the widest effective range and thus the greatest potential to detect—and theoretically then avoid—pedestrians before a fatal crash. However, radar's inability to detect and identify stationary pedestrians and its struggles with small pedestrians, impose a hard ceiling on the technology's ultimate usefulness in pedestrian detection.

Of the three technologies examined, Lidar appears to have the greatest potential for improvement relative to the other technologies. However, even today's state-of-the-art Lidar systems are prohibitively expensive—approximately $85,000 per vehicle—calling into question the feasibility of deployment of the most advanced Lidar systems on mass-production vehicles (Simonite, 2017). Tech experts do predict a decrease in the cost of Lidar as the technology improves, though it's unknown whether the decrease will be either large enough or soon enough for Lidar-based pedestrian detection systems to be considered viable options for a consumer product (Barnard, 2016). In the meantime, regulators would do well to explore additional strategies, independent of vehicle automation, to address the rising rate of pedestrian fatalities.

Our analyses rely on rather generous assumptions about the performance of autonomous vehicles. Testing of these assumptions is beyond the scope of the current study; future research will allow for a more critical examination of these assumptions and should enable more realistic assessments of the potential for autonomous driving systems to reduce pedestrian fatalities.

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Analysis of Crashes Involving Pedestrians across the United States: Implications for Connected and Automated Vehicles

Authors

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This chapter presents an extended abstract of CSCRS-sponsored research that was presented at the 97th Annual Meeting of Transportation Research Board, National Academies, Washington, D.C., 2018.

This study explored how pedestrians can be protected as connected and automated vehicles (CAVs) diffuse through the transportation system. Vehicle-to-pedestrian (V2P) connectivity has the potential to enhance safety by reducing driver and pedestrian errors that result in crashes. To understand the nature of errors contributing to severe crashes, this study analyzes both driver and pedestrian behaviors preceding single vehicle-pedestrian fatal crashes, using county-level data for the U.S. for the period 2013 - 2015 (N= 12,217). Poisson regression and Geographically Weighted Poisson Regression models were estimated with data from the Fatality Analysis Reporting System (FARS)—a database developed by the National Center for Statistics and Analysis at the National Highway Traffic Safety Administration (NHTSA). The analytical results provide insights into the potential of technology to improve pedestrian safety.

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Introduction

The importance of pedestrian safety is reflected in policy and planning, academic research and civil society. Federal and state transportation agencies devote many dollars and staff hours to research and programming, manifest in funding, technical reports, research digests and circulars, and implemented policy.

Single vehicle-pedestrian (SVP) crashes cause a substantial share of U.S. traffic injuries and fatalities, as well as property damage valued in the billions annually (Trottenberg and Rivkin, 2013). The NHTSA (2016) reports that SVP fatal crashes represented 16% (~14,000) of all fatal crashes in the U.S. from 2013 to 2015. A key benefit expected from CAVs is fewer collisions due to human error. This study probed how errors committed by drivers and pedestrians contribute to fatal vehicle-pedestrian crashes. Pedestrians may be expected to continue behaviors like darting into traffic or jaywalking, which CAVs will need to accommodate, with technology that may aid drivers and pedestrians.

This study used national data to explore types of pedestrian errors that CAVs must anticipate, along with driver errors that may be change when driving becomes automated. Counties with high vehicle-pedestrian crash risks may provide early indications of whether CAVs can prevent severe pedestrian-involved crashes, for example, with V2P communication in urban counties with dense interactions between pedestrians and vehicles, e.g., in school zones and downtowns.

Although pre-crash driver behaviors, such as speeding and alcohol consumption, have long been recognized as key contributing factors in roadway crashes, the pre-crash behaviors of pedestrians remain underexplored. This study investigated the correlations of pre-crash behaviors of both drivers and pedestrians with SVP fatal crash frequency, aggregated at the county level, to understand the spatial effects of both driver and pedestrian behaviors on SVP fatal crash frequency. Objectives were to: 1) investigate the spatial distribution of SVP fatal crashes across the U.S.; 2) examine the effects of both driver and pedestrian pre-crash behavior on SVP fatal crash frequency; and 3) explore the spatial correlates of crash frequency with explanatory variables.

Decades of research and advocacy on active living and travel for personal and community health have seen a groundswell of public interest in walkable communities (Buehler et al., 2016; Leinberger and Rodriguez, 2016; ULI, 2015), even in the face of congestion and danger to pedestrians from motorized vehicles. Many communities have acted on public demand and guidance from health and transportation professionals to encourage walking with programming, policies and, sometimes, infrastructure. This trend toward walkability is promoted further by growing evidence that walkability is good not only for safety, public health and sociability, but also for economic development and property values (Diao and Ferreira, 2010; Hack, 2013; Pivo and Fisher, 2011).

Previous studies correlating vehicle-pedestrian crashes with various factors, including driver, vehicle and roadway environments, have been limited in their spatial analysis, especially in the context of understanding pre-crash behaviors. This study focused on understanding which behaviors—of both drivers and pedestrians—correlate with higher incidence of SVP fatal crashes. This study used geo-referenced data to investigate the various correlates of SVP crash frequency and related factors, especially pre-crash behaviors, across regions, estimating a local spatial model for crash frequency. Ultimately the research may inform effective CAV policies to reduce risk to travelers and increase walking activity. The transportation landscape is changing, including the penetration of CAVs. Professional and public discourse has long since passed ‘whether’ and moved on to ‘how’ a CAV transition will unfold (Glancy, 2013; Turnbull et al, 2017; Glus et al., 2017) and how it might impact pedestrians across geographic regions and socio-demographic groups.

Methods

A unique database drew data from two major sources: 1) crash details extracted from FARS, and 2) social-demographic data from the U.S. Census to provide context.

Data

Crash data

Data were pulled together for the period of 2013-2015 for events across the U.S. from FARS—a database containing hundreds of variables related to crashes in different files. Four files from the FARS database were selected for analysis: 1) accident characteristics file, e.g., location, roadway attributes, crash type, county, state, latitude/longitude; 2) file with characteristics of vehicles involved in accidents, e.g., vehicle type and driver pre-crash behaviors; 3) a file related to non-motorist action or circumstance that may have contributed to the crash; and 4) a file containing details about all persons involved in the crash, e.g., injury severity, age, and seating position.

The 92,424 fatal crashes contained in the FARS database for 2013 - 2015 involved 138,974 vehicles and 228,629 persons (16,302 pedestrians and 212,217 vehicle occupants). To analyze direct effects on crash frequency of pre-crash behaviors, this study extracted only SVP fatal crashes (n = 12,217).

Contextual data

Because contextual factors may be contributing factors in crashes (Garver and Lineau, 1996; LcScala et al., 2000; Huang et al., 2010), this study linked select Census variables with crash data to yield insights into the context in which crashes occur. The dataset included county-level population density, education, and median household income.

Models

Visualizing crashes

The study used the spatial visualization tool kernel density estimation (Anderson, 2009) to identify crash hotspots and critical counties, and create a density map of spatial distribution of SVP fatal crashes across the U.S.

Model structure

This study investigated the correlates of single vehicle-pedestrian crash frequency at an aggregated county level. The magnitude and signs of model coefficients can vary across regions; that is, statistically significant correlations in one part of a region might not hold in other parts. Therefore, the study employed a global Poisson regression model to capture the spatial heterogeneity in correlations between crash frequency and explanatory variables.

Spatial modeling

To overcome the limitations of a global Poisson regression model, a local spatial model called Geographically Weighted Poisson Regression (GWPR) was estimated. A GWPR estimates the spatial variations in correlations between response and explanatory variables by relaxing the assumption of a global Poisson regression model that the estimated magnitudes and signs of model coefficients are stationary; that is, the estimated coefficients are no longer fixed but vary across regions in the spatial model.

Inverse distance weighted interpolation IDWI

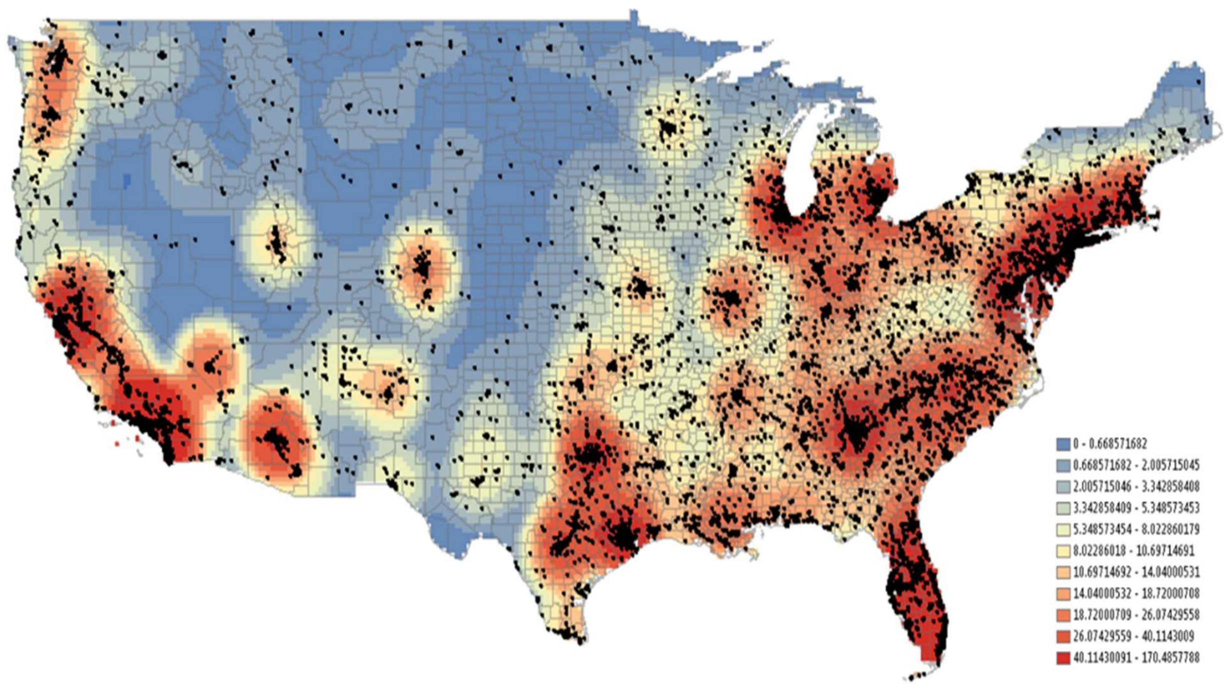
Estimated coefficients from the local GWPR model were used to visualize the spatial variation of coefficients in both signs and magnitudes. A mathematical algorithm called Inverse Distance Weighted Interpolation (IDWI, Bartier and Keller, 1996) generated a smooth continuous coefficient surface across the entire U.S. The IDWI algorithm assumes that each measured location has a local influence that diminishes with distance, and weights locations closer to prediction locations more than those far away.

Findings

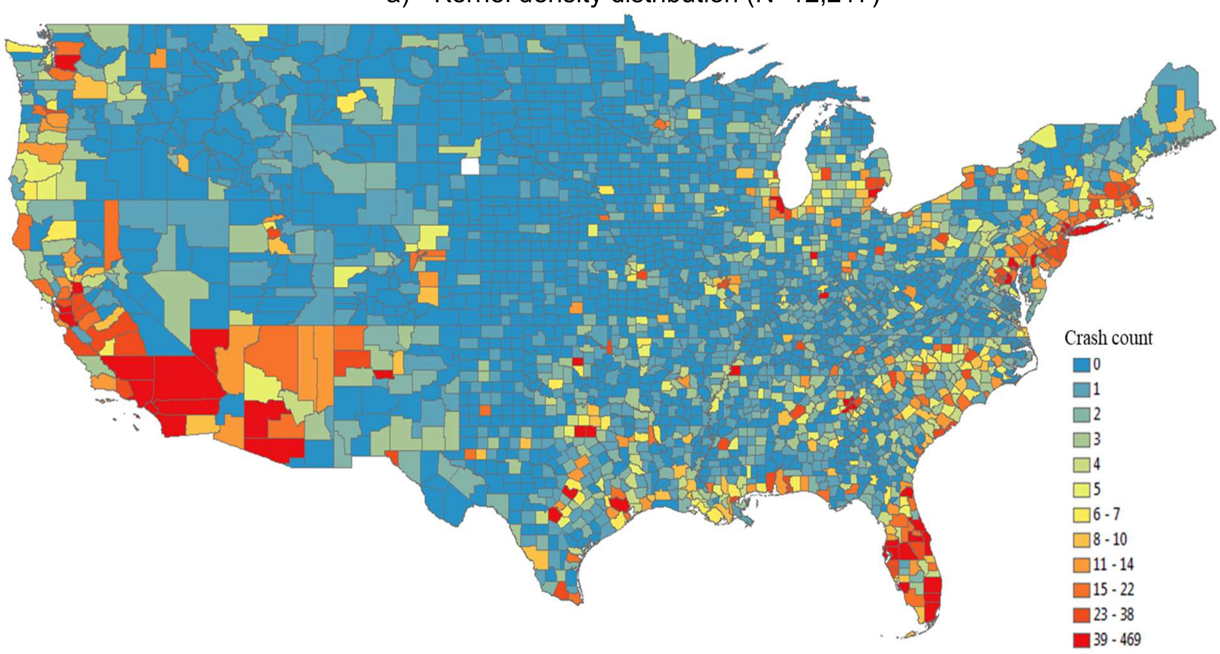
Figure 0-1 shows the disaggregated and aggregated distribution of SVP fatal crashes in the U.S. in 2013-2015. In Figure 0-1(a), each point represents a SVP fatal crash, while blue and red colors indicate low- and high-density areas, respectively. Figure 0-1(b) shows the aggregated county-level crash distribution. The highest crash densities are in mega-regions such as California, Great Lakes (Wisconsin, Michigan, Ohio, Illinois, Indiana), the New York—Washington corridor, the Southeastern Crescent (Georgia and the Carolinas) and Florida. These crash densities are likely related to the surrounding population and economic activity, with more transportation infrastructure, services and activities, and high vehicle/

pedestrian exposure. These counties with high fatal vehicle-pedestrian crash risks can serve as testbeds for V2P communication technologies that may reduce such crashes.

The FARS records provide pre-crash behaviors of both drivers and pedestrians in SVP crashes. Of 24,434 drivers and pedestrians involved in 12,217 fatal crashes, nearly 99.9% (12,203) had a pedestrian fatality, while only 0.3% (33) left a driver dead.



a) Kernel density distribution (N=12,217)



b) Distribution of crash frequency at aggregated county level (N=3,143)

Figure 0-1. Kernel density distribution and aggregated county level crash frequency of all single vehicle-pedestrian fatal crashes, United States, 2013-2015

Table 0-1 shows the descriptive statistics of aggregated county-level SVP fatal crashes across the nation during the period 2013-2015. The 2015 NHTSA summary (NHTSA, 2016) reports the top pedestrian behavioral factors in fatal crashes are failure to yield right-of-way (1,475, or 27.4%), improper crossing of roadway or intersection (893, or 16.6%) and invisibility (800, or 14.9%).

Table 0-1. Descriptive statistics of county-level single vehicle-pedestrian crashes (N=3,143)

Variables		N	Mean	Std Dev	Min	Max
Crash frequency / rate	Crash frequency	3143	3.887	15.604	0	469
	Crash rate by county population (/1000)	3143	0.030	0.053	0	1.069
	Crash rate by county population density	3143	0.040	0.209	0	5
Pedestrian pre-crash behavior	Dart out/ Dash	3143	0.353	1.415	0	30
	Failure to obey traffics signs	3143	0.109	0.807	0	23
	In roadway improperly (standing, lying, walking)	3143	0.463	1.494	0	23
	Inattention (talking, eating)	3143	0.046	0.291	0	8
	Improper crossing (jaywalking)	3143	0.432	2.809	0	104
	Invisibility (dark clothing, no light)	3143	0.396	1.192	0	16
Driver pre-crash behavior	Reckless	3143	0.246	1.067	0	21
	Impairment	3143	0.083	0.483	0	11
	Rules of turning/yield	3143	0.041	0.361	0	14
	License/registration violation	3143	0.103	0.669	0	17
County attributes	% of high school education (%)	3143	84.554	6.912	45	99
	Median household income (/1000 $)	3143	45.937	11.922	19.986	122.238
	% of below the poverty level (%)	3143	16.679	6.498	0.9	53.2
	Population per square mile	3143	259.322	1724.160	0	69467.5

Table 0-2 shows modeling results. The global Poisson model captures the average correlate of crash frequency, while the local GWPR model captures the variations in correlates of crash frequency. Most variables showed statistically significant correlations with the response variables (5% level); the model is statistically significant overall, with high goodness of fit. Positive signs indicate pre-crash behaviors that correlate with increasing frequency SVP crashes.

Global Poisson model

The global Poisson model found most variables to be significant, including pedestrians who dash/dart out, use the roadway improperly, are inattentive, and not visible, as well as vehicle drivers who are reckless, impaired or unlicensed/unregistered. High education and income also have positive coefficients.

Table 0-2. Global Poisson and local WGPR models for SVP fatal crashes

Variables (Dependent = Crash count)		Poisson model β	Poisson model P-value	GWPR β min	GWPR β max	GWPR Lwr Quartile	GWPR Upr Quartile	GWPR Upr-Lwr > 2SE
Pedestrian pre-crash behavior	Dart out/ Dash	0.138	0.000***	0.007	0.399	0.169	0.253	TRUE
	Failure to obey traffics signs	-0.166	0.000***	-2.356	0.174	-0.953	-0.099	TRUE
	In roadway improperly (standing, lying, walking)	0.110	0.000***	0.089	0.657	0.198	0.421	TRUE
	Inattention (talking, eating)	0.048	0.000***	-	-	-	-	-
	Improper crossing (jaywalking)	-0.034	0.000***	-	-	-	-	-
	Invisibility (dark clothing, no light)	0.159	0.000***	-	-	-	-	-
Driver pre-crash behavior	Reckless	0.136	0.000***	-	-	-	-	-
	Impairment	0.001	0.859***	-	-	-	-	-
	Rules of turning/yield	-0.245	0.000***	-	-	-	-	-
	License/registration violation	0.075	0.000***	-	-	-	-	-
County attributes	% of high school education (%)	0.016	0.000***	-	-	-	-	-
	Median household income (/1000 $)	0.049	0.000***	-	-	-	-	-
	% of below the poverty level (%)	0.082	0.000***	-	-	-	-	-
	Population per square mile	0.0001	0.000***	-	-	-	-	-
	Constant	-4.389	0.000***	-0.910	1.517	0.236	0.898	TRUE
Statistic summary	Sample size	3143		Best bandwidth size: 166				
	Log Likelihood at β	-9420.9141						
	Log Likelihood at 0	-922580						
	Adjusted R^2	0.6195		Percent deviance explained: 0.673				
	Prob. > χ^2	0.000						
	AICc	-		14621.391				

Notes:

1. True means the significance of spatial variance of the coefficient.

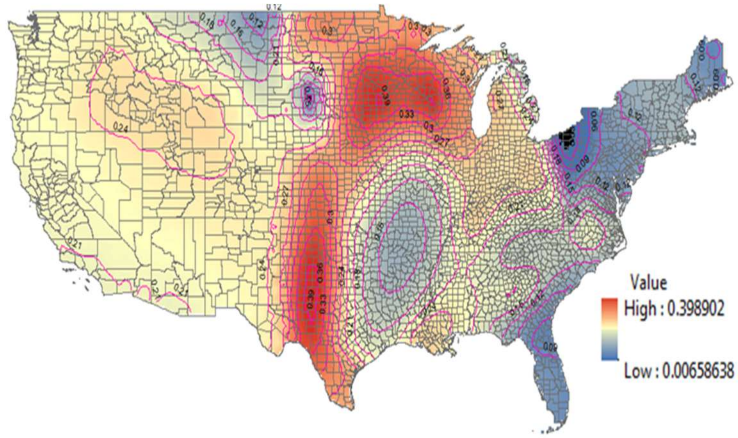
2. Best bandwidth size is the number of subsamples used in each kernel; 166 local closest surrounding cases were used as the subsample for these regressions.

3. *** —statistically significant at 1% level; **—statistically significant at 5% level

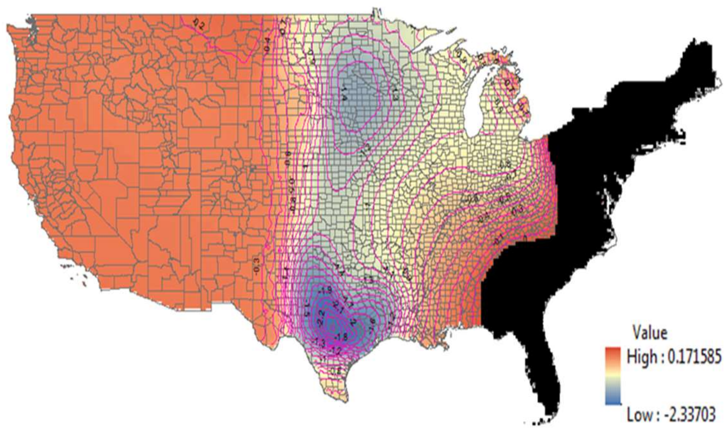
4. Adjusted R^2 refers to 1 – (Log Likelihood at β/Log Likelihood at 0)

Local GWPR model

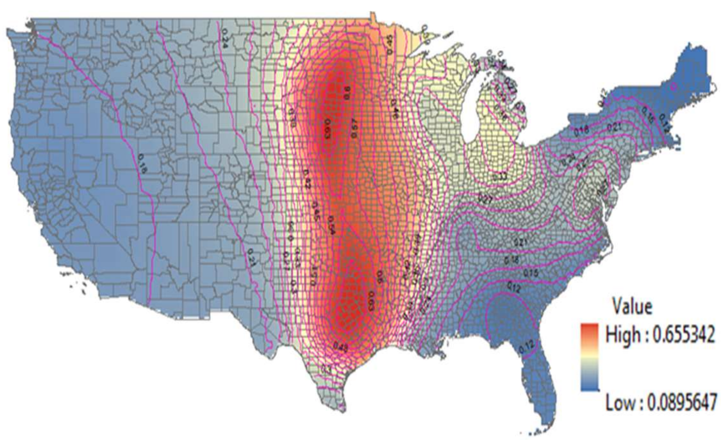
Figure 0-2 shows the spatial distribution of local parameter estimates for high-risk behaviors, including (a) dash/dart out, (b) failure to obey traffic signs, and (c) improper use of the roadway.



a) Dash/Dart out



b) Failure to obey traffics signs



c) In roadway improperly (standing, lying, walking)

Figure 0-2. Local parameter estimates for single vehicle-pedestrian fatal crashes

Note: Black areas indicate the local parameter are not statistically significant at 95% level in that region.

The local GWPR model suggests that the crash frequency of SVP fatal crashes is more likely to be high in the West (e.g., California) and Southeast (e.g., Mississippi), but more low in the Southwest (e.g., Texas) and Midwest. The results highlight how the global Poisson model can hide some variations in both sign and magnitude of coefficients. More dash/dart out behaviors in pedestrians are associated with higher crash frequency in the West and Southeast (e.g., Florida), while crash frequency is much higher in Texas. Improper in-roadway behavior shows similar patterns, associated with higher frequency in the central U.S. These results may inform targeted V2P applications for local conditions.

Limitations of this study include constrained explanatory power because of the few variables included in the model (no measures for roads or traffic). This study used the centroid of each county as the location, which might impact accuracy. In addition, police reports may be incomplete, inaccurate, or subjective. Finally, this study analyzed only the crash frequency of SVP crashes containing at least one fatality; future analysis should cover the entire spectrum of injury.

Conclusions

This study into the pre-crash behavior of drivers and pedestrians in SVP fatal crashes is unique in its geographic scope, quantifying correlations of pre-crash behaviors on crash frequency across regions in the U.S. for vulnerable road users. It applied Geographically Weighted Poisson Regression to address the spatial variations in correlations and the count nature of crash data.

This study revealed pedestrian behaviors that are significantly associated with high fatal crash frequencies, consistent with NHTSA results. Key findings include:

- For dart/dash out behavior and improper roadway use, the Midwest and Southwest are associated with higher crash frequency, and the Northeast with lower.
- Failure to obey traffic signs shows the opposite pattern: much lower estimated coefficients in the Midwest and Southwest regions, higher in Western regions.

These results may be useful for guiding vehicle-pedestrian fatal crash improvement plans. The local GWPR model coefficient map may support safety in specific counties with a higher frequency of such crashes. For example, Western regions where failure to obey traffic signs is associated with higher crash frequency may benefit from appropriate traffic sign enforcement countermeasures or a V2P field tests.

Future research should consider how technology for CAVs in urban settings will deal with unpredictable pedestrian behaviors, potentially by 1) automatically braking to avoid striking pedestrians, 2) predicting trajectories and recognizing pedestrians in the road, or 3) providing early warnings to pedestrians about dangerous behaviors.

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Exploring injury severity correlates of vulnerable roadway users involved crashes

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This chapter presents an extended abstract of CSCRS-sponsored research that will be submitted for presentation and publication.

Vehicle-to-pedestrian (V2P) applications will enable vulnerable roadway user (VRU) safety, mobility, and environmental advancements that current technologies are unable to provide. The research described here aimed to provide insights on reducing injury severities of pedestrian- and bicyclist-involved crashes and enhancing existing V2P applications to address the special safety needs and challenges of these VRUs. Crash data from the Fatality Analysis Reporting System include a measure of injury severity, time-to-death, which served as the independent variable in logit models to analyze the factors contributing to the injury severity of VRU-involved crashes. Ordered logit and multinomial logit models were compared for goodness-of-fit and predictive power.

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Introduction

Traffic crashes on U.S. roadways claimed 35,092 lives in 2015, a 7.2% increase from 32,744 in 2014—the largest percentage increase in nearly 50 years. From 2014 to 2015, pedestrian and bicyclist fatalities increased by 466 (9.5%) and 89 (a 12.2%), respectively, and stand at their highest numbers since 1996 and 1995. The number of pedestrians injured in crashes increased by 5,000 in 2015, a 7.7% increase over 2014.

Over the past decade—but before the very recent spike in deaths, safety programs promoting seat belt use and discouraging impaired driving improved traffic safety and substantially reduced vehicle occupant fatalities. Vehicle technologies such as air bags and electronic stability control also contributed to decreasing vehicle occupant fatalities. As occupant fatalities dropped, the share of non-motorist fatalities increased from 13 percent of total deaths in 2006 to 18 percent in 2015, when 6,317 non-driver VRUs (5,376 pedestrians, 817 bicyclists, and 124 other non-vehicle occupants) were killed in crashes, an average of nearly 18 every day (NHTSA Traffic Safety Facts). Comprehensive research is needed to understand and address the special safety needs and challenges of these VRUs.

Enabled by emerging vehicle, sensing, and control technologies, Smart City research initiatives, big data analytics, and recent advances in driving experiments, traffic safety research will greatly enhance our scientific understanding of the new interactions and phenomena between conventional, connected, and automated vehicles. Connected and automated vehicles (CAVs) that can sense the environment and communicate with other vehicles, infrastructure, and our personal mobile devices may reduce unimpaired driving-related crashes by 80 percent. Currently, the connected vehicle environment includes three major information-sharing relationships: vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P). Some of the anticipated V2P applications, e.g., pedestrian detection systems, mobile accessible pedestrian signal system, and pedestrian-in-signalized-crosswalk warning, will elevate pedestrian safety and mobility. The National Highway Traffic Safety Administration (NHTSA) estimated that these V2P communication technologies could potentially address up to 46 percent of pedestrian-involved crashes.

While vehicle-to-VRU crashes are less common in the U.S. than vehicle-to-vehicle crashes, they often result in severe injuries to non-motorists even at low vehicle speeds. The literature on injury severity of VRU-involved crashes addresses personal factors such as age and gender, behavior, traffic, and environment.

Past studies analyzing injury severity of vehicle-to-VRU crashes have generally focused on characteristics of VRU, vehicle, driver, roadway geometry, and traffic, in order to develop more effective countermeasures and improve VRU safety. Because behaviors such as drug/alcohol impairment or crossing against a light contribute to more than half of the deaths in VRU-involved crashes, recent studies have focused on how VRU risk-taking behaviors, impairment, signal disobedience, and distraction relate to severity of injuries (Sze and Wong, 2007; Schwebel et al., 2012). Although the built environment may play a role—reducing crash risk, improving walkability, and possibly discouraging potential improper behaviors—traffic safety research devotes limited analysis to attributes such as land use, urban form, and transportation facilities.

Two models were used to analyze the factors contributing to injury severities of VRU-involved crashes, and incorporate random parameter features to address heterogeneity in crash data. For comparison and validation, a mixed generalized ordered logit (MGOL) model and mixed logit model were compared to an ordered logit model and multinomial logit model, to assess the effectiveness and appropriateness of these models for goodness-of-fit and predictive power. The results may be useful for refining current and developing new V2P applications to address the special safety needs and challenges of these VRUs.

The results showed that the time-to-death of VRU-involved crashes is significantly associated with involved non-motorist characteristics (age and police-reported alcohol involvement), involved motorist characteristics (drunk drivers, previous recorded crashes, number of occupants), involved vehicle characteristics (vehicle body type, model year, travel speed), roadway characteristics (interstate, junction, roadway profile), and environmental characteristics (light and weather condition). The study found that the proposed MGOL and mixed logit models can address heterogeneity problems in crash data due to the unobserved factors. In addition, the injury severity models that incorporate the random parameter features may reveal new insights and offer superior goodness-of-fit.

Methods

Data Source

The data were obtained from the Fatality Analysis Reporting System (FARS), a census of fatal traffic crashes within the 50 states that involved a motor vehicle traveling on a public roadway and resulting in death within 30 days. Housed in NHTSA, FARS collects information on all qualifying crashes from agencies in each state government through cooperative agreements, drawing on Police Accident Reports (PAR), Vehicle Registration Files, Death Certificates, Coroner/Medical Examiner Reports, State Highway Department Data, Driver Licensing Files, Emergency Medical Service Reports, Vital Statistics, and other State Records. Four data files used for this study included:

- Accident (1975-current): crash characteristics and environmental conditions
- Vehicle (1975-current): information on motor vehicles and drivers involved in crashes
- Person (1975-current): information such as age, gender, vehicle occupant restraint use, and injury severity for all persons involved in crash—motorists and non-motorists
- Pbtype (2014-current): information about crashes between motor vehicles and pedestrians, people on personal conveyances and bicyclists

The data from Accident, Vehicle, Person, and Pbtype files were combined and linked through the common variable ST_CASE—a unique case identifier. The study used only the first reported VRU and involved vehicle ("PER_NO" and "VEH_NO" in Pbtype and Vehicle data files, respectively), then removed crashes involving only VRUs from the dataset, to analyze the factors contributing to the injury severity of vehicle-to-VRU crashes. Only crash records involving at least one vehicle and one VRU were selected into the study.

The variables LAG_HRS and LAG_MINS record the hours and minutes between the time of the crash and the involved non-motorist's time of death. Injury severities were defined on a four-point ordinal scale coded as:

1. died at scene/En route (referred to as injury type 1),
2. died in one day (referred to as injury type 2),
3. died in ten days (referred to as injury type 3), and
4. died in 10 to 30 days (referred to as injury type 4).

The dataset of complete records totaled 10,582 non-motorist involved crashes on U.S roadways during the two-year period. This includes 9,180 pedestrian-involved crashes and 1,402 bicyclist-involved crashes. Table 0-1 shows the distribution of injury severities by non-motorist types. The study analyzed certain collision-related attributes, including characteristics of non-motorists, motorists, vehicle, roadway, and environment.

Table 0-1. Distribution of Non-Motorist Injury Severity by Non-Motorist Type

Injury severity category	Pedestrian	Bicyclist	All non-motorists
2014			
Injury type 1	2130 (48.54%)	267 (40.76%)	2397 (46.22%)
Injury type 2	1632 (37.19%)	250 (38.17%)	1882 (36.29%)
Injury type 3	469 (10.69%)	108 (16.49%)	577 (11.13%)
Injury type 4	157 (3.58%)	30 (4.58%)	187 (3.61%)
Total	4388 (100%)	655 (100%)	5043 (100%)
2015			
Injury type 1	2397 (50.02%)	323 (43.24%)	2720 (47.95%)
Injury type 2	1759 (36.71%)	290 (38.82%)	2049 (36.12%)
Injury type 3	470 (9.81%)	97 (12.99%)	567 (10.00%)
Injury type 4	166 (3.46%)	37 (4.95%)	203 (3.58%)
Total	4792 (100%)	747 (100%)	5539 (100%)

Data Analysis

Analysis of crash injury severities addressed methodological concerns such as omitted variable bias, small sample size, endogeneity, within-crash correlation, and spatial and temporal correlations. The injury severity of the injured non-motorist, measured as time-to-death, was the dependent variable. An MGOL model and mixed logit model (random-parameter logit models) were used to analyze the factors contributing to the injury severities of VRU-involved crashes. The MGOL models addressed the limitations of the ordered discrete outcome models by allowing the thresholds in the ordered logit model to vary for both observed and unobserved characteristics (Eluru et al., 2008). Also employed was a recently developed discrete outcome model that analyzes three or more injury outcomes without explicitly considering their possible ordinal nature.

To validate the effectiveness and appropriateness of the models, an ordered logit model and multinomial logit model were estimated and their performance compared for goodness-of-fit and predictive power. The MGOL model was compared against the ordered logit model, and the mixed logit model was compared to the multinomial logit model to assess the effectiveness of incorporating random-parameter features. The MGOL model was compared against the mixed logit model to assess the appropriateness of implementing the ordered discrete probability models.

Results

The dataset, with 9180 pedestrian- and 1402 bicyclist-involved crashes, was divided into two groups—one for training (2014 data for 4388 pedestrian- and 655 bicyclist-involved crashes), and the other for validating (2015 data for 4792 pedestrian- and 747 bicyclist-involved crashes). The training set was used to fit the models, which then were used to predict the injury severities in the validating set. A likelihood ratio test was performed to evaluate the goodness-of-fit based on log-likelihood values. To evaluate predicted accuracy, the predicted values for each injury severity level were compared to the observed values with three measures: root-mean-squared deviation, mean absolute percentage error, and maximum percentage error between predicted and actual observed values.

The predicted values from the MGORL and mixed logit models are much closer to the observed values, compared to the ordered logit and multinomial logit models. The predictive performance of the MGORL model is also better than the mixed logit model, but the differences are not statistically significant. Because the proposed MGOL model and mixed logit model provide superior goodness-of-fit and predictive performances in the examined dataset, the rest of this chapter focuses on them.

For the injury severities of pedestrian-involved crashes, the mixed logit model found significant associations with increased risks for all injury types for three variables (non-motorist age greater than or equal to 60 years, alcohol-impaired driver, and interstate or highway). Significant associations for decreased risks were found for five variables (involved vehicle occupants—driver only, vehicle travel speed <50 mph, non-junction, roadway profile-level, and daylight conditions) for all four injury types. Significant relationships for other variables were different across the three injury types. For the injury severity of bicyclist-involved crashes, the mixed logit model yielded results that were largely consistent with pedestrian-involved crashes.

Four variables—number of vehicle occupants, vehicle body type, roadway type, and junction type—resulted in random parameters for injury severity in pedestrian-involved crashes. The variability is likely capturing the unobserved heterogeneity in the observations, such as visual noise and other physical and environmental factors that cannot be measured in the dataset.

The MGOL model results are largely consistent with the findings obtained from the mixed logit model, although it is interpreted differently. Compared to the mixed logit model, fewer variables in MGOL model result in random parameters. The finding is consistent with the results of Eluru et al. (2008), whose MGOL model collapsed to a generalized ordered response logit in the final specification for their dataset. Although the MGOL models have the random parameter feature, they cannot effectively address the heterogeneity issues like the mixed logit models do-see Table 0-1.

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Table 0-1. Comparison and Validation of Model Performance

	Pedestrian involved crashes					Bicyclist involved crashes				
	MGOL model	Mixed logit model	Ordered logit model	Multinomial logit model	Observed Shares	MGOL model	Mixed logit model	Ordered logit model	Multinomial logit model	Observed Shares
Log-Likelihood value	-971.70 (37)*	-968.75 (40)	-1041.57 (31)	-1034.00 (32)		-1031.86 (32)	-1026.49 (37)	-1116.68 (28)	-1084.26 (29)	
Predictive likelihood ratio test	$5.90<\chi^2(3)=7.815$**		$139.76>\chi^2(6)=12.592$	$130.50>\chi^2(8)=15.507$		$10.73<\chi^2(5)=11.071$		$169.64>\chi^2(4)=9.488$	$115.53>\chi^2(8)=15.507$	
Predicted market shares										
Injury type 1 (%)	49.963	49.889	48.609	47.321	50.021	42.771	41.427	43.528	43.876	43.240
Injury type 2 (%)	36.007	35.552	36.057	37.865	36.707	39.817	39.463	38.459	38.435	38.822
Injury type 3 (%)	9.478	10.044	10.918	7.175	9.808	12.547	14.369	14.492	14.296	12.985
RMSE (%)	7.45	7.47	7.88	9.69		11.88	12.12	12.78	14.22	
MAPE (%)	10.48	10.50	10.66	12.03		16.67	17.47	21.45	21.69	
Max. Absolute Percentage Error (%)	15.37	16.56	23.14	29.90		21.68	24.55	28.54	28.85	15.37

Note: *The values in parentheses represent the number of estimated parameters.

**The significant level of 0.05 is used

Conclusions

This study explored the use of random parameters in logit models to examine factors that significantly influence injury severity of VRU-involved crashes. The results provide some justification for incorporating the random parameters in injury severity analyses. The proposed MGOL and mixed logit models address heterogeneity issues in crash data due to unobserved factors, and provide superior statistical fit with accurate predictions compared to the ordered logit and multinomial models. Although the MGOL model and mixed logit model have comparable performance in data fitting and prediction, interpretation of estimated results in mixed logit models is more straightforward and easier. In addition, the mixed logit model can identify more significant random parameters compared to the MGOL model.

Compared to the fixed parameters, the random parameters yield more insights into non-motorist-involved crashes. The MGOL model results somewhat confirmed the findings from the mixed logit model, with fewer significant parameters and random parameters. The findings show that the involved non-motorist characteristics (age and police reported alcohol involvement), involved motorist characteristics (drunk drivers, previous recorded crashes, and number of occupants), involved vehicle characteristics (vehicle body type, vehicle model year, and travel speed), roadway characteristics (interstate, junction, and roadway profile), and environmental characteristics (light condition and weather condition) have significant effects on the injury severities of VRU-involved crashes. Among these variables, vehicle body type, interstate, and junction result in normally distributed random parameters, which capture and reflect the unobserved heterogeneity across sampled observations. Understanding what factors are associated with increasing severity of injuries to vulnerable road users may inform policy and programs relating to travel behavior and decision-making by drivers as well as walkers, as well as engineering and systems for road infrastructure and controls.

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Using Driving Volatility as a Leading Predictor of Unsafe Events Involving Vulnerable Road Users - A Naturalistic Driving Environment Study

Authors

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This chapter presents an extended abstract of CSCRS-sponsored research that was submitted for review to the 98th Annual Meeting of the Transportation Research Board, 2019.

New data and analysis techniques are becoming available, providing deeper insights and understanding to address pedestrian and bicycle safety goals. This study uses the SHRP2 Naturalistic Driving Study data to explore how driving volatility well before a crash or near-crash can serve as a leading indicator of pedestrian and bicycle crashes. This study links volatility measures with safety critical events, i.e., crashes and near-crashes. Statistical modeling was used to develop curves for how the probability of a pedestrian or bicycle event changes with acceleration and jerk volatility of a vehicle. Pre-crash driving volatility, based on 20-second pre-crash trajectories, has a statistically significant positive association with the probability of a pedestrian/bicycle crash or near-crash. Interestingly, rigorous models show that probabilities of crashes or near-crashes are more sensitive to volatility in vehicular jerk compared with volatility in acceleration. Other relationships found in the study and the implications of the findings are discussed in the paper.

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Introduction

On a global scale, an estimated 1.25 million people are involved in fatal roadway crashes yearly, with a good proportion of them being pedestrians and bicyclists. The National Highway Traffic Safety Administration (NHTSA) in their Crash Statistics report on driver and pedestrian fatalities, with data from the Fatality Analysis Reporting System (FARS), reported 4779, 4910 and 5376 pedestrian fatalities and 66000, 65000, and 70000 pedestrian injuries for the years 2013, 2014 and 2015, respectively. Pedal cyclist fatality statistics reported a decrease from 749 in 2013 to 729 in 2014, followed by an increase to 818 pedal cyclist fatalities in 2015. As many researchers have pointed out, there is a significant correlation between behavioral factors and crash propensity and a recent study by the FHWA (2018) reports that 90% are influenced to some degree by driver behavior. There was also an issue of poor correlation of police injury severity scale with medical diagnoses. These issues have created a system of pedestrian crash reportage where crucial information, pertaining to the preceding contributory factors of the crash, are either not accounted for or underreported. The difficulty of attaining such information on pre-crash events has been resolved in this study by taking advantage of the real-time monitoring and recording of driver actions, and the driving environment, of the Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS). The potential for studying actual driving tasks and decisions that precede events involving safety critical outcomes has been made possible by the capacity of modern technology to instrument vehicles with a host of data gathering sensors as has been done in the study.

Methods

Naturalistic Driving Data from the SHRP-2 Study was utilized in this research. An in-depth analysis of kinematic factors derived from the dataset, coupled with observed phenomena from video recording were used.

Data

Naturalistic Driving Data

Naturalistic driving studies have the advantage of reporting detailed information into traffic events including “near-miss” scenarios which generally go unreported. Given the very objective nature of the NDS data set, it is possible to analyze pre-conditions which led towards both cases of crashes and near-misses and corroborate these events from video records.

Driving Volatility

The concept of “driving volatility” is characterized by variability from average driving, and captures instantaneous and extreme driving behaviors and decisions (Liu et al. 2015, Wang et al. 2015). The extent of variations in driving, especially hard accelerations/braking and jerky maneuvers are captured within the scope of these measures. Research done by Kim et al. (2016) explored the association between rear-end crash propensity and micro-scale driving behavior, as also recent research has linked historical crash data with driving volatility, while also demonstrating in a Full Bayesian context that the associations between driving volatility and crashes vary across locations. Proactive safety measures to curb the instances of the possibility of crashes at signalized intersections and freeway ramps were discussed in the study.

Calculation of Volatility

In calculating the volatilities for each event, the standard deviation is the most common measure used. This study further quantifies the ratio of the standard deviation to the mean to measure volatility termed the coefficient of variation. The coefficient of variation has been found to be correlate highly with crash risk. The coefficient of variation, C_v, is measured as:

he coefficient of variation is measured as:

$$C_v = \frac{\left(\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}\right)}{|\bar{x}|} \times 100 \qquad (\mathbf{1})$$

Where x_i is the value of observation “i”, $\bar{x}$ is the mean, and “n” are the number of observations.

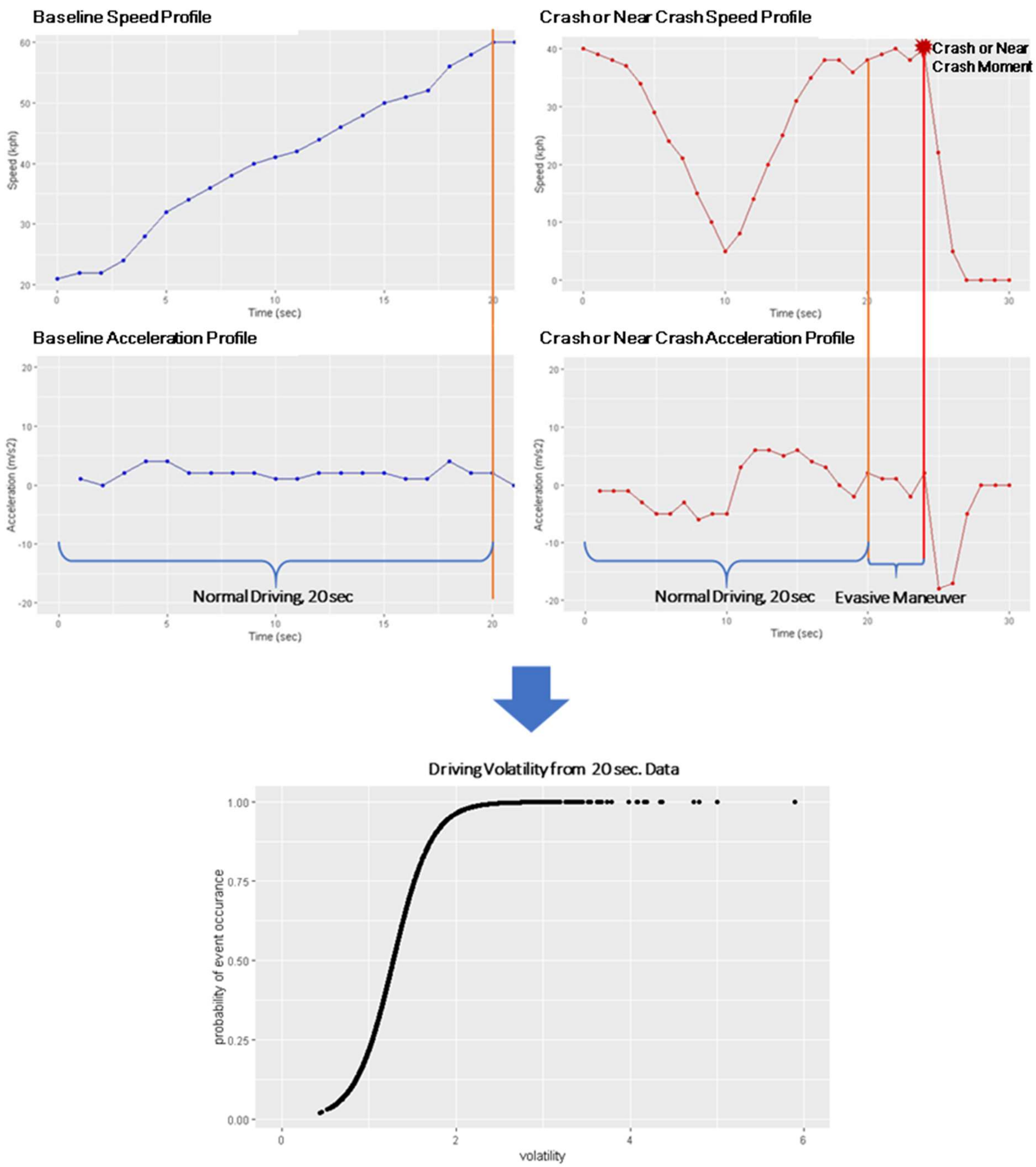

Figure 0-1. Framework for Analysis

Models

Driving volatility works very well as a generalized metric for driving behavior since it showcases the extent of variations in driving carried out by an individual, especially hard accelerations and braking, and also their changes in magnitude with respect to a unit of time, which is defined as jerk. The data from the onboard sensors from the study are high resolution motion data at a frequency of 10 Hz, which allows us to extract and analyze the different volatilities associated with each individual driver and assess their performance immediately prior to the involvement in safety critical events. The sensor records provide real time motion data of about 30 seconds mostly prior to any safety critical outcome, and 20 seconds data for baselines.

To provide a clearer perspective on this, Figure 6-1 shows examples of the "baseline" and crash/near crash data and how the data are used to explore relationships. The typical durations of the baselines are 20 seconds. In the case of crash/near crash, the typical total durations are 30 seconds. In some cases, the driver took evasive action before the crash, whereas in other situations they did not take any evasive action before the collision. Based on the baseline, and pre-crash (excluding the evasive maneuvers) accelerations and vehicular jerk in the lateral and longitudinal directions, we have derived our eight different volatility measures. The eight measures were selected because accelerations and vehicular jerk (the rate of change of acceleration) capture the abrupt lateral and longitudinal movements that can serve as leading predictors of crashes. The volatility measures used are the Coefficient of Variation calculated for the relevant lateral and longitudinal acceleration and vehicular jerk data.

Using the data, the correlations between the volatility measures and crash propensity are explored, while controlling for several other variables; additionally, S-shaped curves shown in Figure 6-1 are developed to explicate the relationship between volatility and crash/near-crash propensity (note that Figure 6-2, which appears later elaborates on the lower part of Figure 6-1). A statistical model is estimated to assess correlations through a multinomial outcome framework of baseline (which signifies a safe outcome), vehicle only involved events and pedestrian-cyclist involved events (which both signify safety critical outcomes). Within the multinomial framework, a function determining the outcome "*i*" of an event "*j*" is defined as:

$$\boldsymbol{Y_{ij}} = \boldsymbol{\beta_i X_{ij}} + \boldsymbol{\varepsilon_{ij}} \qquad (2)$$

Where Y_{ij} is the dependent variable, i.e., the safety outcome *"i"* observed in a traffic event *"j"*; X_{ij} is the vector of independent variables (driving volatility measures and other observed factors); and β_i is the vector of parameter estimates. The error term is denoted by ε. For each safety critical outcome, the probability of a crash or near-crash can be formulated as:

$$\boldsymbol{P_j(i)} = \frac{\boldsymbol{exp[\beta_i X_{ij}]}}{\boldsymbol{\Sigma exp[\beta_i X_{Ij}]}} \qquad (3)$$

Since the logit framework restricts direct interpretation of parameter estimates, marginal effects are estimated for the parameters.

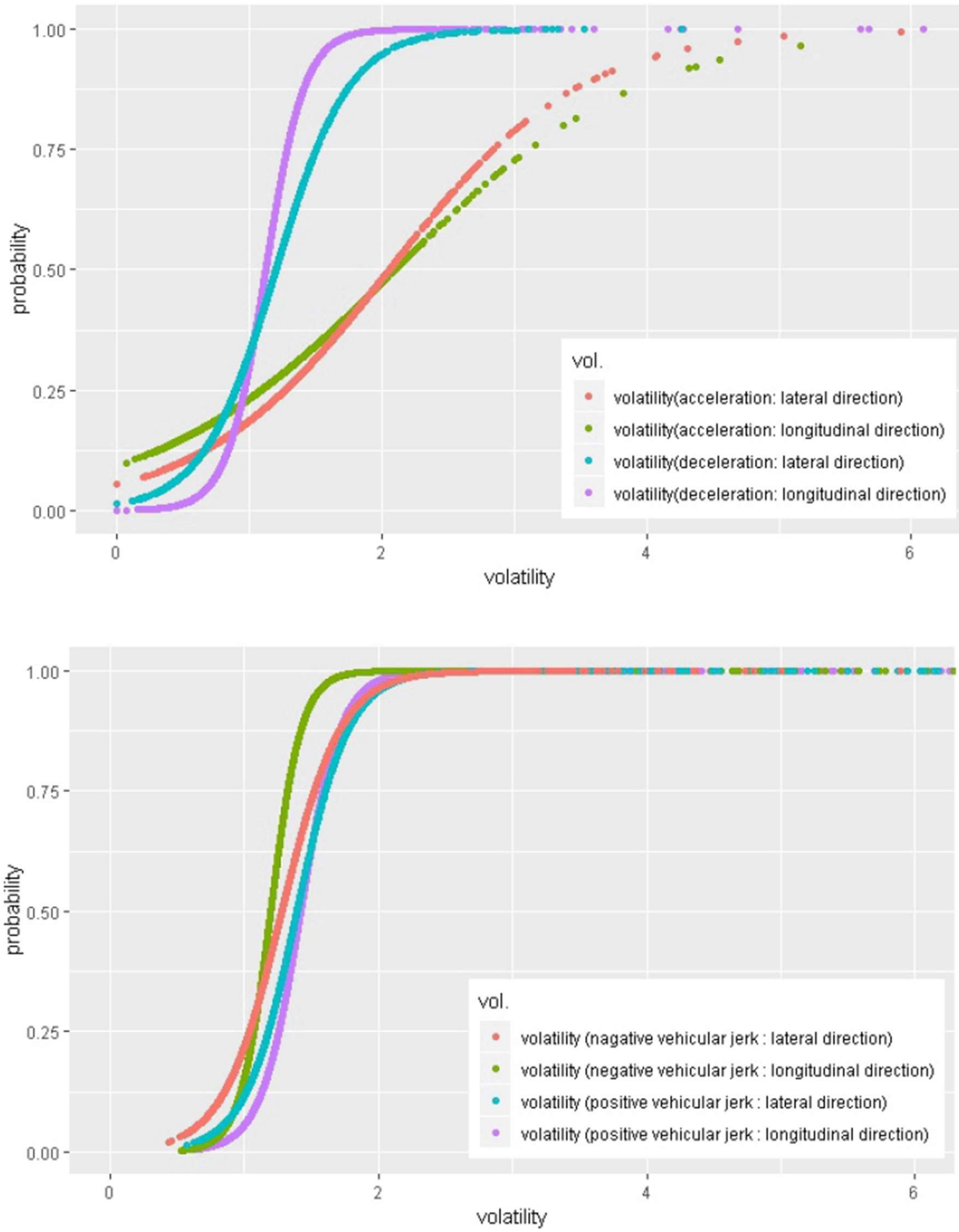

Figure 0-2. Probability Density Curves (baseline vs. crash/near crash) for univariate models of volatility measures.

Table 6-1: Descriptive Statistics of Key Driving Volatility Measures

	Baseline			**Vehicle Only Involved Events (VoE)**			**Pedestrian-cyclist Involved Events (PbE)**			**Difference in Means between VoE and PbE**
Performance Measure	***N***	***Mean***	***Std. Dev***	***N***	***Mean***	***Std. Dev***	***N***	***Mean***	***Std. Dev***	***Δ Mean (PbE –VoE)***
Volatility (Positive vehicular Jerk: longitudinal direction)	7562	0.98	0.18	1851	1.17	0.43	74	1.34	1.25	0.36
Volatility (Negative vehicular Jerk: longitudinal direction)	7562	0.82	0.15	1851	0.90	0.27	74	0.97	0.75	0.15
Volatility (Positive vehicular Jerk: lateral direction)	7562	0.97	0.17	1851	1.16	0.57	74	1.30	0.71	0.33
Volatility (Negative vehicular Jerk: lateral direction)	7562	0.84	0.18	1851	0.91	0.26	74	0.98	0.43	0.15
Volatility (Acceleration: longitudinal direction)	7562	0.80	0.30	1851	0.80	0.32	74	0.81	0.27	0.01
Volatility (Deceleration: longitudinal direction)	7562	0.71	0.19	1851	0.77	0.27	74	0.76	0.68	-0.01
Volatility (Acceleration: lateral direction)	7562	0.99	0.33	1851	0.98	0.48	74	1.04	0.50	0.06
Volatility (Deceleration: lateral direction)	7562	0.71	0.20	1851	0.74	0.26	74	0.76	0.42	0.02

Note: N is sample size; Std. Dev is standard deviation.

Table 6-2. Estimation Results of Multinomial Logit Models for Crash Propensity from Naturalistic Driving Data and Model Comparisons

	Vehicular Jerk based Multinomial logit model					
	Vehicle Only Involved Events			**Pedestrian-cyclist Involved Events**		
Variables	*B*	**Z**	**dy/dx**	*β*	**z**	**dy/dx**
Constant	-3.06	-16.49		-7.45	-14.31	
Key Volatility Indicators						
Volatility (Positive vehicular Jerk: longitudinal direction)	1.30	**8.01**	**0.155**	1.73	**5.74**	**0.009**
Volatility (Negative vehicular Jerk: longitudinal direction)	0.63	**3.26**	**0.075**	0.82	1.70	0.004
Volatility (Positive vehicular Jerk: lateral direction)	2.26	**11.80**	**0.271**	2.32	**7.43**	**0.011**
Volatility (Negative vehicular Jerk: lateral direction)	-0.82	**-4.13**	**-0.099**	-0.56	-1.21	-0.002
Maneuver Judgement						
Safe and legal	-2.08	**-24.54**	**-0.251**	-1.77	**-5.77**	**-0.007**
Safe but illegal	-2.64	**-10.58**	**-0.317**	-2.34	**-2.23**	**-0.010**
Intersection Influence						
Uncontrolled intersection	2.04	**15.79**	**0.246**	1.43	**2.69**	**0.004**
Traffic Signal	1.28	**16.84**	**0.153**	1.34	**5.02**	**0.006**
Roadway Surface condition						
Dry	-0.38	**-4.98**	**-0.045**	-0.44	-1.55	0.002
Summary Statistics						
N	9487					
Prob. > χ^2	0.000					
Pseudo R^2	0.2002					

Notes: Baseline event is considered the base category-all parameter estimates to be interpreted relative to baseline event. Jerk based volatility measures are coefficients of variation.

Findings

- All eight volatility measures showed a higher mean value for both safety critical categories of outcomes (vehicle only events and pedestrian-cyclist involved events), compared to baseline (normal driving safe outcome).
- Comparing between-group variance to within-group variances, we found that within-group variances are greater, suggesting larger variance in volatilities exhibited by drivers involved in the same event outcome category.
- Longitudinal jerk (both positive and negative) and deceleration, for pedestrian-cyclist involved events showed greater mean volatility than for vehicle only involved events (Table 6-1).
- Positive vehicular jerk (both longitudinal and lateral directions) shows greater mean values of volatility than the corresponding directional negative vehicular jerk, in all situations.
- For all the eight volatility measures, there is evidence that driver volatilities in all three event outcome categories are statistically significantly different.

The cumulative probability functions of the predictions (as a function of volatility related measures) obtained from both models are shown in Figure 6-2. In particular, the x-axis in top plot shows the volatility in acceleration/deceleration in longitudinal and lateral direction whereas the y-axis shows the cumulative probability of pedestrian-cyclist involved crash/near-crash event (Figure 6-2).

Analyzing the bottom plot in Figure 6-2, it is evident that vehicular jerk-based volatility measures as a whole can explain instantaneous driving decisions, showing strong sensitivity and display a sharp (and almost equal) rate of change of the probability. Table 6-2 shows the results of multinomial logit model with vehicular jerk-based volatility measures as key explanatory factors and other variables as controls.

Related to pedestrian-cyclist involved crash/near-crash outcomes, the estimation results show that increase in positive vehicular jerk in longitudinal and lateral direction is statistically significantly correlated with occurrence of pedestrian-cyclist involved events (Table 6-2). In particular, a one-unit increase in positive vehicular jerk in longitudinal and lateral direction increases the probability of observing a pedestrian-cyclist involved event by 0.009 and 0.004 units respectively (see marginal effects in Table 6-2).

This suggest that driving volatility well in advance of unsafe event occurrence is significantly correlated with pedestrian-cyclist involved event occurrence. Likewise, increase in volatility of positive vehicular jerk in longitudinal and lateral directions, and volatility of negative vehicular jerk in longitudinal direction are all positively and statistically significantly associated with likelihood of vehicle only involved events (see Table 6-2). Other findings shown in Table 6-2 can be interpreted in a similar way.

Conclusions

Compared to volatility associated with acceleration, the probability of pedestrian-cyclist involved crash/near-crash events is more sensitive to increase in volatility associated with deceleration either in longitudinal or lateral directions. Interestingly, rigorous statistical models show that probabilities of pedestrian-cyclist involved crashes or near-crashes are more sensitive to volatility in vehicular jerk compared with volatility in acceleration. The above volatility related findings have important implications for proactive safety especially for pedestrians and bicyclists. Instantaneous driving decisions can be monitored in real-time and warnings and alerts can be issued to drivers. Such alerts and warnings can potentially help in improving safety.

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Recommendations

This year 1 research effort has (1) underscored the importance of understanding how proactive regulation of automated vehicle technology is necessary to ensure the benefits of CAVs—particularly but not exclusively safety benefits—accrue equitably across the population and (2) identified new areas for research into how CAVs will interact with other technologies, infrastructure, policy, and society. Accordingly, several recommendations have emerged from this project.

Recommendation 1

Maintain infrastructure and policies to support conventional (human-driven) motor vehicles and non-vehicular travel modes, as the roll-out of CAVs and the benefits expected to be derived from them are unlikely to be comprehensively or equitably distributed in the near- to mid-term.

Recommendation 2

Establish minimum criteria for the effectiveness of pedestrian detection and resolution technology to be deployed on all CAVs operating in non-freeway conditions.

Recommendation 3

Support research to expand knowledge on likely relationships between CAVs and other travel modes, in particular, whether and how CAV technology and operational characteristics can be used to enhance safety of vulnerable road users.

Recommendation 4

Support further research to expand knowledge-base regarding the impacts of CAV-supportive infrastructure investments on pedestrian comfort, safety, and the built environment.

Recommendation 5

Support research into how professions currently involved in efforts to maintain/improve roadway safety (e.g., traffic engineering, urban planning, law enforcement) might need to evolve and adapt to new conditions and demands imposed by a CAV-dominant mobility system.

This recommendation has led to the development of a manuscript (in progress) tentatively titled "The automated vehicle boom: a pragmatist planning response to safety and equity implications," which explores how the profession of urban planning can look to outcomes of previous responses to technological innovation to guide best practices with respect to proactive planning for CAVs.

Thinking from this paper has been discussed during a breakout panel session in July 2018 at the Automated Vehicles Symposium (San Francisco CA); another panel discussion based on the work in this paper will take place at the Association of Collegiate Schools of Planning Annual Conference (ACSP) in October (Buffalo NY). The abstract for the ACSP session is below:

"How can planning theory inform the challenges of planning for automated vehicles?"

The rapid pace of innovation in automated vehicle (AV) technology has positioned urban areas on the precipice of massive spatial, economic, and social change. Exuberant media coverage of the emergence of AVs parallels statements by auto manufacturers, technology companies, and futurists touting AVs as a 'savior technology' with potential to solve some of society's most vexing challenges. Predicted benefits of AVs include alleviation of congestion, reduced fossil fuel dependence, improved safety, enhanced urban vitality, and expanded mobility options for low-income travelers and non-drivers.

Despite recent announcements by automotive companies of plans for wide-scale deployment of driverless cars, many experts agree critical limitations in AV technology remain unaddressed (Combs et al., 2018). Given consumer and political pressures to expedite production, the burden of closing technological, infrastructural, and regulatory gaps likely will fall to the public. That is to say: rather than expecting manufacturers to design for today's transportation systems, our systems must evolve to accommodate the specialized yet uncertain operational needs of self-driving cars. The full integration of AVs into contemporary cities will require massive adaptations and investments in infrastructure and new regulations. It will also require an evolution of norms and expectations around access to the street (Millard-Ball, 2016; Stone et al., 2018). However, both the pace of change, and the changes themselves, are likely to introduce a host of unintended consequences and uncertainties that may exacerbate inequalities in transportation, housing, and access to opportunities; disrupt most of what we know about urban and suburban land markets; and even undermine the anticipated benefits of AVs themselves.

The planning profession is uniquely positioned to handle such change. Planners are trained to identify and mitigate unintended consequences, and are accustomed to working under conditions of extreme uncertainty. However, the profession's previous experiences with novel, potentially transformative or disruptive ideas leave room for doubt regarding the profession's readiness for a new technological revolution (Guerra, 2016). Blind faith optimism in "progress" and the belief that rationally-instituted plans, using the latest technology, can "modernize" the city and sweep away a host of social ills was at the heart of Urban Renewal and other prominent 20th century planning interventions. Plans based on such innovations have been widely criticized not only in terms of their unintended negative and inequitable outcomes but also because of the epistemological hubris of the planners hired to design and carry them out at the time.

The impending and likely inevitable shift toward automated mobility presents both an opportunity and an urgent need to re-examine the role of planning during times of transformation and uncertainty. Due to the rhetorical similarity between AV proponents today and Urban Renewal boosters during the post-war era, it is an interesting time to reconsider the role of planning in promoting "progress." What should "progress" mean today compared to previous attempts by the planning field to manage rollouts of disruptive innovation in the public interest?

This roundtable brings together academics with interests in planning theory, transportation equity, and automated mobility to explore new models of planning that might bridge the divide between the rational facilitation approach to progress and Luddite resistance in the face of uncertainty. In doing so, we will engage in a conversation on how planning theory can equip us to plan for the AV era. We will explore questions such as: How do we redefine "progress" in urban development in the AV era? What can planners learn from previous failures in managing technological rollout (or how do existing planning models fail to prepare us)? How can planning models be adjusted to mitigate negative impacts of AVs? Who is left out of planning efforts to support AVs?

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Recommendation 6

Support and test existing and new vehicle-to-pedestrian technologies that can result in better detection, (by cameras and other sensors), processing of data in real-time, and user (pedestrian and vehicle driver) alerts and warnings through notification systems. More field testing is needed to capture the complexity of different pedestrian-involved crash types and risky pre-crash behaviors (especially the behaviors of drivers and pedestrians that contribute to fatal crashes, identified in this research) in different spatial and environmental contexts. Systematic testing can be enabled by a good inventory of V2P technologies that can be field tested and eventually deployed. A key aspect will be to collect the Basic Safety Message data and extract valuable information that can be used to reduce pedestrian-vehicle conflicts and improve safety across modes.

Following-up on understanding risky pre-crash behaviors and human errors, a Year 2 project titled "Developing a Taxonomy of Human Errors and Violations that Lead to Crashes" is underway to examine contributing factors and human errors (Principal Investigator: Asad Khattak, University of Tennessee, Knoxville; Co-Investigator: Eric Dumbaugh, Florida Atlantic University). The project examines human errors and violations more broadly as human error tends to dominate crash occurrence, contributing to 80%-90% of crashes. A better understanding of "critical reasons for the critical pre-crash events" has significant potential in reducing deadly behaviors on roadways. A key gap in relates to the origin of the different types of human errors, e.g., whether they begin with intentional actions or unintentional actions, and how they relate to the built environment. This study will analyze human errors and explore the potential for addressing human errors through CAVs and other safety strategies. Along these lines, a deeper understanding of factors associated with increasing severity of injuries to vulnerable road users may inform policy and programs relating to travel behavior and decision-making by drivers and walkers, as well as engineering and systems for road infrastructure and controls.

Recommendation 7

Future research investments should build links among engineering, planning, policy, public health, and other fields, and account for the emergence and penetration of CAVs. Open questions include how human-driven vehicles will interact with AVs; how CAV penetration will influence walking behavior; and how CAVs will respond to pedestrians' changing behavior as they challenge CAVs in dynamic environments. Given the high cost of mobility—in dollars as well as lives and health, the nation should prioritize safety and accessibility for all modes, with strategically selected technology. In particular, research is needed on new connected and automated technologies that can avoid crashes and meet the mobility needs of diverse users and stakeholders. Crosscutting safety and technology-oriented research, development and deployment efforts should encompass CAVs and infrastructure, and safety technologies and strategies to promote safe and smart communities. A comprehensive research agenda should use partnerships among academia, public sector agencies, and leaders in the private sector, to identify innovative life-saving and community-strengthening models for safe and walkable environments.

Summary of data used/gathered

Primary data

None (no new data was collected by the research team).

Secondary data (not collected by the research team)

Fatality Analysis Reporting System (publically available: https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars)

SHRP2 Naturalistic Driving Study Data (not publicly available-more information at:

https://insight.shrp2nds.us/) The data cannot be shared.

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