Autonomous Vehicles and Safety of Vulnerable Road Users: A Systems Approach
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Walkability in the Connected and Automated Vehicle Era: A U.S. Perspective on Research Needs

Elizabeth Shay\textsuperscript{2}, Asad Khattak\textsuperscript{1}, & Behram Wali\textsuperscript{1}

\textsuperscript{1}University of Tennessee, \textsuperscript{2}Appalachian State University
• Mobility and Safety of Vulnerable Road Users

Mobility—mode share: walking accounts for 10%-12% of all trips

Safety—out of total of ~35,000 transportation fatalities annually
  ~5,000 peds
  ~800 bicyclists
• Walkability and CAVs—Premise

CAVs will reshape mobility and safety in ways we cannot know with certainty—but can reasonably anticipate will be important
Walkability and CAVs—Premise

CAVs will reshape mobility and safety in ways we cannot know with certainty—but can reasonably anticipate will be important.

Walking (behavior) and walkability (environment) are key elements of sustainable systems—active, accessible, livable, efficient, safe, just.

- Public demand for walkability—good for health, households, community
- Economic case for walkability—good for business, property values, growth
- But can CAVs (e.g., ride-hailing) take share away from walking?
Walkability and CAVs—research issues

Brave new world? Entering new uncharted territory

- The “Trolley Problem”: In unavoidable fatal crashes involving CAVs, will CAV passengers or pedestrians be sacrificed?
- How will CAVs respond to new and changing behavior by pedestrians who anticipate that CAVs will be programmed not to hit them?
  - How will non-CAVs react?

Out of scope: Cyber-security, insurance, attitudes toward automation, encouragement & enforcement

Countermeasures:
- Provide exclusive pedestrian interval
- Illuminated No Turn on Red (NTOR) sign

32.2% 7.0%

26.5%
<table>
<thead>
<tr>
<th>CMF</th>
<th>CRI (%)</th>
<th>Quality</th>
<th>Crash Type</th>
<th>Crash Severity</th>
<th>Area Type</th>
<th>Reference</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>40</td>
<td>★★★★★</td>
<td>Vehicle/pedestrian</td>
<td>All</td>
<td>Urban</td>
<td>Liu Chen, Cynthia Chen, and Reed, 2012</td>
<td>The treatment group included both... [read more]</td>
</tr>
<tr>
<td>0.81</td>
<td>19</td>
<td>★★★★★</td>
<td>Angle, Head on Left turn, Rear to rear, Right turn, Side swipe</td>
<td>All</td>
<td>Urban</td>
<td>Liu Chen, Cynthia Chen, and Reed, 2012</td>
<td>The treatment intersections included both... [read more]</td>
</tr>
</tbody>
</table>

- **Pedestrians**—only lightly covered in Highway Safety Manual
Pedestrians—lightly covered in ITS Architecture

- **Two new services for peds added in the ITS architecture**

- **VS1 (veh safety) 2: Pedestrian and Cyclist Safety**
  - Sensing and warning systems-interact with peds, cyclists, etc.
    - Warnings to VRU of possible infringement of crossing by approaching vehicles
    - SPaT-priority for people with disabilities needing additional crossing time
  - Integrates traffic, ped, and cyclist data from detectors & wireless devices (mobile phones) to request right-of-way or provide crossing info

- **PT11: Transit Pedestrian Indication**
  - “Vehicle to device” communications
  - Alerts peds of a transit vehicle & vice-versa, i.e., peds waiting for bus
  - Prevents transit-ped collisions
CAVs—Sandt & Owens, 2017

Issues
• Tech: Detection, V2P, Communication problems
• Infra: Right-of-Way, passing, speed problems
• Travelers: Pickup/drop off, mode shift, driver handoff problems
• Data problems-pre and post crash

Stakeholders active in CAV R&D- Collaborative & Open process
Detection problems & solutions—ML

Sensing techs: Lidar-Radar, DSRC, LTE, Vision

Difficult—Cluttered situations

Sources: Journal papers & report
V2P & P2V

- USDOT identified V2P techs → Alert motorist by detecting ped with sensors
- Only some (~25%) techs alert peds

Research need: Framework to identify technologies for VRU crash reduction

Sources: Sandt & Owens; Azad
What safety gains from CAVs may be expected for peds?

1. Mechanisms for automation → Harm = Σ Crash Costs
2. Literature: Mechanism → Estimates of safety impacts
3. (Hypothesis—for illustration)

Uncertain—Will CAVs increase safety?
Walkability and CAVs—Literature review

Controlled keyword search
- 4 knowledge bases—TRID, ScienceDirect, Web of Science, Google Scholar
- 14 terms relating broadly to CAVs and safety
- generated >400 sources

Deeper look at subset of 82 sources relating explicitly to walkability

Text analytics performed on 70 peer-reviewed papers and technical reports
Trends: Walkability and CAVs

Statistical pattern analysis reveals frequency and proximity of concepts
Trends: Walkability and CAVs
Trends: Walkability and CAVs
Trends: Walkability and CAVs
• Walkability and CAVs—Text analytics

Major themes to emerge:
- Automation-collision avoidance
- Communication/connectivity
  - Platooning & Adaptive Cruise Ctrl
- Shared & electric vehicles
- Walking/built environment
- Moral & ethical issues
Key Topics – Text Analytics

<table>
<thead>
<tr>
<th>Broader Category &amp; Applications</th>
<th>Topic</th>
<th>Keywords</th>
<th>Eigen-value</th>
<th>% Variance</th>
<th>Frequency</th>
<th>Cases</th>
<th>% Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology &amp; Applications</td>
<td>Wireless Communications; Mobile Applications</td>
<td>Applications; Communications; Wireless; Mobile; Connected; Dedicated Short Range Communication; Smart</td>
<td>2.01</td>
<td>1.21</td>
<td>878</td>
<td>47</td>
<td>67.14%</td>
</tr>
<tr>
<td></td>
<td>Adaptive Cruise Control; Controls</td>
<td>Cruise; Adaptive; Adaptive Cruise Control; Control; Lane</td>
<td>1.89</td>
<td>1.41</td>
<td>1627</td>
<td>59</td>
<td>84.29%</td>
</tr>
<tr>
<td></td>
<td>Collision Avoidance Systems</td>
<td>Collision; Avoidance; Warning; Collisions</td>
<td>1.80</td>
<td>1.23</td>
<td>2868</td>
<td>63</td>
<td>90.00%</td>
</tr>
<tr>
<td>Safety</td>
<td>Pedestrian Injuries; Bumper</td>
<td>Bumper; Injuries; Hood; Injury; Crashes; Pedestrian; Crash</td>
<td>2.27</td>
<td>1.24</td>
<td>1363</td>
<td>57</td>
<td>81.43%</td>
</tr>
<tr>
<td></td>
<td>Safety</td>
<td>Pedestrians; Users; Pedestrian; Traffic; Drivers; Safety</td>
<td>1.38</td>
<td>1.06</td>
<td>467</td>
<td>26</td>
<td>0.3714</td>
</tr>
</tbody>
</table>
• Walkability and CAVs—research directions

Three decades into paradigm shift toward walkable livable environments:

May CAVs threaten this progress by shifting walkers to other modes?

Might CAVs enhance gains in walkability?

What responsibility for safety should pedestrians have in CAV era?

Will space-efficient CAVs reduce traffic congestion and parking demand, and allow reallocation of liberated ROW?
• Walkability and CAVs—research directions

Parties to discussion about CAVs, walkability, walking—and larger concerns about safety and vulnerable road users

- Academia
- Public sector agencies
- Private sector leaders
- Manufacturers—vehicles, infrastructure, software/hardware

Forums needed for deliberation and debate...

Thank you!

Shay, Khattak & Wali, TRB 2018: ‘Walkability in the connected and autonomous vehicle era: A US perspective on research needs’
Limitations in Detection Technologies for Automated Driving Systems and Implications for Pedestrian Safety

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³Duke University Pratt School of Engineering
Introduction

Motivation

Recent increases in US pedestrian fatalities

Rapid gains in autonomous-driving technology → rising expectations for near-term ‘self-driving future’

Claim: replacing fallible human drivers with autonomous driving systems → substantial reductions in pedestrian deaths

But technology to detect pedestrians pre-crash is far from perfect!
<table>
<thead>
<tr>
<th><strong>Research Question</strong></th>
<th>Would <strong>perfectly automated vehicles equipped with state-of-the-art pedestrian detection technology</strong> have been capable of pre-crash detection of pedestrians in real-life, fatal crashes?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Findings</strong></td>
<td><strong>Wide</strong> range in virtual performance of hypothetical pedestrian sensors. In theory, AVs have potential to dramatically reduce pedestrian fatalities, but <strong>not</strong> in the near future and <strong>not</strong> without critical caveats.</td>
</tr>
</tbody>
</table>
Methods

1. Identify ‘negotiable’ fatalities

- FARS 2015 pedestrian traffic fatalities
- 1st harmful event & transport-related fatalities ($r$)
- Not physically unavoidable ($u$)
- Negotiable pedestrian fatalities ($n$)
1. Identify ‘negotiable’ fatalities
2. Determine functional ranges of available sensor types

<table>
<thead>
<tr>
<th>Crash condition</th>
<th>Optical camera</th>
<th>LiDAR</th>
<th>Camera + LiDAR</th>
<th>Camera + LiDAR + Radar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dark/low-light</td>
<td>❌</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fog/ precip.</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
<td>✓</td>
</tr>
<tr>
<td>Reflective surfaces</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
<td>✓</td>
</tr>
<tr>
<td>Close-range pedestrian</td>
<td>✓</td>
<td>❌</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Stationary pedestrian</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Methods

1. Identify ‘negotiable’ fatalities
2. Determine functional ranges of available sensor types
3. Calculate overlap

Negotiable fatalities \((n)\)  
Sensor type \(t\)'s functional range fatalities \((t)\)

Fatalities potentially avoided \((f_t)\)

\(f_t / r = \text{Maximum Potential Share of Fatalities Avoided}\)
Findings

• Fatalities
  – 4,773 transport-related fatalities (r)
  – 130 unavoidable (u); 4,643 negotiable (n)

• Conditions of negotiable fatalities
  No good for...
  – 76% dark/low-light cameras
  – 10% fog/precipitation cameras, LiDAR
  – 14% reflective surfaces cameras, LiDAR
  – 10% close-range pedestrians LiDAR
  – 6% stationary pedestrians radar
Findings

Maximum potential share of fatalities avoided

- overall (r=4773)
- urban (r=3357)
- rural (r=954)
- intersection (r=117)
- not intersection (r=4653)
- freeway (r=601)
- not freeway (r=3034)
- victim=minor (r=330)
- victim=not minor (r=4397)

Camera
- LiDAR
- Camera + LiDAR
- Camera + LiDAR + Radar
Conclusions

- Choice of technology matters

  - Cameras: narrow functional range captures few fatalities
  - LiDAR: decent performance with most likely potential for improvement
  - Radar: appears to perform best, but has crucial weaknesses
Conclusions

• Choice of technology matters
  • Assumptions also matter

• Vehicles fitted with best available sensor tech—regardless of cost
  • Perfect signal interpretation, perfect automation, perfect vehicle performance
  • Fatality-avoiding evasive action exists
  • Use of tech does not pose other challenges or health risks
  • Pedestrian-vehicle interaction behavior does not evolve
  • No discrepancies in deployment
Conclusions

- Choice of technology matters
- Assumptions also matter
- Takeaways

- Assuming improvements in affordability of sensor tech...AVs hold promise for reducing pedestrian fatalities over the long term, however:
  - sensor fusion is necessary
  - AVs never likely to be silver bullet
  - In the near term: complementary approaches to improve pedestrian safety and mobility are still critical!
Analysis of Crashes Involving Pedestrians across the United States: Implications for Connected and Automated Vehicles

Meng Zhang *1, Asad Khattak *1, & Elizabeth Shay *2

*1 University of Tennessee, & *2 Appalachian State University
Introduction - CAVs and vulnerable road users

- CAVs & Walkability
- Ped safety & behavior

- National perspective
- Pre-crash behavior & errors
- Human-error typologies

<table>
<thead>
<tr>
<th></th>
<th>Fatal</th>
<th>Non-fatal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pedestrian</td>
<td>12,203</td>
<td>14</td>
</tr>
<tr>
<td>Driver</td>
<td>33</td>
<td>12,184</td>
</tr>
</tbody>
</table>

- Recent Trends
- Systematic Taxonomy of Behaviors
- Simulating CAVs/V2P Scenarios
- Safety Big Data, Tech & Methods
- Knowledge base
- Ped-bike pre-incident maneuvers
- Crash/Near-crash/Baseline-NDS
- Crash distributions across US
- Virtual reality data
- Scenarios
Research Issues

• ~5,000 pedestrian deaths/year
• Assessment of future pedestrian-vehicle conflicts
• Current single vehicle-pedestrian fatal crashes across the U.S.
• Focus: Pedestrian & driver pre-crash actions
Data Sources

Fatality Analysis Reporting System (FARS)

- 2013 - 2015
- Crash type = Single vehicle-pedestrian fatal crashes

Integrated with county level census data

→ Unique database

Data structure in FARS (2013-2015)
Conceptual framework

- **Key correlates:**
  - Pedestrian behavior
    - Dart out
    - Improper X-ing
    - Inattention...
  - Driver behavior
    - Reckless...

- **Control Variables:**
  - Education level
  - Household income
  - Poverty level
  - Population density

- **Crash outcomes:**
  - Fatal crash frequency at county level

- **Single vehicle-ped fatal crashes:**
  - N=12,217
  - Clustered at County level (N=3,143)

- **County census data:**
  - N=3,143
  - Clustered at County level (N=3,143)
Distribution of ped-driver fatal crashes

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

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

Geographically Weighted Poisson Regression (GWPR)
Poisson vs. GWPR model

Poisson: \[ \ln(Y) \sim \sum \beta_j \cdot X_j \]

GWPR: \[ \ln(Y) \sim \sum \beta_{ji} \cdot X_j \]

\[ \beta = \text{Coefficients for variables} \]

\[ X = \text{Independent variables, e.g., pre-crash behavior} \]

Location 1,2,3,4

Spatial Heterogeneity

Poisson

\[ \beta_{11} \quad \beta_{12} \quad \beta_{13} \quad \beta_{14} \]

Stationary

GWPR

\[ \beta_{11} \quad \beta_{12} \quad \beta_{13} \quad \beta_{14} \]

Non-stationary
Results - Distribution of ped behaviors

Note: The percentages are added to 100% (N=12,217).
Results - Distribution of driver behaviors

Note: The percentages are added to 100% (N=12,217).
## Results - Selected variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash frequency/rate</td>
<td>3143</td>
<td>3.887</td>
<td>15.604</td>
<td>0</td>
<td>469</td>
</tr>
<tr>
<td>Crash rate by county population (/1000)</td>
<td>3143</td>
<td>0.030</td>
<td>0.053</td>
<td>0</td>
<td>1.069</td>
</tr>
<tr>
<td>Crash rate by county population density</td>
<td>3143</td>
<td>0.040</td>
<td>0.209</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Pedestrian pre-crash behavior*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dart out/ Dash</td>
<td>3143</td>
<td>0.353</td>
<td>1.415</td>
<td>0</td>
<td>30</td>
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<tr>
<td>Failure to obey traffic signs</td>
<td>3143</td>
<td>0.109</td>
<td>0.807</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>In roadway improperly (standing, lying, walking)</td>
<td>3143</td>
<td>0.463</td>
<td>1.494</td>
<td>0</td>
<td>23</td>
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<tr>
<td>Inattention (talking, eating)</td>
<td>3143</td>
<td>0.046</td>
<td>0.291</td>
<td>0</td>
<td>8</td>
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<tr>
<td>Improper crossing (jaywalking)</td>
<td>3143</td>
<td>0.432</td>
<td>2.809</td>
<td>0</td>
<td>104</td>
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<tr>
<td>Invisibility (dark clothing, no light)</td>
<td>3143</td>
<td>0.396</td>
<td>1.192</td>
<td>0</td>
<td>16</td>
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<tr>
<td>Driver pre-crash behavior*</td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Reckless</td>
<td>3143</td>
<td>0.246</td>
<td>1.067</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>Impairment</td>
<td>3143</td>
<td>0.083</td>
<td>0.483</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>Rules of turning/yield</td>
<td>3143</td>
<td>0.041</td>
<td>0.361</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>License/registration violation</td>
<td>3143</td>
<td>0.103</td>
<td>0.669</td>
<td>0</td>
<td>17</td>
</tr>
</tbody>
</table>

Note: These behaviors are shown at the aggregated county level.
## Results - GWPR vs. Poisson model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Poisson model</th>
<th>Local GWPR model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>β</td>
</tr>
<tr>
<td>Dart out/ Dash</td>
<td>0.138</td>
<td>0.007</td>
</tr>
<tr>
<td>Failure to obey traffic signs</td>
<td>-0.166</td>
<td>-2.36</td>
</tr>
<tr>
<td>In roadway improperly (standing, lying, walking)</td>
<td>0.11</td>
<td>0.089</td>
</tr>
<tr>
<td>Inattention (talking, eating)</td>
<td>0.048</td>
<td></td>
</tr>
<tr>
<td>Improper crossing (jaywalking)</td>
<td>-0.034</td>
<td></td>
</tr>
<tr>
<td>Invisibility (dark clothing, no light)</td>
<td>0.159</td>
<td></td>
</tr>
<tr>
<td>Reckless</td>
<td>0.136</td>
<td></td>
</tr>
<tr>
<td>Impairment</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Rules of turning/yield</td>
<td>-0.245</td>
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<tr>
<td>License/registration violation</td>
<td>0.075</td>
<td></td>
</tr>
</tbody>
</table>

### Statistic summary

- N = 3,143
- $\text{Prob. } > \chi^2 = 0.00$
- $R^2 = 0.619$
- Best bandwidth = 166

- $AICc = 24,503^*$
- $AICc = 14,621$

*Note: “TRUE” means the significance of spatial variance of the coefficient

*: The AICc is reported for Poisson model with the three selected variables
Spatial interpolation

Interpolate coefficients to create coefficient surface

**IDW** - Inverse distance weighted (IDW) interpolation
Local parameter estimates

a) Dash/Dart out

b) Failure to obey traffic signs

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

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

- Key contributors to pedestrian involved fatal crashes
  - Dart-out/Dash, Failure to yield right of way, Improperly present at roadway, Dark clothing/Not visible…
  - Method is scalable to other injury levels
- Substantial variations in pedestrian behavior across regions
  - Systematically accounting spatial heterogeneity
    - Better identification of hazardous areas & correlated behaviors
    - Develop context-sensitive countermeasures → Local policy
  - Results helpful in designing field tests for CAVs in specific areas
- Implications and research needs
  - V2P testing needed in diverse environments
  - Predicting ped-driver trajectories
  - Night vision
- Key Limitations
  - Accuracy
    - Location, police report
Future research - VR simulation-V2P coordination

- Decentralized algorithms
- VR testing platform
- Access to high quality data

Vehicle velocity in comparison to Pedestrian Locations

![Graph showing vehicle velocity](image)