Decoding pedestrian and automated vehicle interactions using immersive virtual reality and interpretable deep learning

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Overview

- Problem Statement: Pedestrians vs. Vehicles Interaction
- Methodology: Deep survival analysis
- Data Challenges: Virtual reality data
- Results and Discussions: Policy Implications
- Conclusions and future work

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Problem Statement:

- AVs will change dynamics of streets in near future
- Impact of our interest:

  Their interactions with pedestrians as the most vulnerable road users

- Recent instances of AV-pedestrian collisions:

Uber Test AV fatal crash in Arizona, 2018

Image: ABC 15

Navya SAS AV bus accident in Vienna, 2019

Image: Navya SAS

Problem Statement:

National Traffic Safety Board:

> *"Uber did not have a formal safety plan in place at the time when one of its self-driving cars killed a woman … **Its autonomous vehicles were not programmed to react to people who were jaywalking**, and the company had been involved in over three dozen crashes prior to that."*

- Rule-obeying AVs that always stop for pedestrians:

Emphasis on investigating mid-block unsignalized crosswalks

- To be prepared for the changes, we require to:

Analyze pedestrian's behaviour while crossing in mixed traffic conditions, at mid-block unsignalized crosswalks

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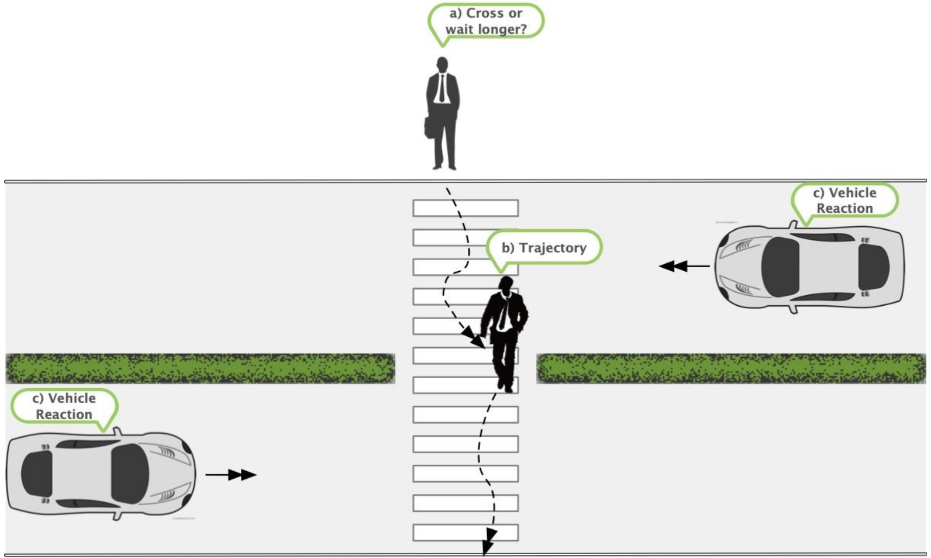
Pedestrians and Drivers Interaction:

- A. Pedestrian Intention:
  - Waiting time before crossing the street
- B. Pedestrian Trajectory:
  - Coordinates, speed, acceleration, etc.
- C. Vehicle reactions



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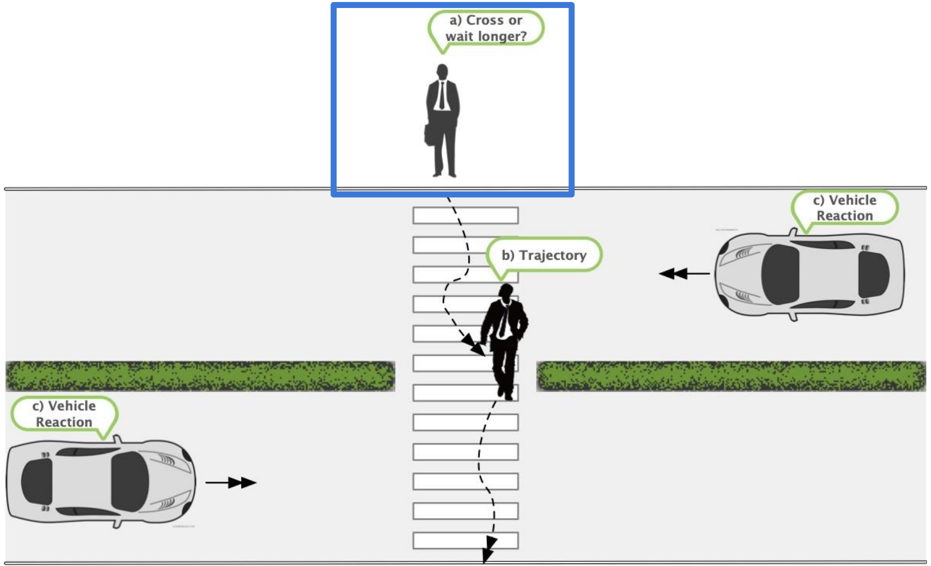

Methodology

- Traditional Method to analyze time before an event: Linear Survival Models
- Survival Function:

$$S(t) = e^{-\int_0^t h(z)dz}$$

- Most common method: Cox Proportional Hazards (CPH):

$$h(t|Z) = h_0(t) \times e^{\sum_i \beta_i Z_i}$$

- Partial Likelihood to be maximized:

$$\prod_{k \in instances} \frac{e^{\sum_i \beta_i Z_{ik}}}{\sum_{j:T_j > T_k} e^{\sum_i \beta_i Z_{ij}}}$$

Methodology

- ***Problem*** Linear Assumption of log-risk function:
  - Cannot capture nonlinearities in complex data
  - Novel data sources: more complex data

- ***Solution*** Replace linear log-risk function with a neural network

$$h(t|Z) = h_0(t) \times e^{g_w(Z)}$$

- ***Loss function*** Average negative logarithm of CPH's partial likelihood

$$L_w = -\frac{1}{N} \times \sum_{k \in instances} \left(g_w(Z_{nk}) - \log \sum_{j: T_j > T_k} e^{g_w(Z_{nj})} \right)$$

Data Challenges :

- Study involves pedestrian jaywalks:

Safety concerns

- Futuristic nature of study:

Not enough AVs are available on the roads.

- Controlled variables:

Observe pedestrian behaviour under different scenarios

Solution:

❖ Stated Preferences Surveys?
  - ➢ Not Realistic
  - ➢ Users do not have prior experience

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VIRE: Controlled Immersive Virtual Reality experiments

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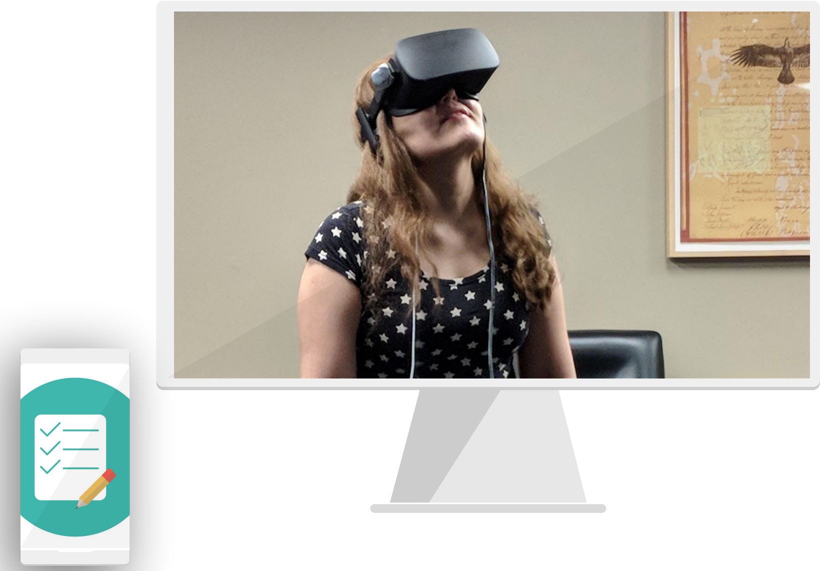
VIRE:

Human-in-the-loop controlled immersive virtual reality experiments

- 3D scenarios created based on theoretical experiment designs.
- Traffic movement is represented using an agent based simulation.
- Interactive virtual environment



VIRE:

- Questionnaire:
    - sociodemographic information, walking habits, health conditions, previous VR experience
- VR:
    - Coordinates, head orientations

VIRE: Controlled Variables

Scenarios defined by:

Factor	Variable	Levels		
Rules and regulations	Speed limit (km/h)	30	40	50
	Minimum allowed gap time (s)	1	1.5	2
Street design	Lane width (m)	2.5	2.75	3
	Road type	1-way	2-way	2-way with median
Automated vehicles	No. of braking levels	1	2	3
	Traffic automation status	Fully human driven	Mixed traffic	Fully automated
Demand	Arrival rate (veh/hr)	530	750	1100
Environmental	Time of day	Day	Night	
	Weather	Clear	Snowy	

Too many possible combinations?
D-Optimal Design

VIRE: Design of Experiment

Too many possible combinations?

D-Optimal Design:

- Find the efficient combination of levels
- Covariances matrix of parameter estimates determine attribute level combinations
- Minimizing the variance = Maximizing the Fisher information matrix
- A D-optimal design for CPH was proposed for the first time
- Scenarios generated to maximize determinant of Fisher information matrix:

$$\mathbf{M}(\xi,\beta)=\sum_{j=1}^{m}\omega_j(1-\exp(-c\exp(\beta_0+\beta_1x_1+\ldots+\beta_kx_k)))_j\begin{bmatrix}1 & x_1 & x_2 & \cdots & x_k\\ x_1 & x_1^2 & x_1x_2 & \cdots & x_1x_k\\ \vdots & & \ddots & & \vdots\\ x_k & x_kx_1 & \cdots & & x_k^2\end{bmatrix}_j$$

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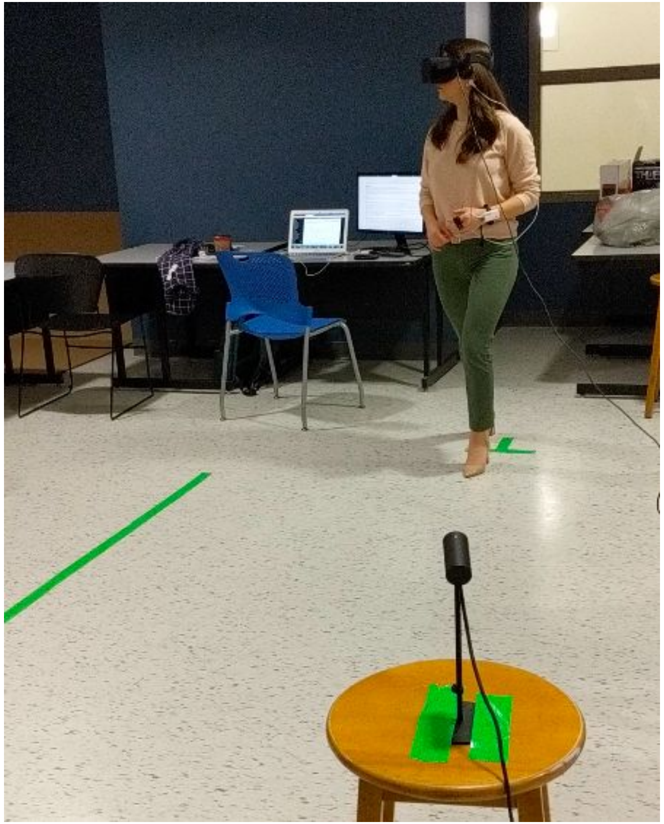
Participants using VIRE:



Data Collection

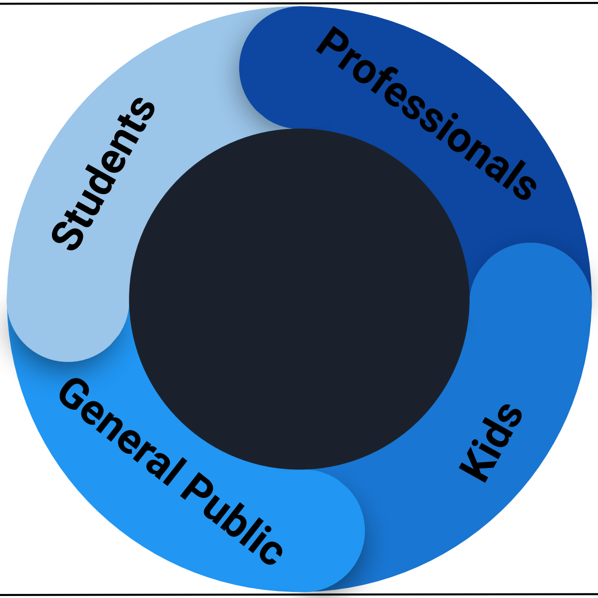
180 participants, over 5 months

Ryerson University:

Mainly Student and young professionals

Markham City Public Library:

General Public



North York Civic Center and Toronto City Hall:

Mainly Professionals familiar with city issues

Maximum City Summer school

Two groups of 10 and 15 year old kids

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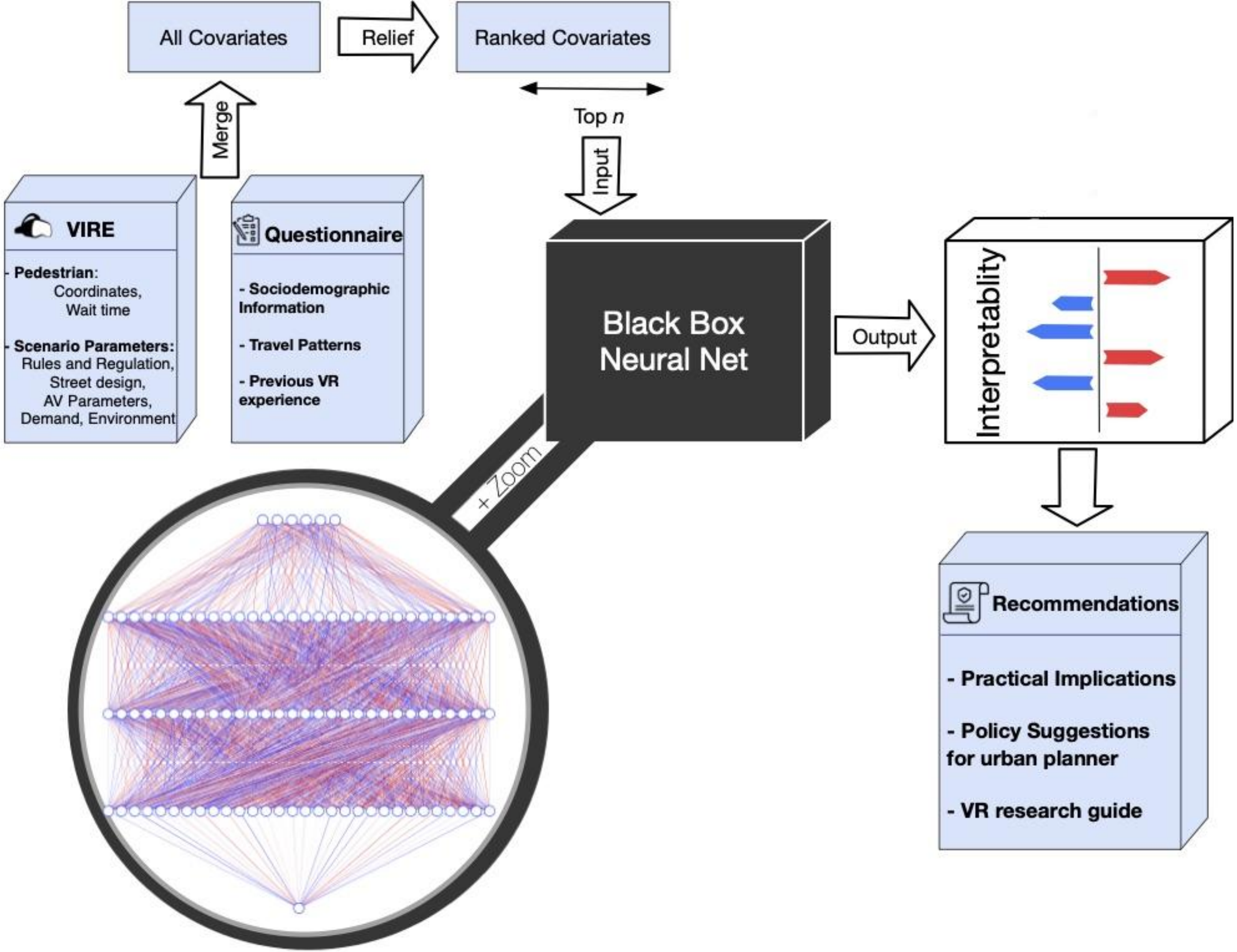
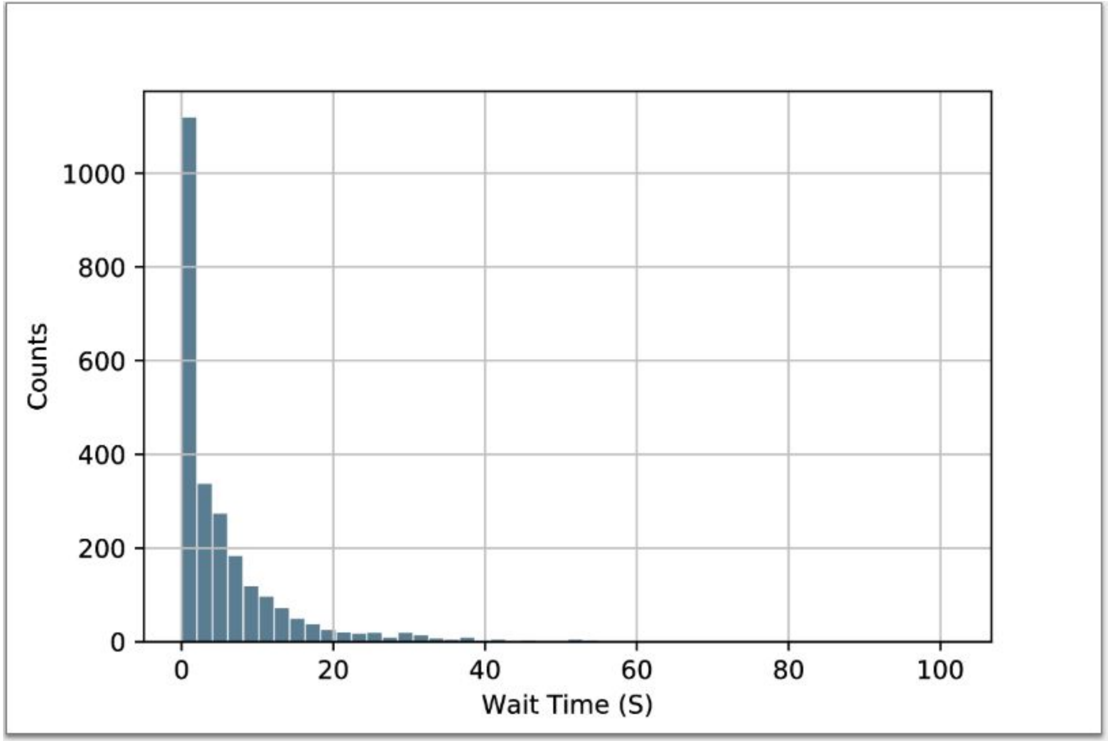
Framework



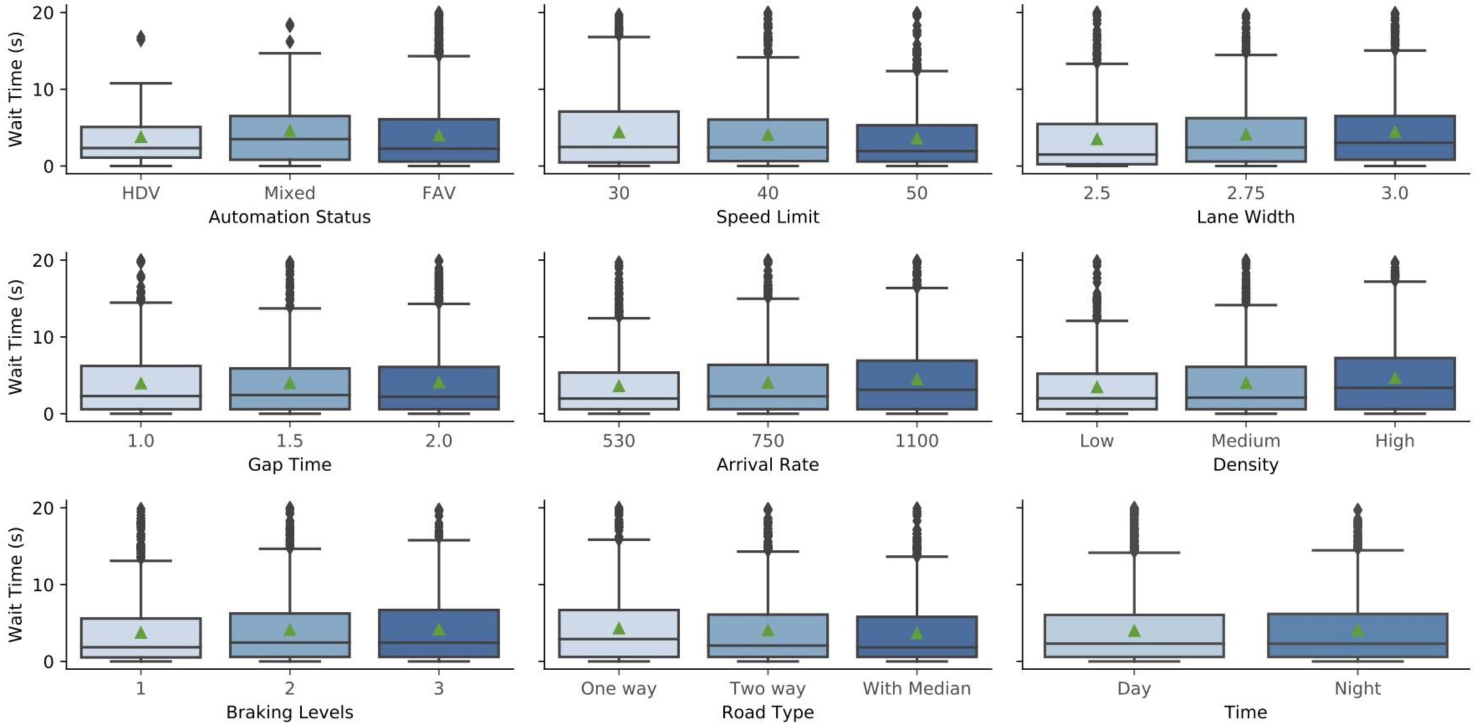
All Covariates
Relief
Ranked Covariates
Merge
Top n
Input
VIRE
- Pedestrian: Coordinates, Wait time
- Scenario Parameters: Rules and Regulation, Street design, AV Parameters, Demand, Environment
Questionnaire
- Sociodemographic Information
- Travel Patterns
- Previous VR experience
Black Box Neural Net
Output
Interpretablity
+ Zoom
Recommendations
- Practical Implications
- Policy Suggestions for urban planner
- VR research guide

Results

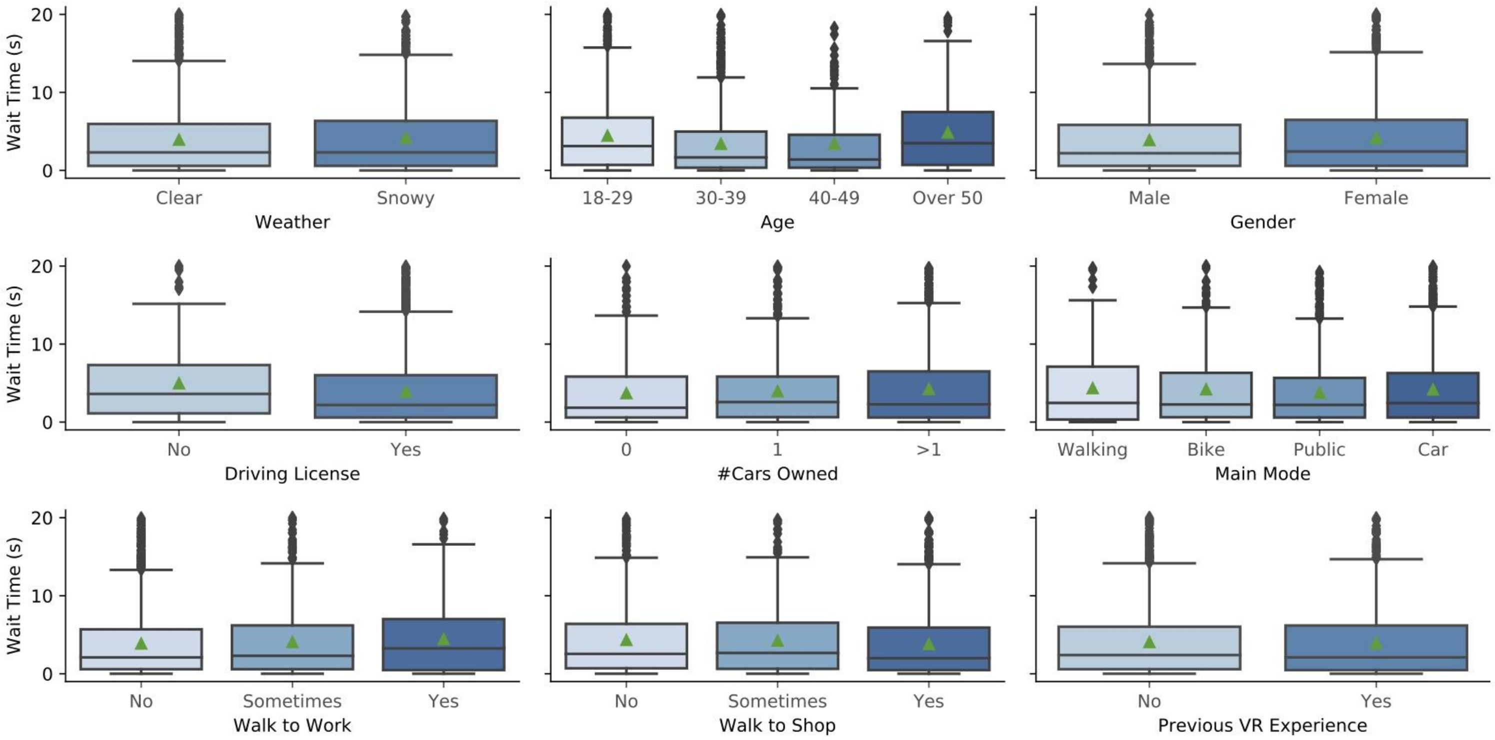
Wait time distribution:



Comparison of wait time:



Comparison of wait time:



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Results

CPH results:

Variable	Coefficient	Hazard Ratio	p-value
Walk to Shopping	0.18	1.20	<0.005
Main Mode: Car	-0.12	0.88	0.03
Age Over 50	-0.17	0.84	0.06
Traffic Density	-0.83	0.43	<0.005
Previous VR Experience	0.14	1.15	<0.005
Age: 30-39	0.32	1.38	<0.005
Lane Width	-0.31	0.73	<0.005
Road Type: Two-way with Median	0.22	1.24	<0.005
No Cars in the Household	0.14	1.15	<0.03
Gender: Female	-0.13	0.87	0.01

Performance Comparison

Model	Number of covariates	C-index: Validation Set	C-index: Test Set
Linear CPH	10	0.60	0.57
DCPH1	21	0.61	0.60
DCPH2	19	**0.64**	**0.62**

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Interpretability

- Performance increases with DCPH, but how each covariate contributes?
- Neural Networks are *black boxes*
- For practical implications, we need them ***interpretable***

- SHAP: (SHapley Additive exPlanations) *(Lundberg and Lee,2019)*
- Post-hoc model-agnostig interpretability method
- Inspired by Shapley Values: “How to fairly distribute the surplus to players?”
- Players: covariates, surplus: change in network output
- Considers the fact that the contribution of a feature depends on the values of other features

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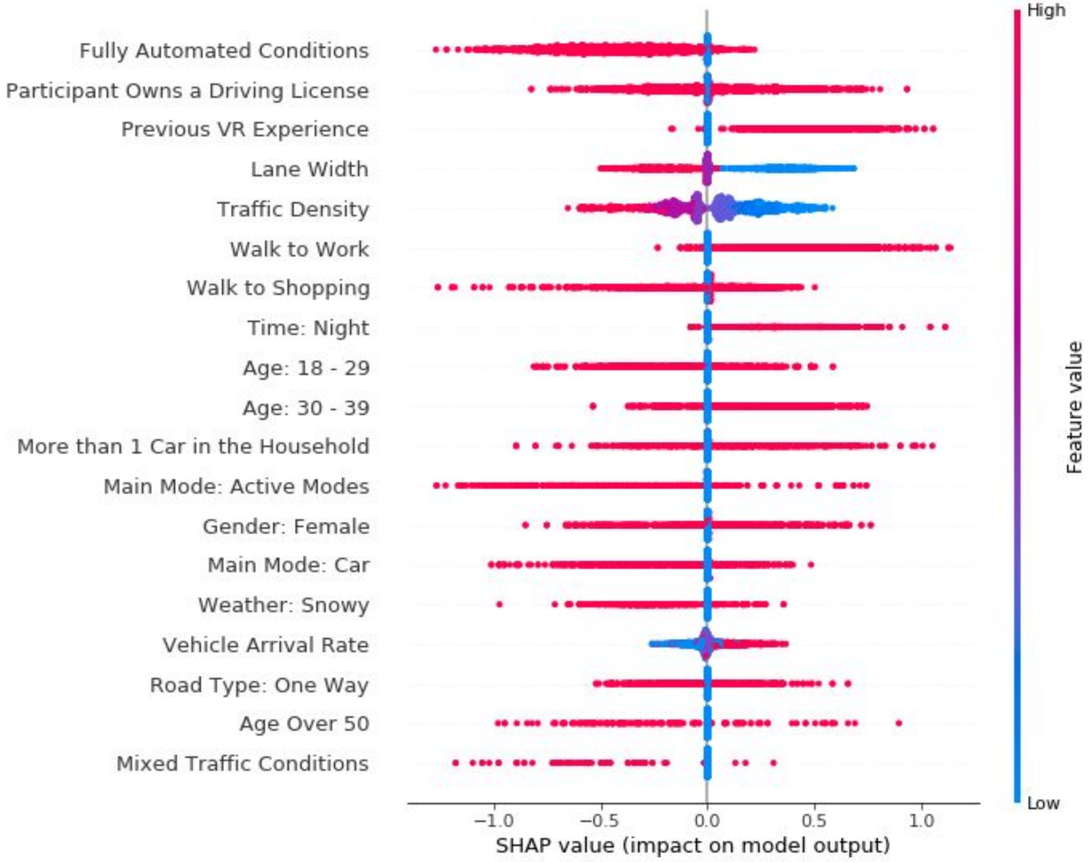
Interpretability

Longer wait times
Shorter wait times



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Discussion

- Participants are more conservative in the presence of AVs:
  - Nationwide educational training programs to familiarize pedestrians with new dynamics
  - VR can play an important role
  - Manufacturers should consider alternative ways to communicate with pedestrians
- Narrower lane widths, lower traffic densities, and better sight distances cause shorter wait times:
  - Wider sidewalks, narrower lane widths, enhanced lighting equipment
- Having frequent walking habits positively affects the crossing experience:
  - Promoting active modes and developing more pedestrian friendly infrastructure
- Extra attention to children and senior participants:
  - Training and educational programs

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Conclusions:

- Before having AVs in urban areas, their impact from a pedestrian perspective should be investigated
- Advance data-driven models improve performance, using rich datasets available
- Virtual immersive reality based digital sandbox:
    - Controlled/safe environment
- Interpretable models are required for policy and decision making

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Future Work:

- Pedestrian behaviour in group
- Applying the model to benchmark datasets
- Pedestrian trajectory prediction
- Developing a comprehensive framework consisting of pedestrian intention decisions and behaviours, as well as AV training

Thank you!

Preprint available at: https://arxiv.org/pdf/2002.07325.pdf

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