Final Project Report

"Analyzing Driver Yielding Behavior at Midblock Crossings Under Different Weather Conditions"

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1. Introduction

Pedestrian safety is a key concern in urban transportation planning, particularly at midblock crossings where the absence of traffic signals increases the vulnerability of pedestrians. Unlike intersections, midblock crossings often rely solely on driver discretion for yielding. This study focuses on driver yielding behavior at a midblock crossing on East Main Street near University Street in Kent, Ohio, analyzing how different weather conditions—clear versus snowy—affect yielding rates and pedestrian wait times.

2. Background and Literature Review

Midblock crossings have been identified as high-risk zones for pedestrians due to their unsignalized nature and the unpredictability of driver responses (Schneider et al., 2018). Research from the Federal Highway Administration emphasizes that median refuges at these crossings can improve safety by allowing two-stage crossing behavior, which increases driver yielding rates (Fitzpatrick et al., 2022).

Weather has also been shown to influence driver behavior. A study by the Minnesota Department of Transportation found that snowy conditions may prompt more cautious driving, potentially increasing yielding rates (Yang, 2024). However, snow can also impair visibility and road surface conditions, reducing pedestrian detectability (Qiu & Nixon, 2008).

Time of day is another variable; some studies suggest that yielding is higher during off-peak times due to lower traffic volumes and reduced driver stress. Additionally, driver compliance tends to improve in environments with clearer road design, including refuge islands and better markings (Zegeer et al., 2005)

3. Methodology

This project used video footage collected at a midblock crosswalk on East Main Street near University Drive, Kent, Ohio (Figure 1 and 2).

3.1 Data Collection: We collected five hours of data on a clear weather day, August 28, and another five hours on a snowy day, November 21.

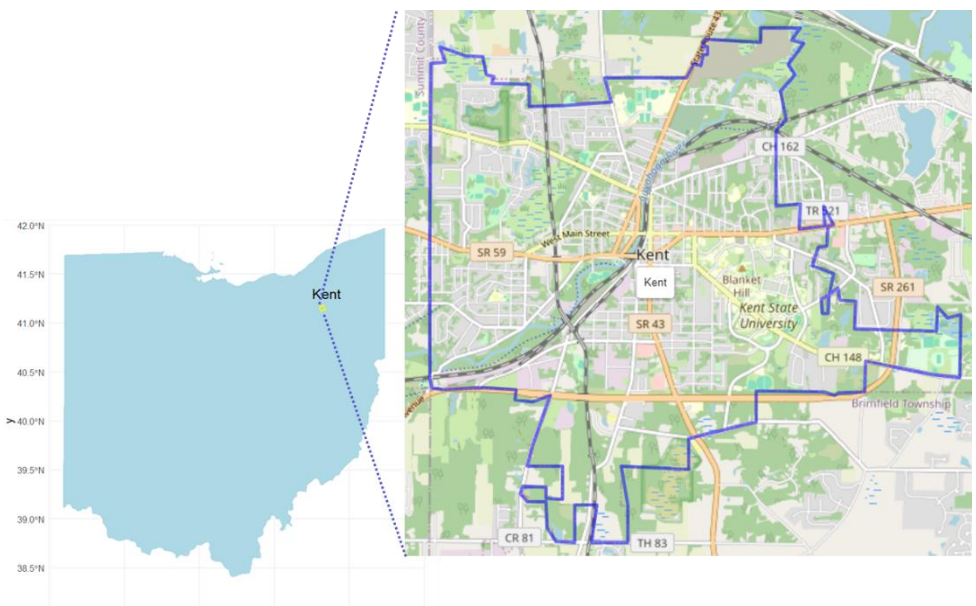


Figure 1. Study area

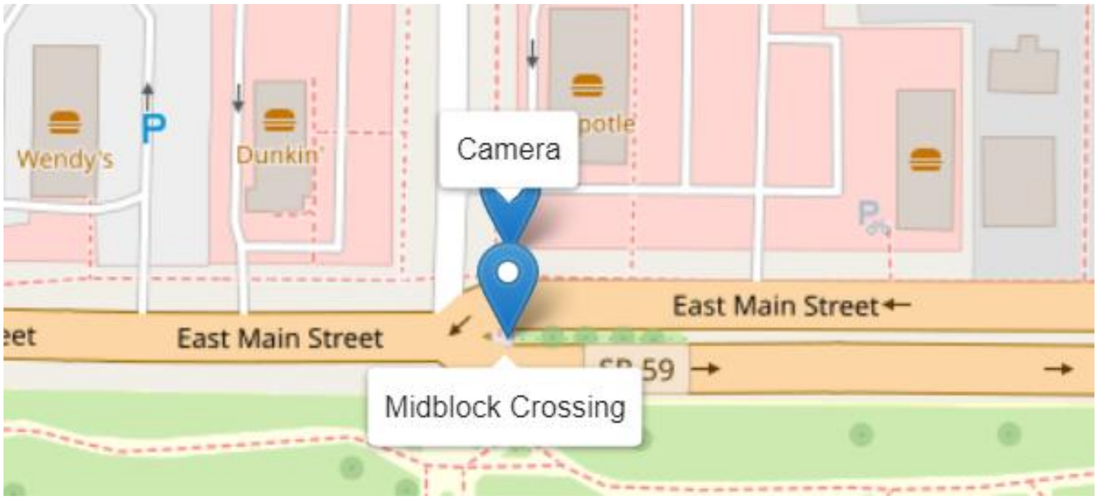


Figure 2. Camera and Midblock crossing location on East Main Street

3.2 Data Extraction

Deep Learning Model Selection: To extract relevant data from the video footage, this study used **YOLOv8 (You Only Look Once, version 8)**—a state-of-the-art deep learning model for real-time object detection and tracking (Van Rossum & Drake, 1995). YOLOv8 was selected due to its high accuracy and ability to handle complex traffic scenarios efficiently. The implementation was carried out in **Python**, using a combination of essential libraries:

- **OpenCV** was employed to split raw video into individual frames, preprocess images (e.g., resizing and normalization), and display detection results using bounding boxes.
- **YOLOv8** processed each frame to detect and classify objects (e.g., vehicles, pedestrians), assigning unique IDs to track their movements across frames.
- **Pandas** organized the extracted data—such as object type, location, and time—in structured tabular formats (CSV).
- **NumPy** supported numerical operations like estimating object speeds through pixel displacement across frames.

The data extraction process followed four key steps: (1) **Frame extraction** at 30 frames per second using OpenCV; (2) **Object detection and tracking** using YOLOv8 to identify object types and assign tracking IDs; (3) **Data extraction** including object type, bounding box coordinates, speeds, trajectories, and timestamps; and (4) **Data storage**, where all outputs were saved in CSV format for subsequent statistical analysis in R.

3.3 Data Cleaning and Preprocessing Using R: After video processing with YOLOv8, the extracted CSV data was imported into **R** for cleaning, analysis, and visualization (RC Team, 2020). This section outlines how R was used to evaluate driver yielding behavior, pedestrian wait times, and time-based patterns across weather conditions.

3.4 Data Preparation

Using readr and dplyr, I loaded and cleaned CSV files for two observation days (August 28 and November 21). The data included timestamps, object types, crossing location (corner or median), and yielding status. Cleaning steps involved removing duplicates, filtering valid time intervals (8 AM–1 PM), and categorizing crossing types.

3.5 Yielding Behavior Analysis: I grouped the data by date, location, and hour to compute **yielding percentages** using:
Yielding Rate=(Total Number of Interactions/Number of Yielding Interactions)×100

3.6 Wait Time Calculation

Pedestrian wait times were calculated using timestamp differences and summarized by hour and location.

3.7 ANOVA Statistical Test

Using the aov() function, I conducted an **ANOVA test** to examine if yielding rates varied significantly by **date**, **location**, and **time**. Results confirmed:

- Significant differences by **date** ($p = 0.0105$)
- Significant differences by **location** ($p = 0.0048$)

3.8 Data Visualization

With ggplot2, I created:

- **Line graphs** for pedestrian wait times
- **Bar plots** for average yielding percentages
- **Heatmaps** to visualize time-location yielding trends

These visuals supported the statistical findings and revealed subtle time-of-day effects.

4. Results

The project yielded several key findings based on statistical outputs and visualizations:

4.1 Yielding Differences by Date

- ANOVA results showed a **significant difference** in yielding between the two weather conditions ($p = 0.0105$), with higher yielding on the snowy day (November 21) (Figure 3).

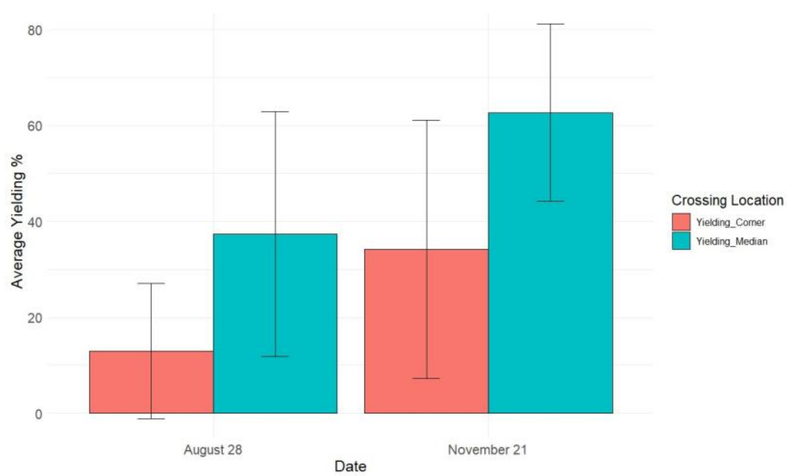


Figure 3. Average Yielding Percentage by Date and Location.

4.2 Location-Based Yielding Behavior

- Yielding rates were **significantly higher at median locations** compared to corners ($p = 0.0048$), supporting the benefits of refuge islands (Figure 4).

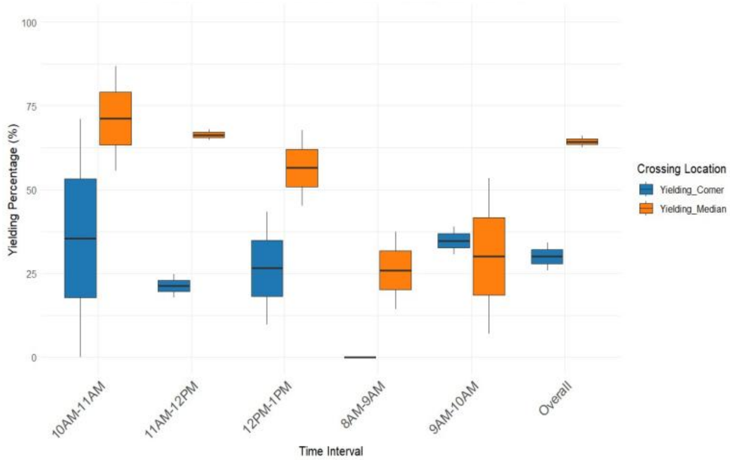
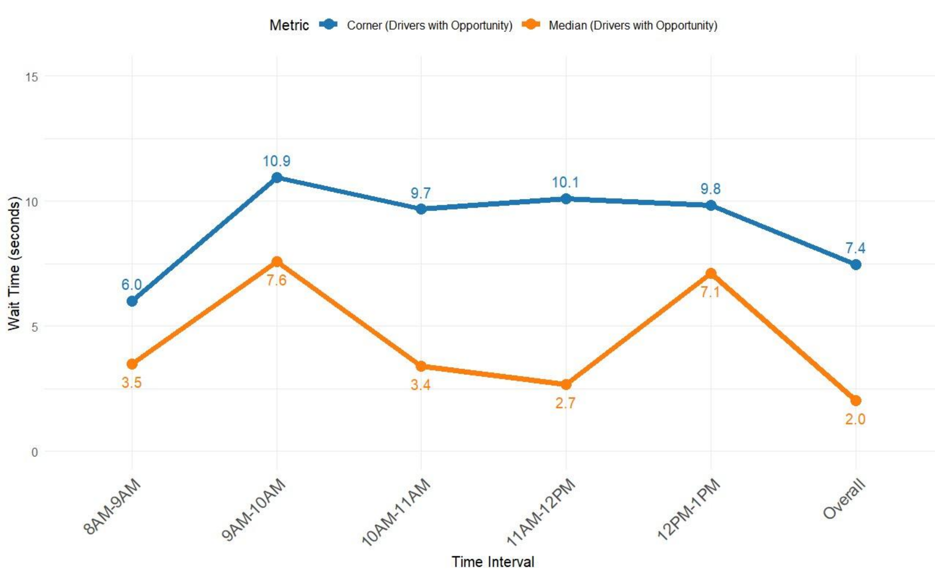


Figure 4. Distribution of Yielding Percentage by Time Interval (August 28 and November 21)

4.3 Pedestrian Wait Times

- Wait times were consistently **lower at the median** than the corner on both dates.
- On the snowy day, corner wait times increased, indicating greater risk due to delayed yielding.



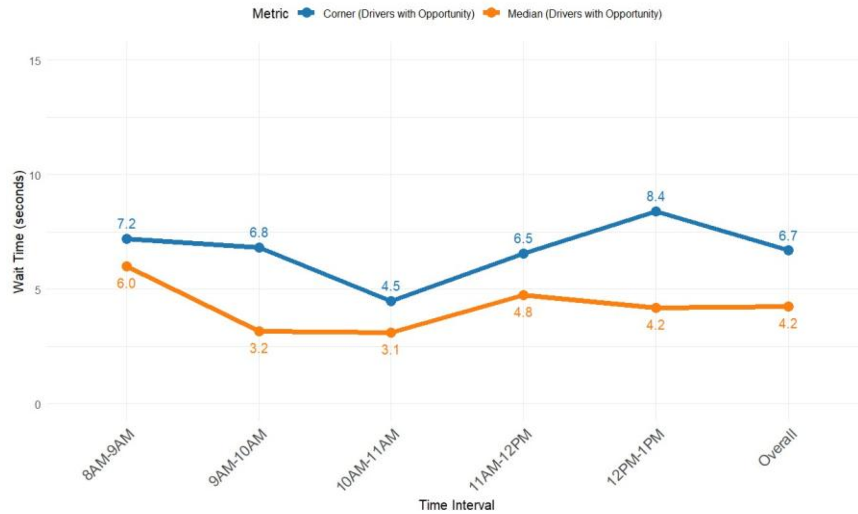


Figure 5. (a) Average Wait Time Comparison for drivers with opportunity: Corner vs Median (August 28), Figure (b): Average Wait Time Comparison for drivers with opportunity: Corner vs Median (November 21)

5. Discussion and Critical Reflection

5.1 Implications of Findings

The results highlight the importance of **physical design features** (e.g., medians) and **weather-aware planning** in pedestrian safety.

- Midblock crossings can benefit from infrastructure upgrades such as **pedestrian signals**, **refuge islands**, and **improved signage** to mitigate risk, especially in adverse weather.

5.2 Limitations

- **Limited data volume**: Only 10 hours of footage were analyzed due to time constraints.
- **Manual processing bottleneck**: Processing each hour of video took ~5 hours, limiting scalability.
- **Weather coverage**: Only clear and snowy conditions were compared; rain, fog, or nighttime were not included.

5.3 Lessons Learned

This project provided me with valuable hands-on experience in using R for data cleaning, processing, visualization, and statistical analysis. I learned how to work with CSV data exported from YOLOv8 by cleaning and structuring it into a format suitable for analysis. Using the dplyr and tidyr packages, I was able to manipulate large datasets and create grouped summaries, such as calculating average yielding percentages based on hour, date, and crossing location. I applied ANOVA tests using the aov() function to statistically evaluate differences in driver yielding behavior across different conditions. Additionally, I used ggplot2 to visualize data trends, which helped reveal key patterns like consistently higher yielding rates at median crossings and subtle time-of-day effects. I also created heatmaps to illustrate how yielding behavior varied across dates and locations, which provided a strong visual complement to my statistical results. Through this process, I not only improved my technical skills in R but also developed a deeper understanding of how data analysis can support traffic safety research and inform urban planning decisions.

5.4 What Could Be Done Differently

- Apply **continuous weather data** (temperature, snow depth, wind speed) for better interpretation.
- Include **multiple intersections** and **longer timeframes** for more robust generalization.

6. References

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