

Measuring the Severity of Violations Committed by Pedestrians at Signalized Intersections

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This thesis contains sections that have been previously incorporated in journal article submissions, as follows:

“Measuring The Severity of Spatial Violations Committed by Pedestrians at Signalized Intersections”

Submitted for journal publication in 2026. This paper has been co-authored by myself, and my supervisors: Dr. Chris Bachmann and Dr. Bruce Hellinga. I am the primary author of this article. This paper includes elements from all chapters of the thesis, excluding Chapter 4: Temporal Violations.

Abstract

Pedestrian safety remains a global concern, with pedestrians accounting for a substantial proportion of road traffic fatalities and injuries. Previous research has examined many factors that influence pedestrian safety however, pedestrian violations at signalized intersections are a major contributor to pedestrian-vehicle conflicts, yet existing traffic safety research primarily treats these behaviours as binary outcomes, either as compliant or non-compliant. This representation fails to capture the varying degrees of severity in different crossing paths, limiting a nuanced understanding of pedestrian risk and road safety. To address this gap, this thesis proposes, applies, and evaluates continuous metrics to characterize the severity of both spatial and temporal pedestrian violations at signalized intersections.

Three spatial violation (SV) metrics and four temporal violation (TV) metrics were developed. To evaluate these measures, observational pilot studies were conducted at a highly active signalized intersection in Waterloo, Ontario, utilizing both drone and street-level video data.

The spatial violation analysis revealed that 48% of pedestrians committed a spatial violation, with the vast majority (86.5%) engaging in corner cutting. Among the spatial metrics, SV Metric 2 (total violation area) and SV Metric 3 (time-step metric) provided the most robust and consistent severity evaluations, whereas SV Metric 1 (maximum lateral distance) tended to overestimate spatial violation severities. The temporal violation analysis found that 7.6% of pedestrians committed a temporal violation, predominantly initiating crossings during the Flashing Don't Walk interval (86.7%). Unlike the spatial metrics, the temporal metrics yielded statistically distinct severity distributions, demonstrating that the measurement of temporal violation severities is highly sensitive to whether the selected metric prioritizes strict legal compliance or practical safety risk.

Ultimately, this research recommends the use of SV Metrics 2 and 3 for spatial analysis and provides a framework for selecting appropriate TV metrics based on specific study parameters. The proposed metrics can be integrated into existing automated traffic data collection systems, supporting future research relating violation severity to conflict severity.

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Dedication

To God, and Jesus my Lord and Saviour.

This journey would have been impossible without your steadfast love and abundant blessings. Thank you for giving me the opportunity to study and helping me complete my studies in Civil Engineering at the University of Waterloo and thank you for helping me complete my master's degree. For always being there for me when I struggled and had doubts, thank you for your guidance and encouragement. For your glory, love, and blessings I dedicate this thesis.

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List of Abbreviations

Acronym	Name
AR	All-Red
ARBQ	Adolescent Road User Behaviour Questionnaire
FDW	Flashing Don't Walk
HTA	Highway Traffic Act
PET	Post-Encroachment Time
PBS	Pedestrian Behaviour Survey
PBQ	Pedestrian Behaviour Questionnaire
SDW	Solid Don't Walk
SSM	Surrogate Safety Measures
SV	Spatial Violation
TTC	Time-to-Collision
TV	Temporal Violation
UN	United Nations
WHO	World Health Organization

1. Introduction

1.1. Background:

Traffic safety is an issue that has been deemed important by both the United Nations (UN) and the World Health Organization (WHO). This is clearly indicated in the Global Plan for the Decade of Action for Road Safety 2021-2030 developed by both WHO and the UN, in which this plan describes a target reduction of road fatalities and injuries by at least 50% (World Health Organization, 2021). The UN and WHO have drafted initiatives that support another key traffic safety strategy: Vision Zero, which is “a strategy to eliminate all traffic fatalities and severe injuries, while increasing safe, healthy, equitable mobility for all” (Vision Zero Network, n.d.).

According to WHO, more than 274,000 pedestrian fatalities are recorded annually (World Health Organization, 2023) whilst in Canada more than 300 pedestrians are killed each year (Eduful, 2023). Furthermore, there has been an upward trend in the number of pedestrians killed in Canada from 2010 to 2019 (Transport Canada, 2025). Based on Transport Canada’s collision database, between 2010 and 2019, most fatal pedestrian collisions occurred at urban intersections (Transport Canada, 2025).

There has been a substantial amount of research completed to analyze the factors that influence pedestrian safety. This research has identified several contributing factors, including traffic speed and volume (Mansfield et al., 2018), pedestrian age and gender (Kemnitzer et al., 2019), and the design of the walking environment and pedestrian infrastructure (Kim et al., 2024). Another important factor that has been heavily studied is pedestrian distraction (Granié et al. 2013), with distracted pedestrians found to be more likely to engage in non-compliant behaviour (Thompson et al., 2013). Many studies share a similar list of factors; however, pedestrian violation behaviour is much less frequently considered. Specifically, a crossing initiated when not legally permitted constitutes a temporal violation, whereas a crossing path that is fully or partially outside the legally specified crosswalk region constitutes a spatial violation. A study was conducted in Vancouver, Canada, where several traffic-controlled intersections with the highest frequency of pedestrian injuries were observed to compare the violating behaviour of pedestrians and motorists. It was observed that at seven of the top eight busiest intersections in Vancouver, there was a substantially higher number of pedestrian violations compared to motorist violations (Cinnamon et al., 2011).

Despite the evidence that pedestrian violations (temporal and/or spatial) may be important factors in road safety, most previous research has considered violations as a binary outcome (violation vs no violation). This aggregate representation is coarse and fails to capture differences in the severity of individual violations. The lack of meaningful violation severity metrics limits the ability to quantify, compare, and model violation behaviour, thereby constraining a more nuanced understanding of its relationship with road safety.

1.2. Problem Statement

Pedestrian safety is a well studied topic but often examined from the scope of distracted behaviour or the pedestrian-vehicle relationship at intersections or mid-block crossings. In other words, the underlying conditions that typically lead to a pedestrian violation and result in a conflict or collision between a pedestrian and vehicle are typically the focus, after which any attempts to quantify these circumstances fall beneath the quantification of a conflict. This relationship leads to some studies hypothesizing that pedestrian violations are a leading cause of conflicts and collisions however, there is a lack of metrics to objectively quantify the severity of a pedestrian violation, both spatially and temporally (Chen et al., 2022). To confirm this hypothesis, it is necessary to first quantify the severity of pedestrian violations, before future research can study their relationship with measures of road safety such as conflicts or collisions.

1.3. Research Objectives

The purpose of this thesis is to propose, apply, and evaluate metrics to characterize the severity of pedestrian spatial and temporal violations at signalized intersections. To do this, this thesis poses and answers the following research questions:

1. What are the pedestrian spatial violation behaviours occurring at signalized intersections?
2. How can the severity of pedestrian spatial violations at signalized intersections be measured?
3. How effectively do the proposed spatial violation measures characterize the spatial pedestrian violation severity?
4. What are the pedestrian temporal violation behaviours occurring at signalized intersections?
5. Do pedestrians change their crossing speed based on the time when they begin their crossing relative to the pedestrian signal intervals?

6. How can the severity of pedestrian temporal violations at signalized intersections be measured?
7. How effectively do the proposed temporal violation measures characterize the temporal violation severity?

1.4. Research Scope

The scope of this research is limited to analyzing pedestrian violation behaviour. Although gaining an understanding in pedestrian violation behaviour and its influence on the propensity and severity of a pedestrian-vehicle conflict is important, this study is not focused on establishing this link. This research proposes metrics to measure pedestrian violations strictly at signalized urban intersections with defined pedestrian crossing areas (e.g., painted crosswalks) and pedestrian signals with a countdown timer. Therefore, the findings in this thesis are not applicable to all intersections and situations (e.g., the proposed spatial violation metrics require painted crosswalks). The spatial scope of this thesis is small, confined to a single intersection and the temporal scope of the data collection ranges from a single hour (spatial violations) to six months (temporal violations). Additional limitations that emerged from research will be discussed in future chapters of the thesis.

1.5. Thesis Structure

This thesis is structured into five chapters, including this chapter. Chapter 1 introduces the study. The background provided indicates the importance of pedestrian safety, some of the global initiatives to improve pedestrian safety, and introduces the idea that pedestrian violations might contribute to pedestrian-vehicle conflicts. The problem statement, research objectives, and research scope define the purpose and limitations of this study. Chapter 2 reviews the existing literature related to pedestrian behaviour, pedestrian violations, attempts to quantify pedestrian violations, including what data collection methods are currently deployed. Chapter 3 focuses on spatial violations and proposes three metrics to quantify and evaluate pedestrian spatial violations. This chapter introduces a pilot study where data is collected to apply these spatial violation metrics, analyze and discuss the results, then explain the limitations of the pilot study and the methodology. Chapter 4 follows a parallel structure to propose, apply, and evaluate metrics for pedestrian temporal violations. Chapter 5 presents the conclusions and future work. The conclusions are presented according to the research goal and objectives described in Section

1.3, summarizing the major findings of the pilot studies, and discussing avenues for future work and improvements.

2. Literature Review

2.1. Types of Pedestrian Behaviour

In traffic safety research, pedestrian behaviour is generally analyzed through two major theoretical frameworks: (1) the psychological and human-factors domain (Granié et al., 2013; Deb et al., 2017), and (2) the infrastructure and signal compliance domain (Brosseau et al., 2013; Dhoke & Choudhary, 2024). Many studies and surveys have been conducted in the psychological domain to understand the intent behind pedestrian decision-making. Taxonomies have been developed by listing commonly observed pedestrian behaviours and then cross-referencing them with existing literature to categorize them by psychological intent. An important tool that resulted from this approach is the Pedestrian Behaviour Scale (PBS), initially developed by Granié et al. (2013) and further validated for North American applications in subsequent research (Deb et al. 2017). The PBS groups pedestrian behaviours into five psychological constructs: violations, errors, lapses, aggressive behaviours, and positive behaviours.

Within the PBS, violations are defined as intentional deviations from formal or informal rules (e.g., deliberately crossing outside the crosswalk to save time). Errors are unintentional failures in spatial or temporal judgement. Lapses are unintentional deviations caused by inattention or memory failures. Aggressive behaviours encompass hostile actions taken towards other road users. Positive behaviours are actions that aid the overall flow of traffic (Deb et al., 2017; Granié et al., 2013)

While surveys such as the PBS provide valuable insight into the intent of road users and offer a useful complement to the observation-based approaches discussed elsewhere in this chapter, they rely heavily on self-reporting, and their results are dependent on the objectivity of the respondent. The most widely used instrument in this space is the PBS (Granié et al., 2013). However, the PBS did not emerge as a settled framework; it built on an earlier UK instrument, the Adolescent Road User Behaviour Questionnaire (ARBQ) (Elliott & Baughan, 2004), which classified adolescent pedestrian behaviour into three categories: unsafe crossing (combining errors and violations into a single factor), dangerous street play, and planned protective behaviour. The ARBQ's structure illustrates that even the categorical distinction between

“errors” and “violations”, which are central to the PBS, are not universally treated as meaningful across all surveys.

Additionally, the five-dimension PBS structure has not been consistently confirmed. In the original French validation study, principal component analysis identified only four empirically distinguishable factors rather than five. Here, violations and errors are combined into a single “transgressions” factor (Granié et al., 2013). Subsequent national adaptations have reported further variations: the American validation confirmed the full five-factor structure (Deb et al., 2017) as did the Serbian validation (Antić et al., 2016). In contrast, the Turkish adaptation converged only on three factors and excluded the positive-behaviour factors entirely (Nordfjærn & Şimşekoğlu, 2013), while the Chinese adaptation found that the lapses dimension was poorly supported (Qu et al., 2016). Further still, other countries such as Vietnam, Thailand, Bangladesh, Kenya, China, and the United Kingdom could only confirm three of the five dimensions as statistically valid (McIlroy et al., 2019).

Table 2.1 summarizes the major self-report pedestrian behaviour instruments identified in this review and their proposed categorizations. At least nine distinct instruments or national validations have been document, and a recent systematic review of the PBS literature spanning 116 identified studies concluded that no single version of the PBS reliably validates all five of its theorized dimensions. Particularly, the positive-behaviour dimension proving to be the most consistently difficult to confirm across translations and iterations of the PBS (Vandroux et al., 2022). As no systematic review of the PBS had been conducted prior to Vandroux et al. (2022), the research community had not previously converged on a single validated categorization. The review’s authors instead offer this as a starting point from which future researchers can make an informed, evidence-based choice between existing versions rather than treating any one categorization as definitively correct.

Table 2.1: Major Self-Report Pedestrian Behaviour Surveys/Questionnaires

Survey	Author(s), Year	Country Or Countries	Basis	Proposed Dimensions
ARBQ	Elliot & Baughan, 2004	United Kingdom	Independent framework for adolescents	Unsafe crossing (errors & violations merged), dangerous street play, planned protective behaviour
PBS (original version)	Granié et al., 2013	France	Synthesis of prior questionnaires	Theoretical: 5 dimensions (violations, errors, lapses, aggressive, positive). Empirically confirmed: only 4 (transgressions, lapses, aggressive, positive)
PBS (US validation)	Deb et al., 2017	United States	Direct validation of PBS	5 factors confirmed
PBS (Turkish validation)	Nordfjærn & Şimşekoğlu, 2013	Turkey	Adaptation of PBS	3 factors (violations, errors, aggressive); positive behaviours excluded
PBS (Chinese validation, CPBS)	Qu et al., 2016	China	Adaptation of PBS	Lapses dimension not well supported
PBS (Serbian validation)	Antić et al., 2016	Serbia	Adaptation of PBS	5 factors confirmed
PBQ (6- country validation)	McIlroy et al., 2019	Bangladesh, China, Kenya, Thailand, UK, Vietnam	Adaptation of Deb et al.'s US PBS	Only 3 factors confirmed as valid (violations, aggressions, lapses)

2.2. Violations

To address the practical considerations of pedestrian safety at intersections, traffic engineering and legal frameworks evaluate pedestrian behaviour based on observable compliance with established infrastructure and traffic control measures, rather than underlying psychological intent. Within this context, non-compliance is defined not by why the pedestrian committed a violation during the crossing but by where and when the crossing occurs relative to the designated crossing boundaries and pedestrian signals.

In Ontario, Canada, pedestrian violations are codified by the Highway Traffic Act of Ontario (HTA). Under Section 144 of the HTA, pedestrian compliance is governed by two strict parameters: signal intervals and pavement markings. Legally, a temporal violation occurs if a pedestrian begins a crossing against a prohibited signal interval, namely the Solid Don't Walk (SDW) or the Flashing Don't Walk (FDW) signal intervals. According to Subsection 2, "No pedestrian approaching pedestrian control signals and facing a solid or flashing "don't walk" indication shall enter the roadway" (*Highway Traffic Act, R.S.O. 1990, c. H.8 | Ontario.Ca, n.d.*). Additionally, for pedestrians who are still crossing after the Walk signal interval, Subsection 28 states: "Every pedestrian who lawfully enters a roadway in order to cross may continue the crossing as quickly as reasonably possible despite a change in the indication he or she is facing and, for purposes of the crossing, has the right of way over vehicles" (*Highway Traffic Act, R.S.O. 1990, c. H.8 | Ontario.Ca, n.d.*). Furthermore, a spatial violation occurs if the pedestrian deviates outside of the painted crosswalk lines during their crossing trip. As mandated by Subsection 22, "Where portions of a roadway are marked for pedestrian use, no pedestrian shall cross the roadway except within a portion so marked" (*Highway Traffic Act, R.S.O. 1990, c. H.8 | Ontario.Ca, n.d.*). Although the HTA provides a strict legal definition in classifying pedestrian crossing events as either entirely lawful or unlawful, traffic safety literature uses more detailed classifications to examine how different forms of violations occur in practice. While legal frameworks such as the HTA define spatial violations simply as either the pedestrian is lawfully inside or unlawfully outside of the legal crossing area and temporal violations as a lawful or unlawful crossing, computer vision and automated video analytics in advanced traffic safety research have enabled further characterization of the crossing behaviour of pedestrians (Ismail et al., 2010).

For example, Ismail et al. (2010) applied automated video-based tracking to conduct a before-and-after evaluation of a pedestrian scramble-phase treatment at an intersection in Oakland, California. Their work demonstrated that vision-based systems can move beyond static violation of collision counts to detect and quantify pedestrian-vehicle conflicts directly from trajectory data. By capturing not only a decline in conflict frequency following the treatment but also a shift in where conflicts occurred relative to the crosswalk. Their analysis illustrated a level of behavioural nuance that a binary compliant/non-compliant classification would obscure.

While spatial violations are intrinsically linked to intersection geometry and human path-choice decision making (Brosseau et al., 2013), temporal violations are linked to signal timing, pedestrian waiting duration, and external traffic conditions (Xing et al., 2022). Studies have also recognized some common patterns in the types of spatial violations leading to further categorization. Two common types of spatial violations are corner cutting and crossing outside the crosswalk. Corner cutting is when a pedestrian is outside of the legally defined crossing area for either just the first and/or last part of the crossing because the pedestrian is “skimming” the corner of the crosswalk to save a few meters and seconds of walking. Crossing outside of the crosswalk refers to pedestrians who are outside of the legally designated crossing area for the entirety of the crossing (Chen et al. 2022). Contrary to spatial violations, no evidence of categorization of temporal violations can be found in the existing literature. The most relevant attempt to categorize temporal violations describes the behaviours as “dangerous temporal non-compliance (D-TNC)” or as “non-dangerous temporal non-compliance (ND-TNC)” (Dhoke & Choudhary, 2024). In other words, did the temporal violation result in a conflict with a vehicle.

While the type of violation defines the overall pattern of crossing behaviour, a large challenge remains in quantifying the magnitude of these violations. The following section reviews the current state of literature regarding the quantification of violations.

2.3. Quantifying Pedestrian Spatial and Temporal Violations

Despite established patterns in spatial crossing behaviours, the literature lacks approaches that quantify the magnitude or severity of both pedestrian spatial and temporal violations. Instead, existing studies focus predominantly on quantifying the severity of conflicts. Driven by the widespread adoption of Surrogate Safety Measures (SSMs) and the Traffic Conflict Technique (TCT), researchers have focused on proximity indicators such as Post-Encroachment

Time (PET) and Time-To-Collision (TTC) to evaluate conflicts or near-miss events (Ismail et al., 2010). While PET and TTC are effective for evaluating the temporal risk of a collision between two road users, they do not measure the severity of a potential spatial violation as a contributing factor, nor do they consider the possibility of a temporal violation.

When spatial violations are recorded in the existing literature, they are typically treated as either a binary or categorical variable. Safety reports focus on the probability and frequency of spatial violations occurring or identifying what percentage of pedestrians crossed outside of the crosswalk rather than how far outside of the crosswalk the pedestrians traveled. Even in trajectory-based studies that actively attempt to model spatial violation severities, methodologies ultimately still rely on temporal measures. For example, Chen et al. (2022) recently extracted spatial trajectory information to study pedestrian violations when traversing a crosswalk that crossed an exclusive right-turn lane. The researchers applied K-means clustering to time and speed indicators to categorize pedestrian-vehicle conflict severities (slight, moderate, and severe), which were then predicted in a multivariate ordered logistic regression using the type of spatial violation as a key independent variable. The spatial violation was only represented at the aggregate level in terms of the type of violation (corner cutting, outside crosswalk crossings, and irregular crossings) rather than quantitatively measuring the severity of the spatial violation itself.

Like spatial violations, temporal violations are also typically treated as either a binary or categorical variable. Existing observational studies focus on whether a pedestrian's crossing complied with the applicable signal interval, or whether a conflict has occurred rather than quantifying how far into the respective signal interval or cycle phase the crossing was made (Cloutier et al., 2022; Wu et al., 2021).

For instance, Cloutier et al. (2022) conducted an observational study of child pedestrian rule compliance at crosswalks around parks in Montreal, Canada, recording the crossing behaviour of 731 children. By classifying each crossing as strictly compliant or non-compliant based on whether the crossing was completed before the signal interval ended. Their temporal compliance measure treated a pedestrian who missed the legal crossing interval by a fraction of a second identically to one who missed it by several seconds. Similarly, Wu et al. (2021) developed a real-time safety model for pedestrian red-light running at two signalized intersections in Nanjing,

China. Their model aggregated video-derived counts of red-light-running pedestrians per signal cycle, as a simple binary occurrence. Consequently, this approach did not capture critical severity factors, such as how deeply into the red interval the pedestrian crossed or their spatial proximity to conflicting traffic.

These gaps in the literature highlight the necessity for continuous, objective metrics to measure the severity of spatial and temporal violations, which is what this thesis provides. This thesis introduces a novel set of three Spatial Violation Severity (SV) metrics and four Temporal Violation Severity (TV) metrics that can be used to expand beyond simple binary compliance/non-compliance categorizations and robustly measure violation severities to distinguish between different violation behaviours.

2.4. Data Collection Methods

There are many methods used to collect data; such as surveys, manually observing and recording pedestrians and vehicles, and automated data collection systems. One of the more notable surveys, the PBS (refer to Section 2.1) is a self-reported assessment and provides a deeper insight into a pedestrian's state of mind. The PBS also records decisions rather than the physical movement of pedestrians (Granié et al., 2013). While understanding the pedestrian's psyche is important, this does not provide information that can be used for quantitative analysis of pedestrian violations. Then, the simplest method to collect data is to utilize real-time human observations, by observing and recording pedestrian movements at an intersection or through video collection devices which are often deployed by municipalities or 3rd part data collection companies such as Miovision (Miovision, n.d.) or Ouster BlueCity (Ouster, n.d.). One obvious issue with utilizing human observations is that the level of accuracy is highly variable between observers, while automated systems have more consistent accuracy and precision across devices.

Miovision primarily utilizes camera-based systems to conduct traffic and pedestrian studies for municipalities. Miovision's devices collect multimodal traffic data on a minute-by-minute basis, including pedestrian counts, bicycle counts, vehicle classifications (cars, trucks, buses), and custom classifications like e-scooters (Miovision, n.d.). Miovision offers continuous safety monitoring, where vehicle and pedestrian movements are constantly recorded. The locations of conflicts and conflict rate are determined using post encroachment time (PET).

Other surrogate safety measures provided are the vehicles running red-lights and when pedestrians cross outside of the Walk interval (Miovision, n.d.).

In contrast, Ouster BlueCity represents an alternative approach to intersection monitoring by utilizing continuous 3D LiDAR (Light Detection and Ranging) sensors rather than video cameras. BlueCity's system captures millions of data points per second to create a real-time spatial point cloud. This allows for the continuous trajectory tracking and highly accurate classification of vehicles, cyclists, and pedestrians at a centimeter level (Ouster, n.d.). Similar to Miovision, BlueCity provides advanced safety analytics through continuous intersection monitoring. By tracking the exact physical paths and micro-kinematics (such as instantaneous speed and acceleration) of all road users, the system maps near-misses and dynamically calculates surrogate safety measures like PET and TTC, while simultaneously flagging specific infractions such as vehicle running red-lights and pedestrians crossing against the Walk signal interval (Ouster, n.d.). Notably, BlueCity's "jaywalking" analytics module includes a visualization that plots pedestrian trajectories over an image of the intersection, alongside heatmaps of pedestrian activity for a selected time window (Ouster, n.d.). This output format closely resembles the trajectory-based approach adopted in this thesis, providing further evidence that the data needed to compute the proposed SV and TV metrics is already being collected by commercial systems.

The current features of these automated data collection systems collect a substantial and diverse amount of data that already have many practical applications. This thesis proposes several metrics that can quantify the severity of a pedestrian violation that use data currently collected by Miovision and Ouster BlueCity and thus, these metrics can be integrated into these types of systems to provide further insights into road user behaviours.

3. Spatial Violations

3.1. Proposed Spatial Violation Metrics

This thesis proposes three metrics to quantify spatial violations of pedestrians making crossings at signalized intersections. The metrics assume pedestrian path trajectories and intersection geometry data are available in real world coordinates as inputs.

Key characteristics of the intersection geometry considered are illustrated in Figure 3.1. The characteristics are the crosswalks, sidewalk quadrants, and spatial violation zones. The crosswalk refers to the legally designated crossing area for pedestrians, the sidewalk quadrant is the “safe zone” that determine the origin and destination of a pedestrian’s crossing trip, and the spatial violation zone is the area of the intersection where a pedestrian would be in a spatial violation if the pedestrian crosses in that space. Note that intersections with pedestrian scrambles would need to be characterized differently (i.e., spatial violation zones would be defined differently) but the proposed metrics are still applicable.

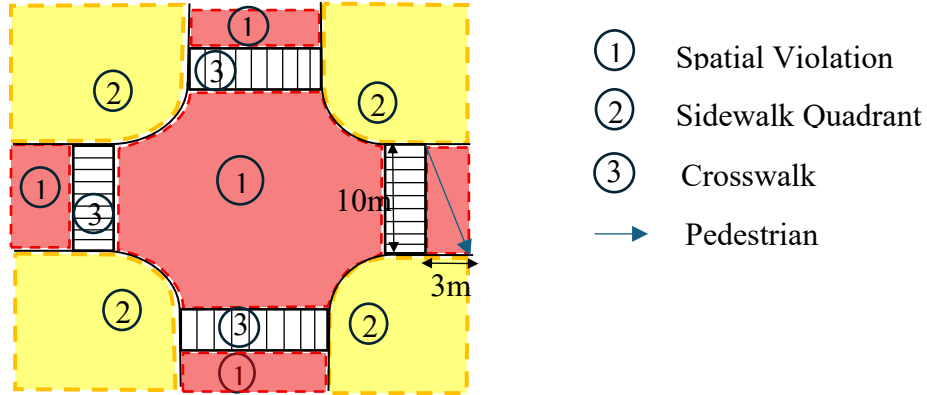


Figure 3.1: Example of a Pedestrian Trajectory at a Basic Intersection

3.1.1. Spatial Violation Severity Metric 1

Violation Severity Metric 1 (SV Metric 1) is the simplest proposed metric. It calculates the violation severity by determining the pedestrian’s maximum lateral distance from the edge of the nearest crosswalk and presents the violation severity in terms of meters as seen in Equation (3.1).

$$SV = d_{out} \quad (3.1)$$

Where:

SV = spatial violation severity (m)

d_{out} = maximum lateral distance outside of the crosswalk (m)

For example, according to SV Metric 1 the trajectory from Figure 3.1 would results in:

$$SV = d_{out} = 3.0 \text{ m}$$

The spatial violation determined by this metric is easy to understand and visualize. However, this metric doesn't consider how long, or for what fraction of the crossing, the pedestrian was outside the designated crosswalk. For example, consider two pedestrian crossing paths. For path 1, the pedestrian engages in corner cutting and in the last few seconds of the crossing, walks outside the crosswalk such that the maximum lateral distance outside the crosswalk is 3m. For path 2, the pedestrian traverses the roadway but does so entirely outside the crosswalk, maintaining a constant lateral deviation of 3m. Violation Severity metric 1 quantifies both paths as having the same violation severity (3m).

3.1.2. Spatial Violation Severity Metric 2

To overcome the shortcomings of SV Metric 1, SV Metric 2 takes into consideration the magnitude of the violation along the entire crossing path. SV Metric 2 achieves this by calculating the area between the pedestrian's violation travel path and the edge of the nearest crosswalk as seen in Equation (3.2).

$$SV = A_{out} \tag{3.2}$$

Where:

SV = spatial violation severity (m^2)

A_{out} = total violation area outside of the crosswalk (m^2)

For example, applying SV Metric 2 to the pedestrian trajectory from Figure 1 would result in:

$$\begin{aligned} SV &= A_{out} \\ &= \frac{3 \times 10}{2} \\ &= 15m^2 \end{aligned}$$

The spatial violation determined by this model is also easy to understand and visualize, and it appropriately differentiates between different crossing paths. However, this metric does not consider the time taken by the pedestrian to make the crossing. In the context of road safety studies, the concept of exposure is related to extent and duration. For example, consider two

pedestrians who take exactly the same path to cross the road but pedestrian 2 does so at a lower walking speed, SV Metric 2 quantifies the violation severity to be the same for these two crossings. However, road safety concepts suggest that the crossing for pedestrian 2 should have a higher violation severity.

3.1.3. Spatial Violation Severity Metric 3

SV Metric 3 considers walking speed in the severity calculations by considering the amount of time the pedestrian spends outside of the designated crosswalk area. For this metric, time is discretized and violation severity is computed as the summation across each time step of the product of the lateral distance outside the crosswalk area and the time step interval duration (Equation (3.3)).

$$SV = \sum_{i=1}^N d_{out,i} \cdot \Delta t \quad (3.3)$$

Where:

SV = spatial violation severity (m·s)

$d_{out,i}$ = the average lateral distance outside of crosswalk at timestep (m)

Δt = the time-step interval duration (s)

i = time interval index

N = number of time intervals required for the pedestrians to complete their crossing

It is important to note that SV metric 3 is not very sensitive to Δt but is sensitive to the time taken by the pedestrian to complete the crossing. For example, consider a pedestrian who completes the trajectory shown in Figure 1 in 10s.

Assume the temporal resolution of the trajectory is one position every 0.5 seconds (i.e. $\Delta t = 0.5s$), then $N = 20$ -time intervals and

$$\begin{aligned} SV &= \sum_{i=1}^{N=20} d_{out,i} \cdot \Delta t = \frac{0 + 0.15}{2}(0.5) + \frac{0.15 + 0.3}{2}(0.5) + \dots + \frac{2.85 + 3}{2}(0.5) \\ &= 15 \text{ m} \cdot \text{s} \end{aligned}$$

If the temporal resolution of the trajectory is chosen to be one position every second (i.e. $\Delta t = 1s$), then $N = 10$ -time intervals and

$$\begin{aligned}
SV &= \sum_{i=1}^{N=10} d_{out,i} \cdot \Delta t = \frac{0 + 0.3}{2}(1.0) + \frac{0.3 + 0.6}{2}(1.0) + \dots + \frac{2.7 + 3}{2}(1.0) \\
&= 15 \text{ m} \cdot \text{s}
\end{aligned}$$

This shows that SV from Metric 3 is not sensitive to the selected temporal resolution for a linear trajectory. However, there will be small differences for nonlinear trajectories. Now let's assume the time to cross takes only 5s (i.e., the pedestrian walks more quickly or runs) and Δt is chosen to be 0.5s, then $N = 10$ -time intervals and

$$\begin{aligned}
SV &= \sum_{i=1}^{N=10} d_{out,i} \cdot \Delta t = \frac{0 + 0.3}{2}(0.5) + \frac{0.3 + 0.6}{2}(0.5) + \dots + \frac{2.7 + 3}{2}(0.5) \\
&= 7.5 \text{ m} \cdot \text{s}
\end{aligned}$$

In this case, the violation severity is smaller because although the pedestrian took the same path, they only took half as much time to complete the crossing. SV Metric 3 can differentiate between pedestrians that have the same violation area (i.e., same value from SV metric 2) but different walking speeds, resulting in differing violation severities.

This metric appears to be the most robust, but the unit of measure for the severity (meter-seconds) is not as easy to understand or intuitive when compared to SV metrics 1 (meters) or 2 (meters-squared).

3.2. Pilot Study

To apply and evaluate the proposed spatial violation severity metrics, a pilot study was conducted to collect, process, and analyze real-world pedestrian data at a signalized intersection.

3.2.1. Study Site

The data for this pilot study was collected at the intersection of King St. and University Ave in Waterloo, Ontario which can be seen in Figure 3.2. This site was selected due to its immediate proximity to a major post-secondary institution with a student population of approximately 23,500, which provides a large pedestrian demographic in the area primarily comprised of university-aged young adults.

In addition to this location's proximity to a major post-secondary institution, there are also commercial plazas that contain food establishments, financial institutions, and other small

businesses. This site is also a highly active transit zone, with two bus stops located directly at the intersection on King St. and another two bus stops situated within 100 m from the intersection on University Ave. In 2025, the Annual Average Daily Traffic (AADT) was 32,402 vehicles/day and the Annual Average Daily Pedestrian Traffic (AADPT) was 6,167 pedestrians/day in both directions of King St. and University Ave. The intersection is controlled by traffic signals running time of day timing plans with actuated protected left turn intervals on each approach and with dedicated pedestrian signal heads. There are marked ladder crosswalks at all four legs of the intersection. The intersection also has 3 painted bike lanes at the West, South, and East crossings. However, the designated bike lanes extend past the intersection only North and West of the intersection.



Figure 3.2:(a) Map of the Great Lakes Region showing the location of Waterloo, Ontario and (b) the study site in Waterloo

3.2.2. Data Collection

Video data were collected using a 1080p at 60 fps camera mounted on a drone to record pedestrian movements from a top-down perspective (Figure 2b) at an altitude of approximately 50m. One hour of video data were collected on Wednesday October 1, 2025, between 12:00 pm – 1:05 pm in two 30-minute blocks, with a 5-minute period in between to change the drone battery. The time and date for data collection were selected by monitoring weather conditions and observing historical pedestrian volumes. Based on historical pedestrian volumes, 12:00 pm – 1:05 pm is when the peak pedestrian volumes can be observed and the weather conditions during

this time were clear sunny skies, a temperature of 18°C, and negligible wind. The clear sunny skies contributed to having optimal pedestrian visibility in the video footage and the negligible wind allowed for stable video footage. During the video collection period there were 408 pedestrian crossings at the West crosswalk, 291 pedestrian crossings at the North crosswalk, 180 pedestrian crossings at the East crosswalk, and 238 pedestrian crossings at the South crosswalk for a total of 1,117 pedestrian crossings.

3.2.3. Data Processing

Processing the video data to extract pedestrian trajectories consists of several steps as outlined in Figure 3.3. The complete Python implementation of the trajectory processing, including the calculation of the spatial violation severity metrics described in Section 3.1 is provided in Appendix A. Throughout this study, specific naming conventions are utilized to differentiate between the data at different stages of the data processing. *Track* refers to the raw pedestrian trajectory data obtained directly from the drone footage prior to any filtering. *Track ID* represents the unique identification number assigned to each raw track by the You Only Look Once (YOLO) object detection model (YOLOv8) whilst *Trajectory* refers to the post-processed tracks that represent complete crossings between adjacent sidewalks (it should be noted that a pedestrian that crosses multiple crosswalks will be represented by multiple *Trajectories*). These trajectories are then identified by a unique *Trajectory ID*.

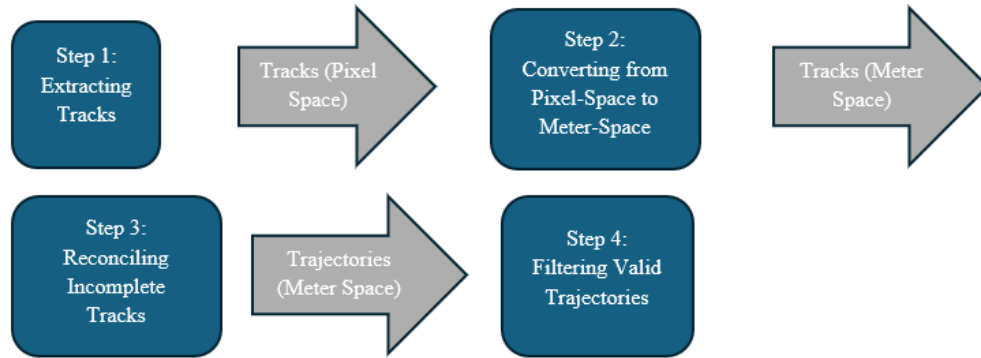


Figure 3.3: Flowchart of the Data Analysis Process

Step 1: Extracting tracks

The drone video data was processed frame-by-frame using a custom-trained YOLO object detection model. The YOLO model was trained on a dataset of 300 images of pedestrians

crossing the study site. The 300 images were taken from the collected video data, sections of the images were labelled to train the YOLO model, and 230 images were used in training the model and 70 images for validation. This YOLO model was trained to recognize pedestrians, draw stable bounding boxes around the pedestrians, and assign a unique Track ID to each detected pedestrian. The output from this process was a set of tracks with unique track IDs with coordinates in pixel-space.

Step 2: Converting from Pixel-Space to Meter-Space

The output from Step 1 is a set of tracks in pixel space. However, it is necessary to convert this to real-world coordinates to apply the violation severity metrics. Step 2 carries out this conversion through the application of a homography matrix. The homography matrix provides a means of converting constant pixel dimensions to real-world dimensions that vary across the image due to camera angle, height, and orientation. The homography matrices were developed (2 matrices since data collection occurred in two 30-minute blocks) by identifying the pixel coordinates of nine stationary landmarks within the frame such as traffic signal poles, utility boxes, and bus shelters, and then mapping these landmarks to their real-world geographic coordinates using latitude and longitude.

The homography matrix was validated by measuring the real-world distance between the nine landmarks through online measurement tools, then comparing these distances against the estimated distances determined by the homography matrix. Through this validation process, it was determined that the average error between the measured distances and the estimated distances is approximately 1.04%, indicating that the pixel-space to meter-space conversion and the utilized scale are sufficiently accurate. See Appendix B for the full homography calibration procedure, the validation results for both calibration matrices, and the Python code used to perform the pixel-to-meter transformation. The output from Step 2 is a set of tracks in real-world coordinates (meter space).

Step 3: Reconciling Incomplete Tracks

A review of the video data with the YOLO bounding boxes revealed several errors in the tracking of pedestrians, which are common to automated computer vision systems. These video processing errors can be grouped into the following three categories:

1. Pedestrian paths fragmented into multiple tracks, each with their own unique Track ID;
2. Parts of the pedestrian path not captured by a track; and
3. Bounding boxes were swapped between pedestrians crossing in close proximity, leading to the incorrect combination of a portion of a one pedestrian's path with a portion of a path from another pedestrian.

An examination of the video indicated that bounding box swapping (Error 3) did not occur with significant frequency and therefore no attempt was made to develop a method for automatically identifying and/or correcting these errors.

Three methods (linear interpolation, linear extrapolation, or both) were used to address errors 1 and 2 and piece together tracks to form trajectories that more accurately represent paths. For this study, the linear interpolation process was considered as either *stitching* or *gap interpolation*, to distinguish the extent of the interpolation that was completed. Some examples of stitching, gap interpolation, and extrapolation can be seen in Figure 3.4.

Stitching is a process that identifies fragmented tracks that share the same origin and destination sidewalk quadrants, as well as the same travel direction. If the temporal and spatial gap between two fragment tracks was within 1.0 second and 1.2 meters, it is assumed that the two tracks belong to the same pedestrian path and the missing data frames are linearly interpolated.

Gap Interpolation uses the same logic as stitching, however, it does so for larger gaps between fragmented tracks. In Gap Interpolation, the temporal and spatial gap parameters were expanded to a maximum threshold of 3.0 seconds and 3.6 meters. These parameters were selected to represent the approximate width of a traffic lane and the approximate time for a pedestrian to walk across a single traffic lane, as pedestrians passing by vehicles that are in a lane often created breaks in the tracks.

Extrapolation is a process applied to tracks where the YOLO bounding boxes lose detection of the pedestrian just before the sidewalk is reached. The compass bearing from the last 60 frames (1.0 second) of the pedestrian's track coordinate data is computed and the missing coordinates are estimated via linear extrapolation. Extrapolation is limited to a maximum of 5.0 meters (which is representative of the combined width of one road lane and one bike lane) to attempt to connect the track to the destination sidewalk.

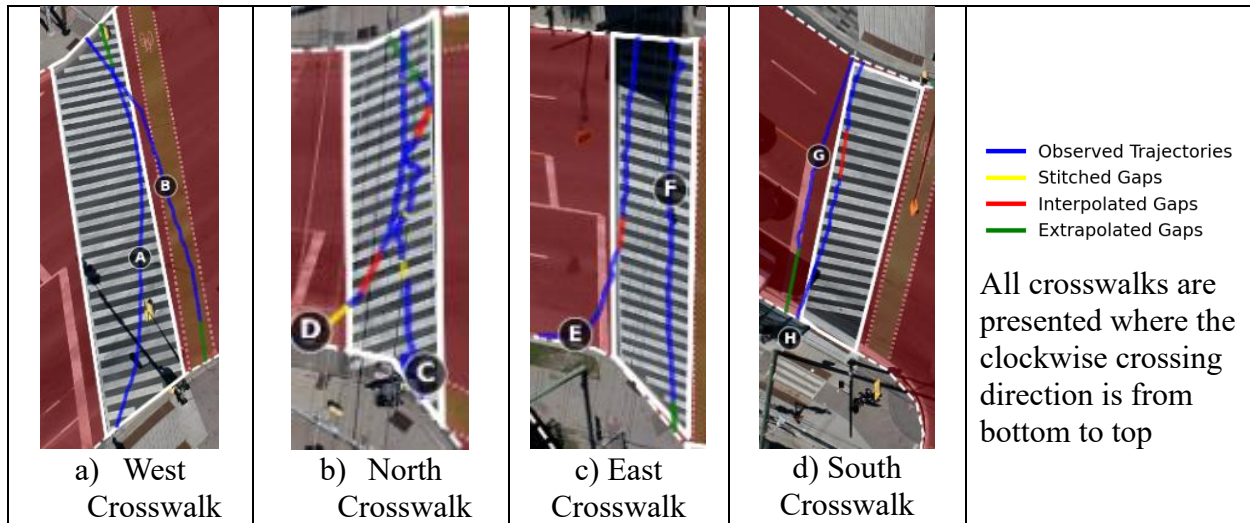


Figure 3.4: Examples of application of Stitching, Gap Interpolation, and Extrapolation.

The frequency at which stitching, gap interpolation, and extrapolation, were applied is provided in Table 3.1. Approximately 30% of the tracks were impacted by one or more of stitching, gap interpolation, or extrapolation methods. Following this stage, the tracks were considered trajectories and were used as input to the next step.

Table 3.1: Summary Table of Tracks and Impact of Error Correcting

	No. of Tracks	Fraction of Total Tracks involved in Synthetic Data Generation
Total Tracks	1455	----
Tracks Involving only Stitching	42	2.9%
Tracks Involving only Gap Interpolation	75	5.2%
Tracks Involving only Extrapolation	202	13.9%
Tracks Involving a Combination of Synthetic Data Generation methods	114	7.8%

Step 4: Filtering Valid Trajectories

Following the stitching, gap interpolation, and extrapolation process, the dataset was comprised of reconstructed pedestrian trajectories that required final validation. To ensure the integrity of the violation severity calculations, a two-stage filtering process was implemented to ensure that only valid crossings made by pedestrians were evaluated.

Filter 1 checked that each trajectory represented a complete and logical crossing, hence a “valid” crossing. A trajectory is valid if the trajectory’s origin and destination sidewalk quadrants are different. Invalid trajectories were removed from the dataset.

Filter 2 checked that each valid trajectory was made by a pedestrian. The YOLO model is unable to perfectly distinguish between pedestrians and non-pedestrians (e.g., cyclists, motorcyclists, and e-scooters). A filter was developed to distinguish between pedestrians and non-pedestrians based on recorded speed. A subset of the video data was manually reviewed to label trajectories as either pedestrians or non-pedestrians and the speeds were extracted from the labelled trajectory data. Several speed measures were evaluated, but the maximum three-second average speed was selected for the filter. The threshold speed for determining whether the trajectory was made by a pedestrian or non-pedestrian was determined by analyzing the distribution of the three-second average speed from the labelled trajectories (Figure 3.5). The selected speed threshold was 3.8 m/s (13.7 km/h). Any valid trajectory with a maximum three-second average speed exceeding the threshold speed was classified as a non-pedestrian and then removed from the dataset. The threshold of 3.8m/s is much greater than typical pedestrian walking speeds, but this threshold accounts for pedestrians who may walk quickly or even run during part of their crossing.

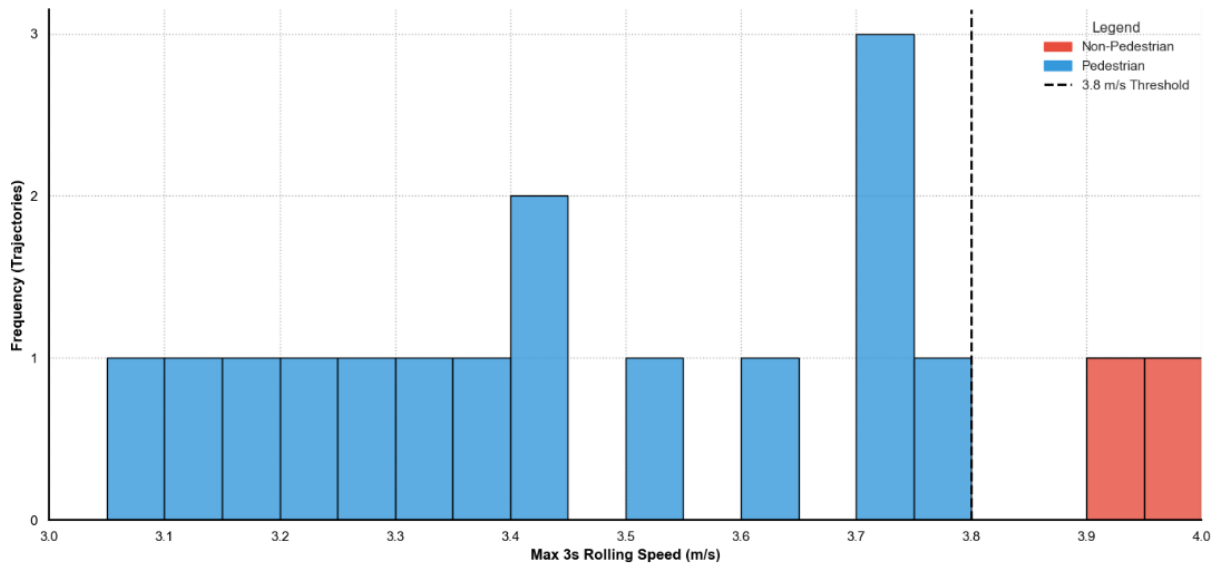


Figure 3.5: Distribution of Crossing Speeds between 3.0 - 4.0 m/s

The effect of Filters 1 and 2 and the size of the final dataset is provided in Table 3.2. As can be seen from the results in Table 2, most invalid trajectories are identified by Filter 1. The final trajectory dataset contained 1082 trajectories associated with pedestrian crossing events. As stated in Section 3.2.2, manual counts from the video data indicated 1117 pedestrian crossings. Consequently, the trajectory dataset captures 96.8% of pedestrian crossings.

Table 3.2: Effect of Step 4 Filters and Final Trajectory Dataset

	No. of Trajectories	Proportion of Total Trajectories
Trajectories from Step 3	1455	100%
Trajectories Removed by Filter 1	347	23.8%
Trajectories Removed by Filter 2	26	1.8%
Trajectories in Final Data set	1082	74.4%

3.3. Results and Discussion

This section presents the findings from the pilot study to answer the first three research questions posed in Chapter 1 of the thesis, namely:

1. What are the pedestrian spatial violation behaviours occurring at signalized intersections?
2. How can the severity of pedestrian spatial violations at signalized intersections be measured?
3. How effectively do the proposed spatial violation measures characterize the pedestrian violation severity?

The next sections address each question in order.

3.3.1. What are the Pedestrian Spatial Violation Behaviours?

Table 3.3 provides a summary of the pedestrian spatial violation behaviour observed at the study site and at each crossing at the intersection. The data in Table 3.3 were obtained from the trajectory data resulting from Step 4 in Section 4. Trajectories for which the violation severity was greater than zero were classified as ones for which a spatial violation occurred. Violations were further classified by type. If the trajectory path was entirely outside the crosswalk area, then the violation was categorized as “crossing outside the crosswalk”, otherwise it was classified as “corner cutting”.

The proportion of violations occurring at each crossing varies (from 19.1% to 35.1%) but this variation is highly impacted by the variation in the number of pedestrians at each crossing.

More interestingly, the proportion of pedestrians committing a violation also varies by crossing, ranging from a low of 35.6% (North crossing) to a high of 59.6% (East crossing). Overall, 48% of pedestrians observed to make a crossing at the study intersection committed a spatial violation.

A chi-square test of homogeneity was performed to determine whether the proportion of pedestrians committing a spatial violation were statistically different amongst the four crosswalks. The null hypothesis was that the proportion of pedestrians committing a violation is the same across all four crosswalks. The test indicated that there is a statistically significant difference between the proportion of spatial violations and crossing locations ($\chi^2(df=3) = 39.29$, $p = 1.50 \times 10^{-8} < 0.001$).

Overall, the vast majority (86.5%) of spatial violations were classified as corner-cutting, while only 13.5% were crossing outside of the crosswalk. The relative distribution of violation type was more consistent across the different crosswalks than the proportion of violations. Nevertheless, a Chi-square test of homogeneity showed that there is a statistically significant difference in the types of violations committed across the four crossings. Examination of the data in Table 3.3 suggests that this difference is largely due to the South crosswalk, which has a higher proportion of crossing outside the crosswalk violations compared to the other three crosswalks.

It should be noted that the results in Table 3.3 are unique to the study site and may not be directly transferable to other intersections in Waterloo or elsewhere. It is expected that the propensity for pedestrians to engage in spatial violations, and the type of spatial violation committed, is impacted by crossing and intersection geometric characteristics, vehicle volumes, prevailing vehicle speeds, pedestrian population characteristics, local driver and pedestrian behavioural norms, nearby land uses, location and type of public transit stops/stations, etc. The dataset used in this research is limited to a single intersection preventing the exploration of the influence of these factors, but this is an area for further research.

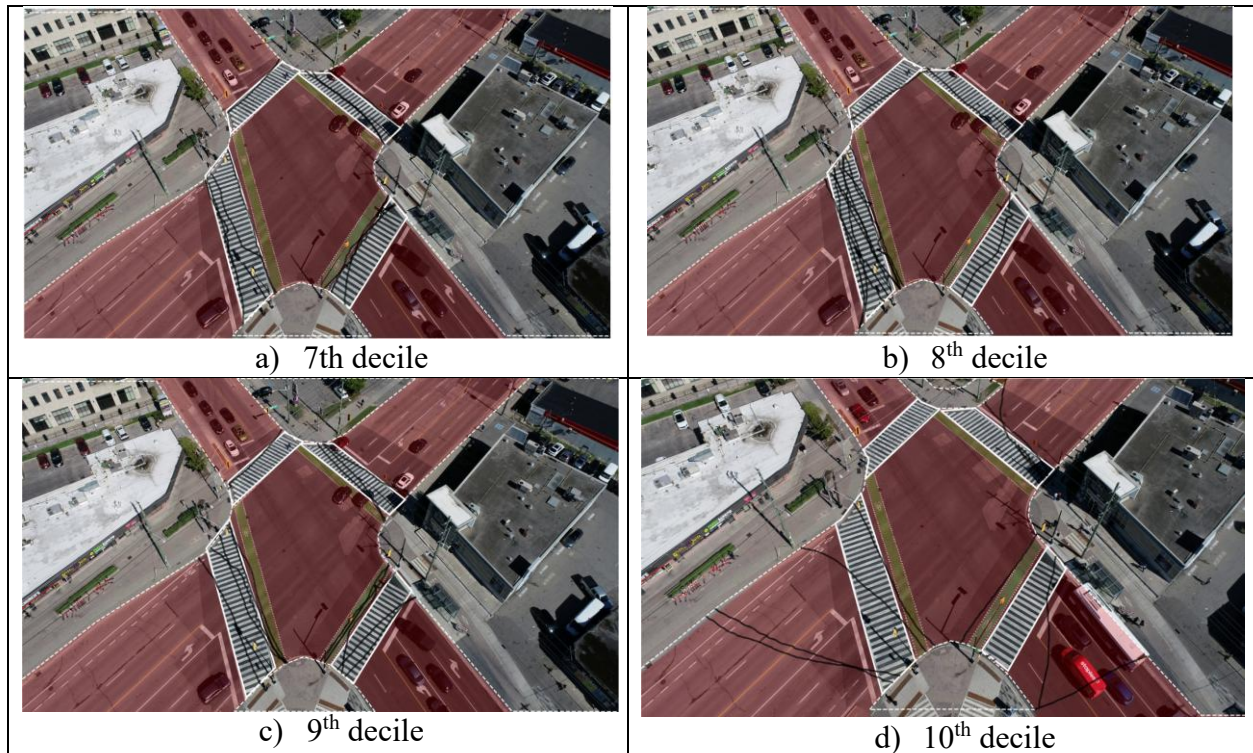
Table 3.3: Pedestrians and Spatial Violations per Crossing

Crossing	Number of Trajectories	Number of Trajectories for which a Violation Occurred	Proportion of violations occurring at crossing (%)	Proportion of Pedestrians Committing a Spatial Violation (%)	Proportion of Violations by Type (%)	
					Corner Cutting	Crossing Outside Crosswalk
East	203	121	23.1%	59.6%	88.4%	11.6%
North	281	100	19.1%	35.6%	89.0%	11.0%
South	200	119	22.7%	59.5%	76.5%	23.5%
West	398	184	35.1%	46.2%	90.2%	9.8%
All Combined	1082	524	100%	48.4%	86.5%	13.5%

3.3.2. How can Spatial Violation Severities be Measured?

The previous section presented the frequency and distribution of spatial violations. This section presents the results of the violation severities as determined from the application of the three proposed violation severity metrics to the crossing trajectories.

A high degree of variability in pedestrian crossing behaviour was observed within the collected dataset. This variability is illustrated in Figure 3.6, which presents randomly selected pedestrian trajectories from the four highest deciles of spatial violation severity as determined through the application of SV Metric 1. Trajectories in Figure 3.6a represent trajectories for which a spatial violation occurred, but the spatial violations are quite minor – typically with pedestrians walked just outside of the marked crosswalk or minor corner cutting when entering or exiting the crosswalk. The trajectories from the 9th decile exhibit more substantial spatial violations and some pedestrians walking outside the crosswalk for the entire crossing. It is not until the 10th decile that we observe very severe spatial violations.



Marked crosswalk areas outlined in solid white line; sidewalk areas outlined with dashed white line; roadway shaded in light red; trajectories denoted in solid black lines

Figure 3.6: A Sample of Pedestrian Crossing Trajectories with Spatial Violations Grouped in Deciles in Increasing Violation Severity using SV Metric 1

Further analysis indicates that the observed variability in pedestrian crossing behaviour is driven largely by pedestrians who are crossing outside of the crosswalk rather than pedestrians who corner cut. Table 3.4 provides descriptive statistics for the violations of each type. From these results, it can be observed that the mean, median, and standard deviation in spatial violations are all larger for crossing outside of the crosswalk violations than for corner cutting violations.

Table 3.4: Descriptive Statistics for Crossing Outside the Crosswalk Violations and Corner Cutting Violations

	Crossing Outside Crosswalk Violations			Corner Cutting Violations		
	SV Metric 1 (m)	SV Metric 2 (m ²)	SV Metric 3 (m·s)	SV Metric 1 (m)	SV Metric 2 (m ²)	SV Metric 3 (m·s)
Mean	2.93	19.81	14.16	1.17	3.11	2.70
Median	1.87	10.84	8.38	0.74	0.60	0.66
Standard Deviation	3.20	30.46	23.92	1.65	8.42	7.84
Maximum Violation Severity	18.65	182.06	167.73	17.78	142.36	122.15
Number of Observations	71			453		

Figure 3.7 shows the cumulative relative distribution of the violation severity for the 524 trajectories for which a spatial violation occurred. Across all three models, the cumulative relative frequency increases rapidly at low violation severities before gradually approaching 100% at higher severities, indicating that severe violations are relatively uncommon and that the distributions of violation severities are strongly skewed towards lower severities. The steep initial increase in each curve suggests that most spatial violations involve minor deviations outside of the crosswalk, while the gradual flattening of the curves at higher severity values indicate that only a small portion of the spatial violations account for the most severe violations. This observation is consistent with the sample of trajectories by violation severity decile presented in Figure 3.6.

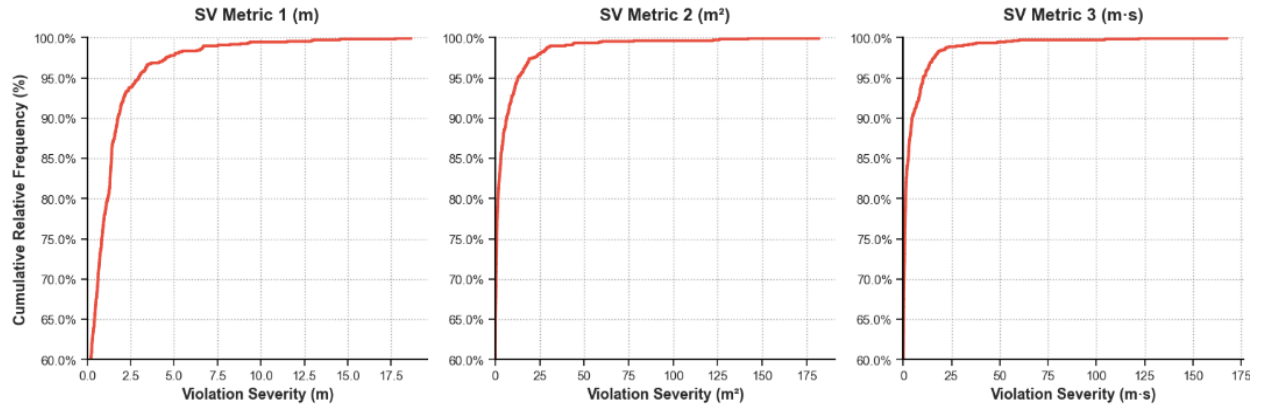


Figure 3.7: Cumulative Relative Frequencies of the Violation Severities based on the three SV Metrics

Figure 3.8 shows the cumulative relative frequencies of violation severities at each crosswalk according to the three metrics and Table 3.5 shows the results of a two-sample K-S statistical test used to determine if there was a statistical difference between the distribution of violation severities and the crosswalk location. Each pair of crosswalks were compared to each other three times (once for each metric), and it was determined for each pair of crosswalks using any metric, there is a statistically significant difference between the spatial violation severities at each crosswalk location. This result is consistent with the observation from Table 3.3 that the proportion of pedestrians committing a spatial violation also varied by crosswalk location. These results further support the hypothesis that pedestrian violation behaviour (both in terms of the probability of committing a violation and the severity of the violation) is influenced by intersection geometry.

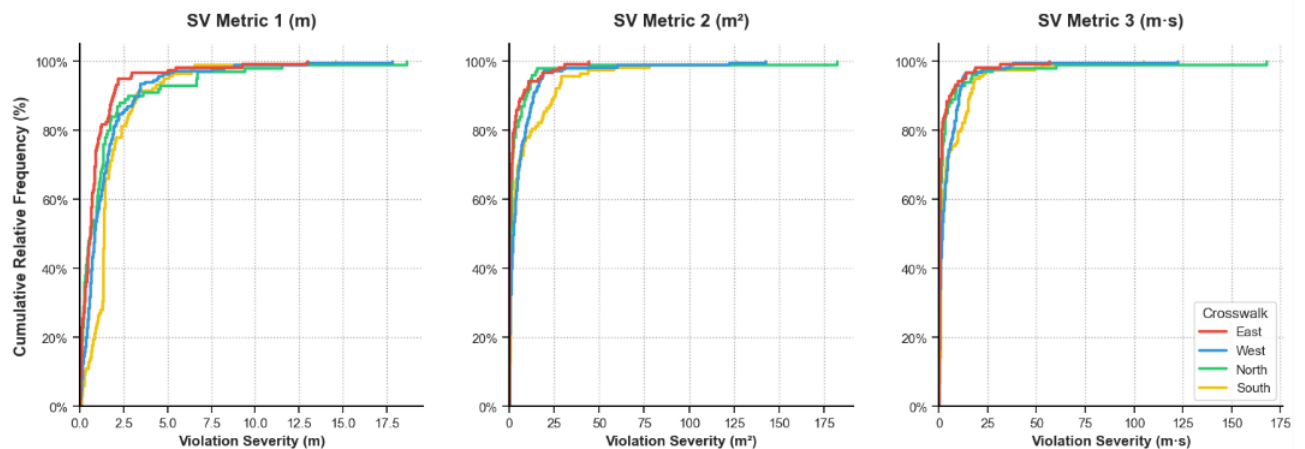


Figure 3.8: Cumulative Relative Frequency of Violation Severities for each Crosswalk

Table 3.5: Summary of K-S Statistical Test Results Between Each Pair of Crosswalks

SV Metric	Comparison Pair	KS Statistic	P-Value	Significant Difference? (P < 0.05)
1	East vs North	0.24	1.81E-06	Yes
1	East vs South	0.32	1.70E-09	Yes
1	East vs West	0.13	1.73E-02	Yes
1	North vs South	0.33	4.87E-12	Yes
1	North vs West	0.17	1.41E-04	Yes
1	South vs West	0.25	6.36E-08	Yes
2	East vs North	0.20	1.64E-04	Yes
2	East vs South	0.24	9.24E-06	Yes
2	East vs West	0.12	3.83E-02	Yes
2	North vs South	0.29	3.52E-09	Yes
2	North vs West	0.16	2.36E-04	Yes
2	South vs West	0.17	9.08E-04	Yes
3	East vs North	0.22	1.62E-05	Yes
3	East vs South	0.30	2.02E-08	Yes
3	East vs West	0.12	3.63E-02	Yes
3	North vs South	0.36	7.18E-14	Yes
3	North vs West	0.17	9.88E-05	Yes
3	South vs West	0.20	3.29E-05	Yes

3.3.3. How Effectively do the Proposed Spatial Violation Measures Characterize the Pedestrian Spatial Violation Severity?

This thesis has proposed three different violation severity metrics. A natural question is do these different metrics provide similar or different relative assessments of the severity of different crossing paths. To answer this question, two types of analysis were conducted, namely (1) a comparison of the distributions of the normalized violation severities from each of the three proposed violation severity metrics, and (2) a rank error analysis was performed to determine the level of inconsistency between the rankings that result from the application of the proposed violation severities.

Comparison of Normalized Distribution of Spatial Violation Severities:

The violation severities from each of the three proposed metrics were normalized by dividing the violation severity from metric j for violation trajectory i , by the maximum violation severity from metric j determined across all violation trajectories. In this way, the normalized violation severities ranged from a value of 0 to 1. Figure 3.9 indicates that Metrics 2 and 3 provide very

similar distributions of violation severity but that Metric 1 produces a distribution of violation severities with a higher proportion of crossings with relatively higher severities than Metrics 2 and 3. Table 3.6 summarizes the results of two-sample K-S statistical tests that determines if there is a statistically significant difference between the cumulative relative frequencies of the normalized violation severities. It was found that the cumulative relative frequency distributions of normalized violation severities differed significantly between Metrics 1 and 2 and between Metrics 1 and 3. This result is expected since Metric 1 only considers the maximum distance outside the crosswalk and it also suggests that this metric is not very robust and may overestimate violation severities. No statistically significant difference was observed between Metrics 2 and 3. This result can also be expected if crossing speeds do not vary significantly.

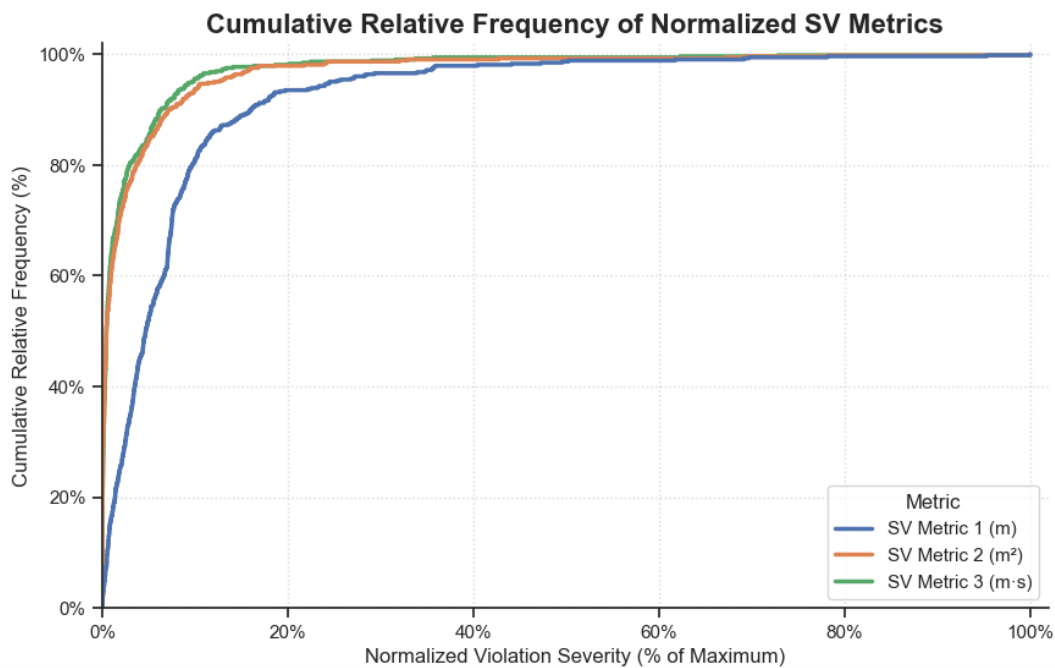


Figure 3.9: Comparison of the Distributions of Normalized Violation Severities by the Three SV Metrics

Table 3.6: KS Test Results for Pairwise Comparisons of Normalized Violation Severities

Comparison between SV Metric Pairs	KS Statistic	P-Value	Significant Difference? (P < 0.05)
SV 1 & SV 2	0.23	3.40E-15	Yes
SV 1 & SV 3	0.18	1.17E-09	Yes
SV 2 & SV 3	0.05	3.44E-01	No

Comparison of Rank Consistency:

Since the three models attempt to quantify spatial violation severities using different measures, it is necessary to evaluate the methodological consistency. The three SV Metrics were evaluated by examining the similarity of the ranked order of pedestrian crossings using Rank Error Analysis. Rank Error Analysis measures how different the metrics are from each other when applied to identify the most severe (worst) violations.

Two measures of ranking inconsistency were used. Rank Error (RE) measures the number of trajectories that are not identified by both SV metrics as being in the top- n set of the worst violations (Equation 3.4). The Relative Rank Error (RRE) represents the RE as a proportion of the top- n set of the worst violations (Equation 3.5).

$$RE_n = n - m \quad (3.4)$$

$$RRE_n = \frac{n - m}{n} \quad (3.5)$$

Where:

n = the number of crossing trajectories within the sample

m = the number of trajectories identified by both SV metrics within n

For both RE_n and RRE_n , a lower value indicates a greater similarity between the rankings with RRE_n expressing this similarity as a percentage of disagreement and RE_n yields the number of trajectories that do not appear on both rankings.

The Rank Error (Equation 3.4) and the Relative Rank Error (Equation 3.5) were computed for each of the three-metric pair-wise comparisons as a function of n , the number of the pedestrian trajectories considered in the sample selected as the top- n set of trajectories. Figure 3.10 shows error between the pairs of SV metrics for values of n up to 100 (i.e., the 100 most severe spatial violations). Similar to Figure 3.9, this figure shows that Metrics 2 and 3 provide much more similar rankings (smaller RE and RRE values) across the range of n than Metric 1 with either Metric 2 or 3. For example, for the top 20 most severe violations, Metrics 2 and 3 only include 4 different trajectories, whereas Metrics 1 and 2 include 9 different trajectories, and Metrics 1 and 3 include 7 different trajectories.

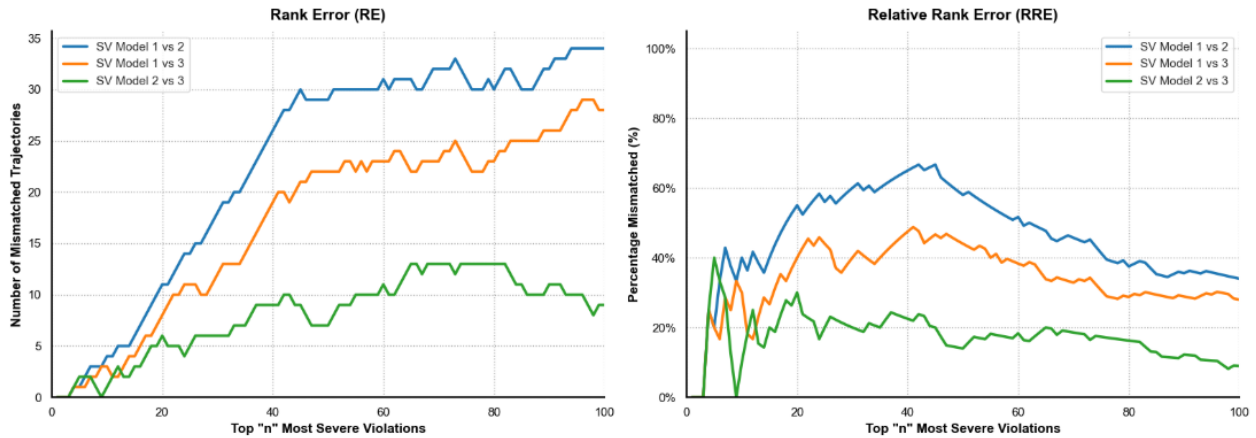


Figure 3.10: Rank Error (RE) and Relative Rank Error (RRE) Progression for the Three Model Pairings

3.3.4. Limitations

While the proposed trajectory processing pipeline and the developed SV metrics present a robust methodology for quantifying spatial violations, it is necessary to acknowledge some of the constraints of this research. The limitations of this study primarily stem from three areas: the physical and environmental constraints of aerial drone video data collection, the inherent noise associated with automated computer vision tracking such as bounding box jitter and visual distortion, and the geographically specific nature of the study site. Recognizing these limitations is critical for accurately interpreting the spatial violations and SV metrics, ensuring that the findings are not extrapolated beyond the scope of this study.

The observational dataset for this research is constrained both temporally and geographically. Data collection was limited to a single one-hour observation period. While this one-hour window successfully captured a high volume of pedestrian crossing events, it limits the ability to analyze variations in spatial violations across different times of day, days of the week, lighting conditions, or weather conditions. Additionally, since the selected intersection is situated adjacent to a major post-secondary institution, the observed pedestrian demographics are heavily skewed towards post-secondary students and young adults. Traffic psychology literature indicates that age heavily influences walking speed, gap acceptance, and risk tolerance (Granié et al., 2013). The frequency and distribution of spatial violations observed in this study may not

reflect spatial violations that occur at intersections with more diverse populations, or intersections with completely different pedestrian demographics.

The quantitative accuracy of the spatial metrics and the volume of valid crossing data are heavily dependent on the performance of the YOLO tracking model. Any bounding box inconsistencies or tracking errors that are not detected and removed or corrected during the data processing steps impact the violation severity calculations. To mitigate the fragmentation of some of the trajectory data, a linear interpolation or extrapolation was implemented for stitching and gaps. However, a limitation within the matchmaking process between potential tracks to be joined together exists. In the situation where a pedestrian was dropped by the YOLO bounding box, and there are multiple candidate tracks that could be stitched or gap interpolated to the pedestrian, the algorithm was designed to select the first valid candidate track rather than utilizing an optimization process to determine the most suitable candidate track. Although the constraints used in the stitching and gap interpolation process ensured the number of false positive stitches were minimized, the lack of this optimization process means that there is a small fraction of highly complex pedestrian trajectories that may have a sub-optimal synthetic recreation. Nevertheless, since these cases represent relatively small proportions of the complete dataset (Table 1), this impact is expected to be minor overall.

4. Temporal Violations

4.1. Proposed Temporal Violation Types and Metrics

This chapter of the thesis proposes four types of temporal violations and four metrics to quantify the severity of temporal violations of pedestrians making crossings at signalized intersections. The metrics assume pedestrian entry times into the crosswalk with respect to the lengths of the signal intervals and the crossing times are known as inputs.

4.1.1. Types of Temporal Violations

While the categorization of different types of spatial violations has been proposed in prior literature, there is an absence of a similar classification system for temporal violations. It is important to consider that there are two assumptions being made about the pedestrian and vehicle signal timing plans that must be clarified. Assumption 1: There is always some overlap between the SDW and red vehicle interval in the parallel vehicle stream. Assumption 2: The pedestrian signal does not require a push-button activation to change the pedestrian signal or provide an extended signal length. To categorize observed crossing patterns relative to signal cycles, four types of temporal violations are proposed: (1) *Early Starters* are pedestrians who begin crossing during the All-Red interval before the Walk interval. (2) *Start in FDW* are pedestrians who begin crossing anytime during the FDW interval. (3) *Start in AR after FDW* are pedestrians who begin crossing during the All-Red interval after the FDW interval and (4) *Start in SDW* are pedestrians that begin crossing during the SDW interval but not in the All-Red intervals. Figure 4.1 shows the crossing behaviours with respect to the pedestrian and vehicle signal indications. It is important to note that within each of the four categories, there is potential for further sub-categorization to further describe the violation behaviours; such as crossing on a Left-Turn signal or a Right-Turn signal. However, due to insufficient observations to analyze these types of crossings, only the main four categories are considered.

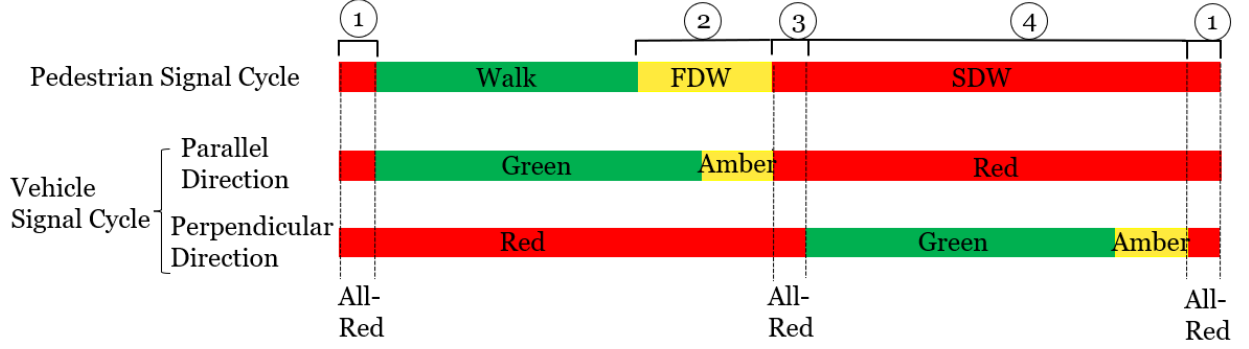


Figure 4.1: Phase Diagram for the determination of the Types of Temporal Violations

4.1.2. Temporal Violation Severity Metric 1

Temporal Violation Metric 1 (TV Metric 1) is a unique metric as it does not measure any aspect of the pedestrian's crossing time; rather it measures the timing of the violation itself. Specifically, how far the pedestrian's crossing began from the nearest legal crossing interval (better known as the Walk interval). TV Metric 1 expresses this severity in seconds, reflecting how many seconds before or after the Walk interval the pedestrian began their crossing, as shown in Equation (4.1).

$$TV = T_{tw,min} \quad (4.1)$$

Where:

TV = temporal violation severity (s)

$T_{tw,min}$ = minimum time to the nearest walk signal interval (s)

It is important to note that TV metric 1 does not distinguish between any temporal violations that may be committed during the FDW or the SDW, since it only measures the time to the nearest Walk interval regardless of which interval the pedestrian is in the crosswalk. Figure 4.2 illustrates this using a clock-style diagram rather than a conventional bar or timeline. Due to the fact that the pedestrian signal cycle repeats continuously, plotting the Walk, FDW, and SDW intervals as arcs around a circle (with time progressing clockwise) allows a full cycle to be shown without a break at an arbitrary "start" time.

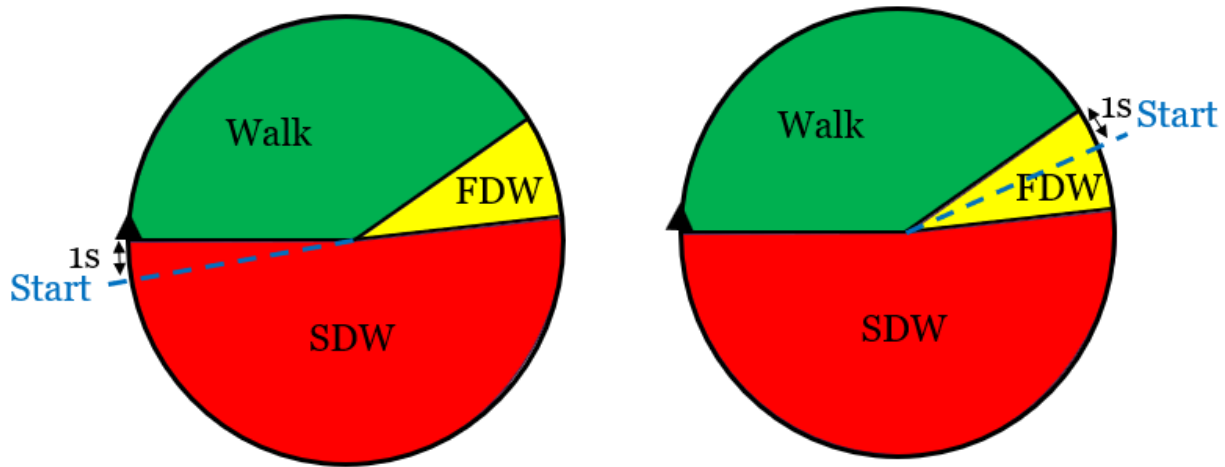


Figure 4.2: Example of an Early Starter (left) and Late Starter (right) temporal violation

The temporal violation severity according to TV metric 1 for the early starter and the late starter in Figure 4.2 is the same, $TV = 1s$. This symmetry reflects a further limitation of TV metric 1, because it only measures the minimum time to the nearest Walk interval, it cannot distinguish whether a pedestrian began crossing before or after the legal interval. However, to further highlight the fact that TV metric 1 does not distinguish between the FDW or SDW signal intervals another example is shown in Figure 4.3.

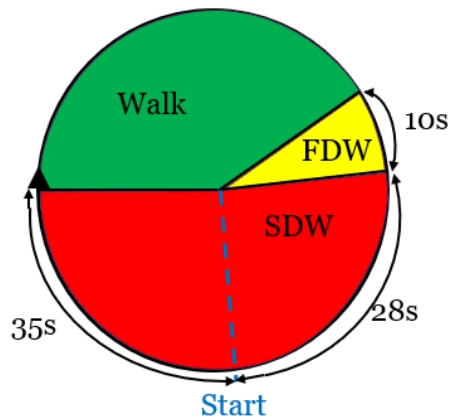


Figure 4.3: Example of a SDW runner

In this case, to determine what the temporal violation severity is, TV metric 1 would be utilized as:

$$TV_{Before\ Walk} = 35s$$

$$TV_{After\ Walk} = 28 + 10 = 38s$$

$$TV_{Before\ Walk} < TV_{After\ Walk}$$

Thus, $TV_{tw, \min} = 35s$.

By not distinguishing between the FDW and SDW intervals, and by relying on a single moment in time, this metric captures a fundamentally different behaviour: the severity of a pedestrian's initial decision to violate the signal.

4.1.3. Temporal Violation Severity Metric 2

Temporal Violation Metric 2 (TV Metric 2) adheres to the legal definition of a temporal violation by including crossing time during the FDW, if the crossing begins during this interval, and the crossing time during the SDW (Equation (4.2)).

$$TV = aCT_F + CT_S \quad (4.2)$$

Where:

TV = temporal violation severity (s)

CT_F = crossing time during FDW signal interval (s)

CT_S = crossing time during SDW signal interval (s)

$$a = \begin{cases} 1, & \text{if crossing begins during FDW signal interval} \\ 0, & \text{if crossing does not begin during FDW signal interval} \end{cases}$$

To demonstrate how TV Metric 2 measures temporal violations, Figure 4.4 shows three different crossings, where the outer ring represents the vehicle signal in the perpendicular direction to the pedestrian crossing, the inner ring represents the vehicle signal parallel to the pedestrian crossing, and the center circle represents the pedestrian signal interval.

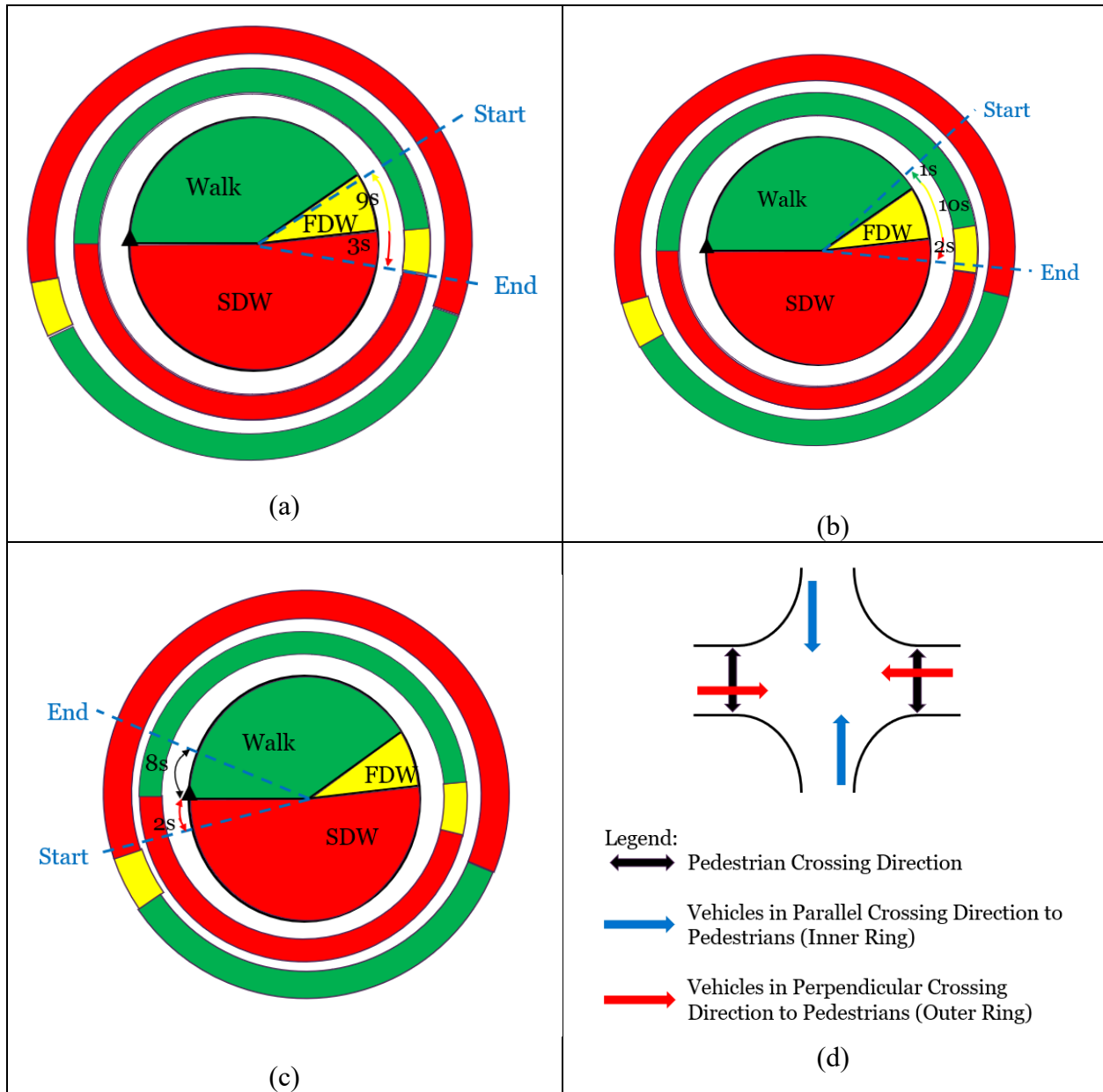


Figure 4.4: (a) is a situation where the crossing begins during the FDW interval, (b) is a situation where the crossing begins during the Walk interval, (c) is a situation where the crossing begins during an All-Red, and (d) a schematic of an intersection for the associated signal intervals

Applying TV Metric 2 to the three pedestrian crossings from Figure 4.4 would result in:

Example a)

$$\begin{aligned}
 TV &= aCT_F + CT_S \\
 &= (1)(9) + 3 \\
 &= 12 \text{ s}
 \end{aligned}$$

Example b)

$$\begin{aligned} TV &= aCT_F + CT_s \\ &= (0)(10) + 2 \\ &= 2 \text{ s} \end{aligned}$$

Example c)

$$\begin{aligned} TV &= aCT_F + CT_s \\ &= (0)(0) + 2 \\ &= 2 \text{ s} \end{aligned}$$

Examples b) and c) highlights a limitation in TV metric 2, where strictly using the legal definition of a temporal violation may not fully reflect the severity of the pedestrian's crossing behaviour from a practical standpoint. In both cases, the amount of time spent in the FDW or SDW are approximately the same however, because one of the crossings began during the Walk interval the severity is severely reduced.

4.1.4. Temporal Violation Severity Metric 3

Temporal Violation Metric 3 (TV Metric 3) attempts to improve upon TV Metric 2's limitation by ignoring when the crossing begins with respect to the nearest legal crossing interval and only considers the amount of time the pedestrian is engaged in crossing when the signal interval is SDW (Equation (4.3)).

$$TV = CT_s \tag{4.3}$$

Where:

TV = temporal violation severity (s)

CT_s = crossing time during SDW signal interval (s)

To demonstrate how TV Metric 3 measures temporal violation severity, Figure 4.5 presents three example crossings using the same-interval schematic introduced in Figure 4.4, where the outer ring represents the vehicle signal in the perpendicular direction to the pedestrian

crossing, the inner ring represents the vehicle signal parallel to the pedestrian crossing, and the center circle represents the pedestrian signal interval.

Notably Figures 4.5b and 4.5c illustrate crossings completed in exceptionally short durations, indicative of pedestrians that are running across the crosswalk. These examples are to represent specific scenarios of pedestrians who sprint across the intersection to exploit gaps in between vehicles at different points of the signal cycle.

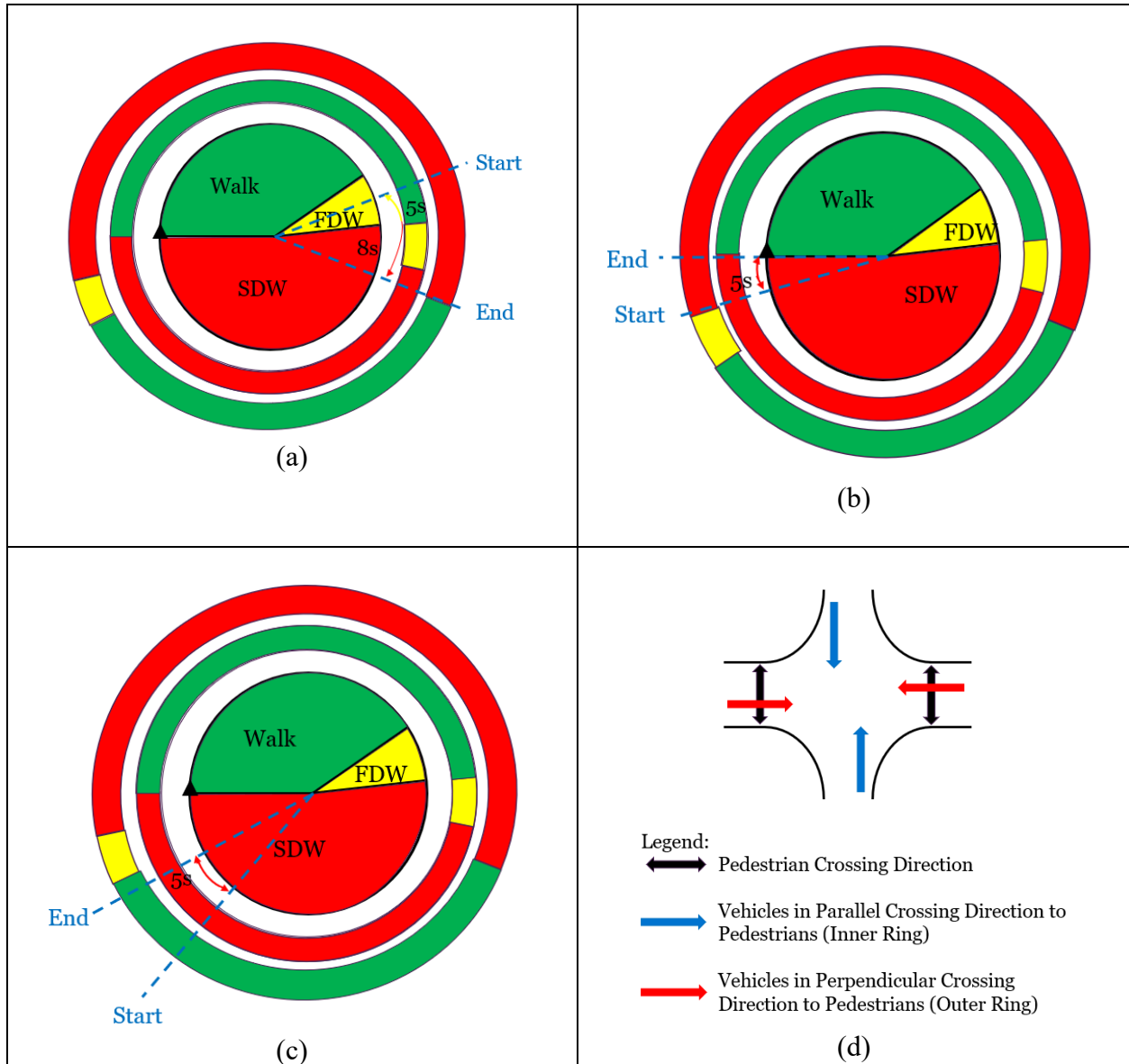


Figure 4.5: (a) is a situation where the crossing begins during the FDW interval and (b) is a situation where the crossing begins and ends during an All-Red interval (c) is a situation where the crossing begins and ends during the SDW interval, and (d) a schematic of an intersection for the associated signal intervals

Example a)

$$TV = CT_s$$

$$TV = 8s$$

Example b)

$$TV = CT_s$$

$$TV = 5s$$

Example c)

$$TV = CT_s$$

$$TV = 5s$$

Example b) and Example c) show a limitation of this metric, where in both situations the temporal violation begins and ends during the SDW signal interval, however, there is no distinction between the two violations with respect to the overall phase. Practically, the violation severity of Example b) could be less than the severity of Example c) because the violation occurring during Example b) happens during the All-Red signal interval, where no vehicles should be crossing the intersection, while this is not the case for Example c).

4.1.5. Temporal Violation Severity Metric 4

To accommodate for the limitations in TV Metric 3, Temporal Violation Metric 4 (TV Metric 4) attempts to address this by differentiating between the severity of a pedestrian's crossing time during the SDW interval, which also aligns with the Vehicle All-Red signal interval before the following Walk/Green interval, and the crossing time during other portions of the SDW interval. TV Metric 4 will primarily provide a way to distinguish between the severity of an Early Starter and the severity of a Start in SDW as shown in Equation (4.4).

$$TV = \alpha \cdot CT_s \tag{4.4}$$

Where:

TV = temporal violation severity (s)

CT_s = crossing time during SDW signal interval (s)

α = calibration coefficient between 0 and 1 to distinguish between violations during the All-Red interval

Due to insufficient data to accurately calibrate α , if the temporal violation occurs during the All-Red signal phase, assume $\alpha = 0.5$; otherwise, assume $\alpha = 1$. As mentioned in Section 4.1.4, the practical violation severity associated with an Early Starter is assumed to be less than the violation of a Start in AR after FDW or Start in SDW, due to the lack of vehicles crossing through the intersection. However, because of the small sample size for which TV Metric 4 is applicable, TV Metric 4 was excluded from the subsequent analyses. Therefore, TV Metric 4 remains as a proposed metric that should be improved upon and analyzed in subsequent analyses.

4.2. Pilot Study

To apply and evaluate the proposed temporal violation severity metrics, another pilot study was conducted to collect, process, and analyze real-world pedestrian data at a signalized intersection.

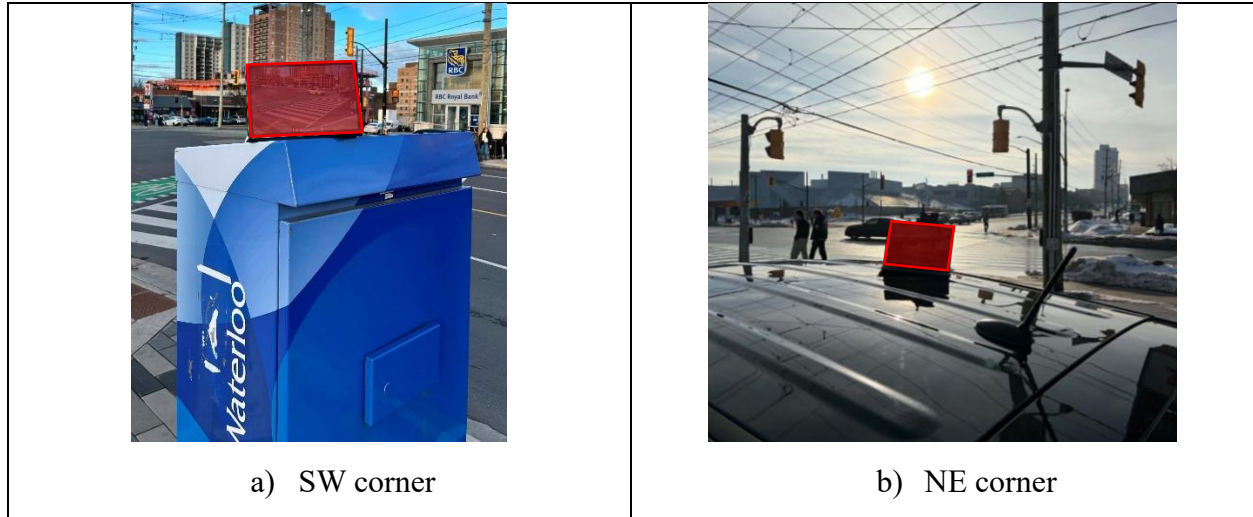
4.2.1. Study Site

The study site for this pilot study is the same study site used for the analysis of the spatial violation severity metrics: the intersection of King St. and University Ave. in Waterloo, Ontario. Refer to Section 3.2.1 for detailed characteristics of the study site.

4.2.2. Data Collection

Video data was collected using a 1080p at 30 fps camera of a handheld mobile device to record pedestrian crossings from a street-level view (Figure 4.6). Video data were collected on six different occasions between October 2025 – March 2026, in one-hour blocks. The time and dates for data collection were selected by monitoring weather conditions and observing historical pedestrian volumes. Data collection captured both peak and off-peak pedestrian volumes across a variety of weather conditions, including clear skies, active snowfall, and melting snow. In total, 3-hours of video data was collected at the South and North crosswalks while 2-hours of video data was collected at the East and West crosswalks. During the video collection period, there

were 326 pedestrian crossings at the West crosswalk, 457 pedestrian crossings at the North crosswalk, 192 pedestrian crossings at the East crosswalk, and 706 pedestrian crossings at the South crosswalk for a total of 1,681 pedestrian crossings.



Video collection device highlighted by the red rectangle.

Figure 4.6: Images of the video recording device set up at a higher vantage point to record pedestrian crossings at the street level

4.2.3. Data Extraction

Within each video, there are several key elements that can be observed and are necessary to complete the analysis which are the pedestrian's crossing location (*North, East, South, or West*), crossing direction (*Clockwise or Counter-clockwise*), the time into the signal interval (*Walk, FDW, or SDW*) when the pedestrian began their crossing, the time to the nearest *Walk* signal interval when the pedestrian began their crossing, the pedestrian's crossing time during the *FDW* interval and the pedestrian's crossing time during the *SDW* interval.

Step 1: Recording Crossing Times

When a pedestrian steps into the crossing areas shown in Figure 4.7, the video timestamp, the signal interval, time into the signal interval, and time into the cycle phase are recorded. Then, when a pedestrian steps out of the crossing area, the video timestamp is also recorded which provides the crossing time for each crossing event. Additionally, the start and end of each signal interval is also determined. In contrast to the automated filtering used for spatial violations, temporal data extraction relied on manual filtering. Any pedestrian who initiated or completed

their crossing outside the designated crossing area of beyond the video frame was excluded from the dataset.



Only crossings that start and end in the shaded-red area considered for the pilot study.

Figure 4.7: Screenshots from Video Footage of each Crosswalk at King St. and University Ave.

Step 2: Determining Average Pedestrian Crossing Speeds

From Step 1, a set of crossing times across each of the four crosswalks is determined. Since each crosswalk is a different length, it is necessary to normalize each crossing by the crossing length to study the behaviour of each crossing. The length of each crosswalk was determined by measuring its centerline on Google Earth Pro, yielding approximate lengths of 18.9m, 21m, 17.8m, and 27.5m for the North, East, South, and West crossings respectively.

Not all pedestrians cross directly through the middle of the crosswalk which will introduce an additional level of error in the average pedestrian crossing speeds. Using Google Earth Pro, the approximate length of the longest opposite corner of the highlighted areas in Figure 4.7 was measured and used to determine the maximum error in crossing speeds which is estimated to be 11% at the West crosswalk and 24% at the others.

4.3. Results and Discussion

This section presents the findings from the pilot study to answer the last four research questions posed in Chapter 1 of the thesis, namely:

1. What are the pedestrian temporal violation behaviours occurring at signalized intersections?
2. Do pedestrians change their crossing speeds based on the time they begin their crossing relative to the pedestrian signal intervals?
3. How can the severity of pedestrian temporal violations at signalized intersections be measured?
4. How effectively do the proposed temporal violation measures characterize the pedestrian violation severity?

The next sections address each question in order.

4.3.1. What are the Pedestrian Temporal Violation Behaviours?

Table 4.1 provides a summary of the pedestrian temporal violation behaviour observed at the study site and at each crossing at the intersection. The data in Table 4.1 were obtained from the crossing data from Step 1 in Section 4.2.3. The crossings for which the violation severity was greater than zero were classified as ones for which a temporal violation occurred.

The proportion of temporal violations occurring at each crossing varies (from 10.9% to 31.3%) but this variation is highly impacted by the variation in the number of pedestrians crossing at each crossing and the amount of video data collected at each crosswalk. Interestingly, the proportion of pedestrians committing a temporal violation also varies by crossing, ranging from a low of 5.2% (South crossing) to a high of 11.3% (West crossing). Overall, 7.6% of pedestrians observed to make a crossing at the study intersection committed a temporal violation, which is substantially lower than the proportion of pedestrians committing a spatial violation (48.4%).

A chi-square test of homogeneity was performed again to determine whether the proportion of pedestrians committing a temporal violation is statistically different amongst the four crosswalks. The null hypothesis is that the proportion of pedestrians committing a temporal violation is the same across all four crosswalks. The test indicated that there is a statistically significant difference between the proportion of temporal violations and crossing locations ($X^2(df=3) = 12.99, p = 4.65 \times 10^{-3} < 0.005$).

Overall, the majority (86.7%) of temporal violations were classified as Start in FDW, while only 3.9% were Early starters, 4.7% were Start in AR after FDW, and 4.7% were Start in SDW. Although the relative distribution of temporal violations appears to be consistent across the different crosswalks, the chi-square test of homogeneity showed that there is a statistically significant difference in the types of violations committed across the four crossings. Examination of the data in Table 4.1 suggests that this difference is largely due to the East crosswalk, which has a lower proportion of Start in FDW violations compared to the other three crosswalks.

It should be noted that the results in Table 4.1 are unique to the study site and may not be directly transferable to other intersections in Waterloo or elsewhere. It is expected that the propensity for pedestrians to engage in temporal violations, and the type of temporal violation committed, is impacted by crossing and intersection geometric characteristics, vehicle volumes, prevailing vehicle speeds, pedestrian characteristics, local driver and pedestrian behavioural norms, nearby land uses, location and type of public transit stops/stations, etc. The dataset used in this research is limited to a single intersection preventing the exploration of the influence of these factors, but this is an area for further research.

Table 4.1: Pedestrians and Temporal Violations per Crossing

Crossing	Number of Observed Crossings	Number of Observed Crossings for which a Violation Occurred	Proportion of violations occurring at crossing (%)	Proportion of Pedestrians Committing a Temporal Violation (%)	Proportion of Violations by Type (%)			
					Early Starter	Start in FDW	Start in AR after FDW	Start in SDW
East	192	14	10.9%	7.3%	14.3%	57.1%	14.3%	14.3%
North	457	40	31.3%	8.7%	5.0%	92.5%	2.5%	0%
South	706	37	28.9%	5.2%	2.7%	83.8%	2.7%	10.8%
West	326	37	28.9%	11.3%	0%	94.6%	5.4%	0%
All Combined	1681	128	100%	7.6%	3.9%	4.7%	86.7%	4.7%

4.3.2. Do Pedestrians Change their Crossing Speeds based on the Time when they begin their Crossing Relative to the Pedestrian Signal Intervals?

It is hypothesized that pedestrians are motivated to complete their crossing before the cross-street green begins and cross street vehicles are permitted to enter the intersection. Therefore, it is expected that pedestrians who begin their crossing late (i.e., during the FDW), increase their walking speeds in order to complete their crossings before the start of the cross-street green. This section tests this hypothesis through the analysis of pedestrian crossing speeds based on the signal interval when the crossing begins. Table 4.2 shows the results of t-tests that determine whether there is a statistically significant difference between the average crossing speeds of pedestrians depending on when the pedestrians started their crossing. The results from these tests indicate that there is a statistically significant difference between pedestrians that begin crossing on the Walk signal interval (Legal Crossings) and the FDW signal interval (Start in FDW Crossers) as well as a statistically significant difference in the pedestrians' crossing speeds between those who begin crossing in the Walk signal interval and the SDW signal interval (Start in AR After FDW and Start in SDW Violators). However, no statistically significant difference was found between the crossing speeds between pedestrians who begin crossing during the FDW and SDW signal intervals. Note that pedestrians who started their crossing Early (i.e., in the All-red period prior to the walk interval) were not included in the tests in Table 4.2 due to their small sample size.

Table 4.2: T-Test Comparisons of Average Crossing Speeds as a function of when the pedestrian began their crossing

	Legal Crossings vs Start in FDW		Legal Crossings vs Start in AR After FDW & Start in SDW		Start in FDW vs Start in AR After FDW & Start in SDW	
	Legal Crossings (Start in Walk interval)	Start in FDW	Legal Crossings (Start in Walk interval)	Start in AR After FDW & Start in SDW	Start in FDW	Start in AR After FDW & Start in SDW
Mean	1.54 m/s	1.82 m/s	1.54 m/s	1.75 m/s	1.82 m/s	1.75 m/s
Variance	0.11	0.23	0.11	0.23	0.23	0.23
Observations	1553	111	1553	12	111	12
Hypothesis	0					
Df	118		11		14	
T Stat	-6.03		-2.20		-0.16	
P(T<=t) one-tail	9.73E-09		0.03		0.44	
t Critical one-tail	1.66		1.75		1.71	
Statistically Significant?	Yes		Yes		No	

These results indicate that the pedestrians adjust their crossing speeds based on the signal interval. On average, pedestrians cross faster when initiating their crossing during the FDW and SDW signal intervals compared to those that begin their crossing during the Walk signal interval. This could be a result of the presence of a countdown timer at the intersection, which could motivate pedestrians to walk faster, especially as the timer gets closer to zero. Another possibility is that the presence of incoming vehicles could also contribute to pedestrians crossing faster, particularly during the FDW.

The difference in average crossing speeds for pedestrians beginning their crossing during the FDW (Start in FDW violations) versus SDW (Start in AR After FDW & Start in SDW) intervals was not statistically significant. This result is unexpected, but it is possible that this is a result of there being three types of pedestrians that cross during the SDW. These three types are also reflected by three of the types of temporal violations, namely: Early Starters, Start in AR after FDW, and Start in SDW, all of which occupy different temporal spaces of the SDW signal interval. Early Starters are likely to share similar characteristics as pedestrians who cross during the Walk signal interval and thus, were excluded from the statistical analysis in Table 4.2. Pedestrians that Start in AR after FDW may have the highest crossing speeds as these are

pedestrians that attempt to complete their crossing during the All-Red signal interval (when no vehicles are likely to be making any movement through the intersection). The behaviour of Start in SDW is difficult to anticipate because based on the signal cycle, this is the most dangerous time to make a crossing however, the expectation is that these violators will also display some of the highest crossing speeds. Although all three types of SDW violations were observed, there are too few observations of each type to make meaningful conclusions.

4.3.3. How can Temporal Violation Severities be Measured?

This section presents the results of the temporal violation severities as determined from the application of the three proposed temporal violation severity metrics to the pedestrian crossings.

A lower degree of variability in the pedestrian crossing behaviour was observed within the collected dataset for temporal violations in comparison to spatial violations. This variability is illustrated in Figure 4.8, which represents the distribution of when the pedestrian entered the crosswalk relative to the signal cycle. Due to the cyclic nature of signal phases, there is a maximum level of variability that is not controlled by the pedestrian behaviour but by the pre-existing signal cycles.

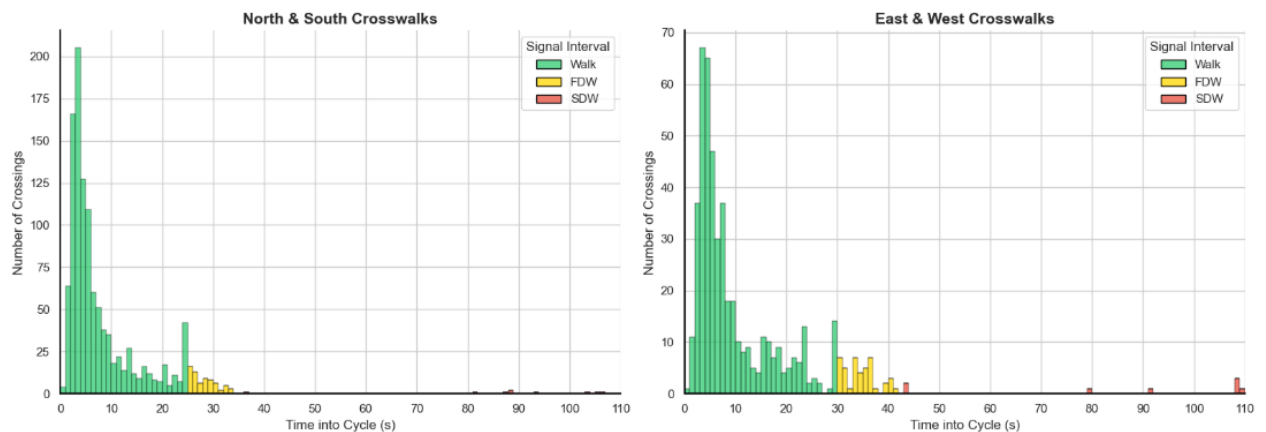


Figure 4.8: Distribution of when pedestrians start their crossing with respect to the signal cycle.

Further analysis indicates that the observed variability and the maximum severity are driven largely by the type of temporal violation. Table 4.3 provides descriptive statistics of each type of temporal violation. From these results, it can be observed that the mean, median, standard

deviation, and maximum violation severity are all smaller for early starters than the other three type of violations.

Table 4.3: Descriptive Statistics for Early Starter Violations, Start in FDW Violations, Start in AR after FDW Violations, and Start in SDW; all violations severities measured in seconds

	Early Starters			Start in FDW			Start in AR after FDW			Start in SDW		
	TV Metric			TV Metric			TV Metric			TV Metric		
	1	2	3	1	2	3	1	2	3	1	2	3
Mean	1.80	2.00	2.00	4.32	11.17	4.32	6.17	9.83	5.83	15.50	12.00	12.00
Median	1.00	1.00	1.00	4.00	12.00	3.00	3.00	9.00	6.00	17.50	10.50	10.50
Standard Deviation	1.30	1.73	1.73	5.12	5.26	3.04	6.62	5.42	4.07	6.22	3.69	3.69
Maximum Violation Severity	4.00	5.00	5.00	35.00	21.00	11.00	16.00	16.00	11.00	21.00	18.00	18.00
Number of Observations	5			111			6			6		

Figure 4.9 shows the cumulative relative distribution of the violation severity for the 128 crossings for which a temporal violation occurred. For TV metric 1, the cumulative relative frequency increases rapidly at low violation severities before gradually approaching 100% at higher severities, indicating that severe violations are relatively uncommon and that the distribution of violation severities is strongly skewed towards lower severities.

For TV Metric 2, the cumulative relative frequency increases gradually before approaching 20%, from which point the cumulative relative frequency increases at a relative steady rate until 100% is reached. This suggests that there is a small portion of temporal violations that are of low severity while there is an even distribution of moderate-to-severe temporal violations.

For TV Metric 3, the cumulative relative frequency increases at a relatively steady rate before approaching approximately 90%, from which point the cumulative relative frequency gradually approaches 100% at higher severities, indicating that severe violations are relatively uncommon and that the distribution of violation severities are relatively even.

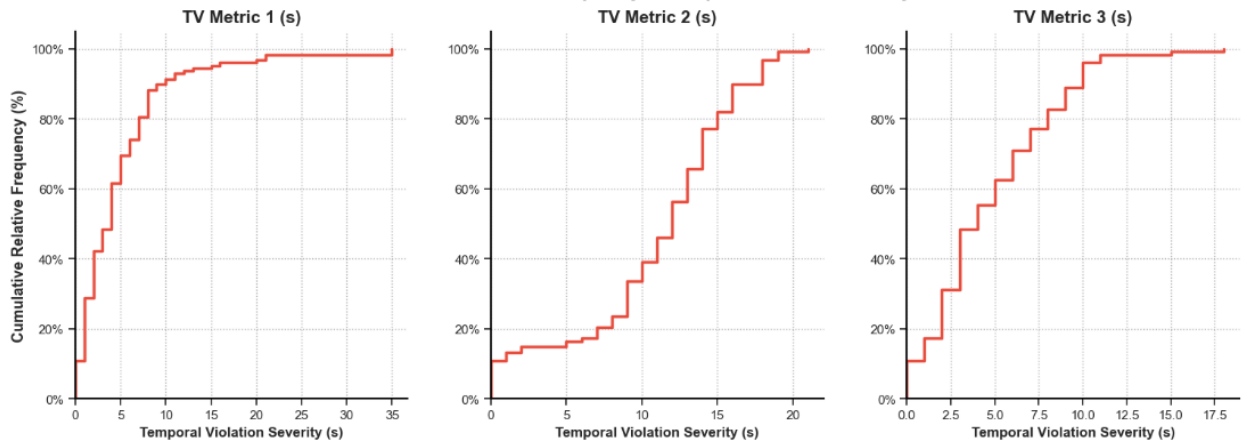


Figure 4.9: Cumulative Relative Frequencies of the Temporal Violation Severities based on the three TV Metrics

Figure 4.10 shows the cumulative relative frequencies of violation severities at each crosswalk according to the three TV metrics and Table 4.4 shows the results of a two-sample K-S statistical test used to determine if there was a statistical difference between the distribution of violation severities and the crosswalk location. Each pair of crosswalks were compared to each other three times (once for each TV metric), and unlike the results for the spatial violation metrics where there is a statistically significant difference between the violation severities at each crosswalk location, for temporal violations statistical significance depends on the metric and pair of crosswalks.

For example, TV Metric 1 is not sensitive to crossing speed or crosswalk geometry because it measures severity in terms of when initial moment a pedestrian enters the crosswalk with respect to the overall signal phase rather than the duration of the pedestrian crossing thus, the expectation is that the severity values are similar across all crosswalks (no statistically significant difference). This is confirmed in Table 4.4 where the results for TV metric 1 show that there is no statistically significant difference between the temporal violation severities and the crosswalk locations except between the East and North crosswalks, which could be a result of the specific geometry of the intersection, or the human error in the data extraction.

Although TV Metric 3 may be sensitive to crossing speed and crosswalk geometry, the severity values are not expected to be statistically different because the metric only considers time during the SDW interval. As a result, it quantifies the temporal violations of three groups:

Early Starters, Start in AR after FDW, and Start in SDW violators. Early Starters and Start in AR after FDW share similar violation severities regardless of their crossing location, making Start in SDW violators the only sub-group with a potentially meaningful difference in violation severity. This is shown in Table 4.4, where there is no statistically significant difference between the temporal violation severities and the crosswalk location except between the North and West crosswalks.

For TV Metrics 1 and 3, observations aligned with expectations that there are no statistically significant differences in violation severities across different crosswalk locations. However, the uniformity of this finding is not applicable to TV Metric 2 because this metric is inherently sensitive to both crossing speed and intersection geometry which are measured as the total legal violation crossing time. TV Metric 2 is sensitive to crossing speed and intersection geometry because it incorporates the pedestrian's crossing time during the FDW or SDW intervals. At larger intersections, this crossing time will naturally be greater than at small intersections, which directly inflates the temporal violation severity values. Consequently, the resulting severity metric is heavily dependent on the pedestrian's crossing speed and the physical length of the crosswalk. As shown in Table 4.4, statistically significant differences in the severities when comparing the West crosswalk against the East, North, and South exist. This finding is critical because the West crosswalk is the longest crosswalk at the study site, and these empirical observations validate the hypothesis that temporal severity, as measured by TV Metric 2, is linked to crossing location.

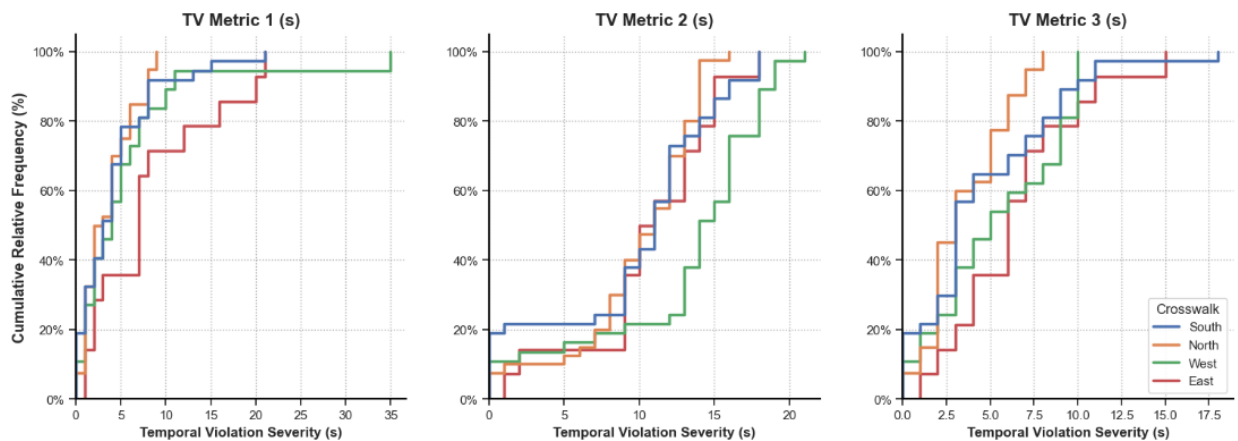


Figure 4.10: Cumulative Relative Frequency of Temporal Violation Severities for each Crosswalk

Table 4.4: Summary of K-S Statistical Test Results Between Each Pair of Crosswalks

TV Metric	Comparison Pair	KS Statistic	P-Value	Significant Difference? (P < 0.05)
1	East vs North	0.48	1.12E-02	Yes
1	East vs South	0.38	1.00E-01	No
1	East vs West	0.34	1.61E-01	No
1	North vs South	0.19	4.89E-01	No
1	North vs West	0.18	5.32E-01	No
1	South vs West	0.09	9.93E-01	No
2	East vs North	0.19	7.94E-01	No
2	East vs South	0.20	7.55E-01	No
2	East vs West	0.45	2.54E-02	Yes
2	North vs South	0.21	4.08E-01	No
2	North vs West	0.52	6.26E-05	Yes
2	South vs West	0.52	2.43E-04	Yes
3	East vs North	0.40	5.58E-02	No
3	East vs South	0.25	5.00E-01	No
3	East vs West	0.15	9.50E-01	No
3	North vs South	0.27	1.37E-01	No
3	North vs West	0.37	1.12E-02	Yes
3	South vs West	0.17	6.65E-01	No

4.3.4. How effectively do the proposed temporal violation measures characterize the pedestrian violation severity?

Similar to Chapter 3, this thesis proposes another set of violation severity metrics, in this case for temporal violations. Whether these metrics provide a similar or different relative assessment of the severity of different crossings is a question that should be considered. To answer this question, the same two types of analysis were conducted, namely (1) a comparison of the distributions of the normalized violation severities from each of the three proposed violation severity metrics, and (2) a rank error analysis was performed to determine the level of inconsistency between the rankings that result from the application of the proposed violation severities.

Comparison of Normalized Distribution of Temporal Violation Severities:

The violation severities from each of the three proposed temporal violation metrics were normalized by dividing the violation severity from metric j for violation crossing i , by the maximum violation severity from metric j determined across all crossings resulting in a violation. In this way, the normalized violation severities ranged from a value of 0 to 1. Figure 4.11 indicates that the distribution of violation severities for all three TV metrics is different. TV Metric 1 has a higher proportion of crossings with a lower violation severity whilst TV Metric 2 has a higher proportion of crossings with moderate-to-high violation severities, and TV Metric 3 has a relatively evenly distribution of violation severities (extreme violations being rare). Table 4.5 summarizes the results of two-sample K-S statistical test that determines if there is a statistical difference between the cumulative relative frequencies of the normalized temporal violation severities. It was found that the cumulative relative frequency distributions of normalized temporal violation severities differed significantly between all pairwise comparisons of the TV Metrics. This result is expected since all three TV Metrics are very different from each other. It is also important to note that there is a sub-set of violations for which TV Metric 3 will have the exact same violation severity as TV Metric 1 and another sub-set of violations for which TV Metric 3 will have the exact same violation severity as TV Metric 2, namely the pedestrians who are Early Starters and who Start in SDW, respectively.

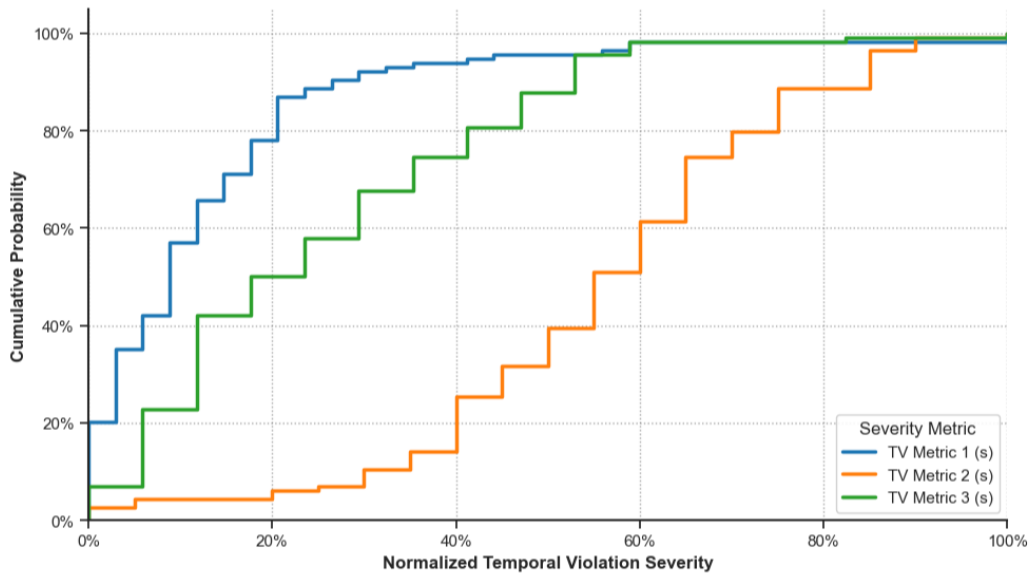


Figure 4.11: Comparison of the Distributions of Normalized Violation Severities by the Three TV Metrics

Table 4.5: KS Test Results for Pairwise Comparisons of Normalized Violation Severities

Comparison between TV Metric Pairs	KS Statistic	P-Value	Significant Difference? (P < 0.05)
TV 1 & TV 2	0.85	1.63E-42	Yes
TV 1 & TV 3	0.37	2.83E-07	Yes
TV 2 & TV 3	0.61	8.93E-20	Yes

Comparison of Rank Consistency:

Similar to the spatial violation metrics, the three TV metrics attempt to quantify temporal violation severities using different measures thus, it is necessary to evaluate the ranking consistency. The three TV metrics were evaluated by examining the similarity of the ranked order of pedestrian crossings using Rank Error Analysis (refer to Equations 3.4 and 3.5).

The Rank Error (Equation 3.4) and the Relative Rank Error (Equation 3.5) were computed for each of the three-metric pair-wise comparison as a function of n , the number of pedestrian crossings considered in the sample selected as the top n crossings. Figure 4.12 shows error between the pairs of TV metrics for values of n up to 100 (i.e., the 100 most severe temporal violations). Similar to Figure 4.11, this figure shows that there are no clear similarities between the TV metrics however, these figures show that the severity of temporal violation is highly dependent on which metric is selected. For example, for the top 10 most severe temporal violations, Metrics 1 and 2 include 3 different trajectories, whereas Metrics 1 and 3, and Metrics 2 and 3, include 8 different trajectories in their rankings. It is important to note that while the three SV metrics were all measuring the severity of a legal spatial violation, amongst the TV metrics only one of the metrics is representative of a legal temporal violation, the other two are derivative metrics influenced by the legal definition but not directly a measurement of a legal violation.

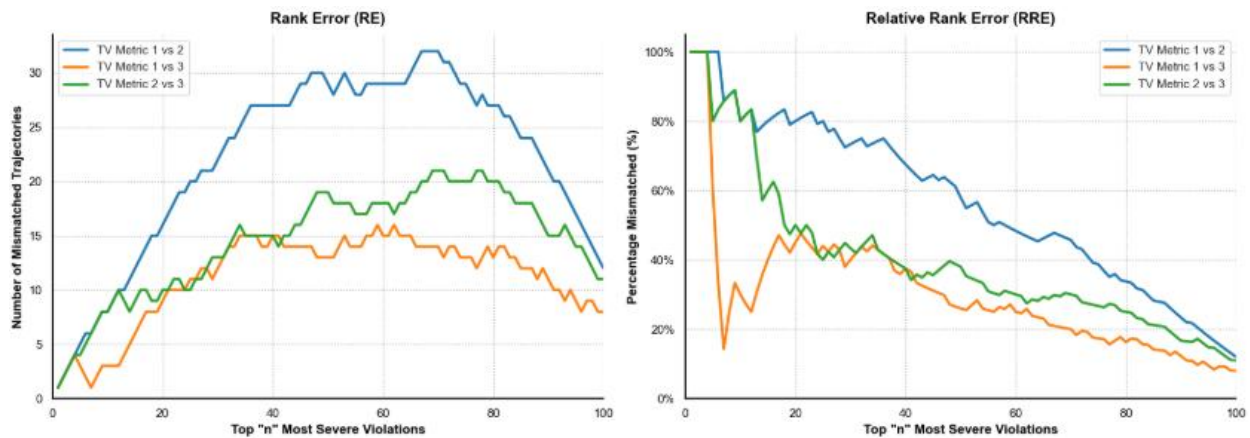


Figure 4.12: Rank Error (RE) and Relative Rank Error (RRE) Progression for the Three TV Metric Pairings

4.3.5. Limitations

While the proposed TV metrics and the data extraction process present a methodology for quantifying temporal violations, it is necessary to acknowledge some of the constraints of this research. The limitations of this study primarily stem from three areas: the geographically specific nature of this study, the amount of data collected, and the inherent error associated with visual observation. Recognizing these limitations is critical for accurately interpreting the temporal violations and TV metrics, ensuring that the findings are not extrapolated beyond the scope of this study.

The observational data collection for this research is constrained both temporally and geographically. Data collection took place over the course of three seasons (Autumn, Winter, and Spring). However, with only 2-3 hours of available per season, it is difficult to analyze variations in temporal violations across all days of the week, times of day, lighting conditions, or weather conditions. Additionally, since the selected intersection is situated adjacent to a major post-secondary institution, the observed pedestrian demographics are again skewed towards post-secondary students and young adults. As mentioned within the limitations of the spatial violation analysis, age heavily influences crossing behaviour (Granié et al., 2013). The frequency and distribution of temporal violations observed in this study may not reflect temporal violations that occur at intersection with more diverse populations, intersection with completely different

demographics, or even intersections with different traffic signal configurations (no FDW countdown timer for pedestrians).

The quantitative accuracy of the temporal violations is heavily dependent on the video resolution, point of view of the video, and the human ability to accurately track and record pedestrian crossings. The video data available provided all timings to the nearest second, which introduces some level of rounding error. In tandem with the video resolution, a human will be unable to pinpoint the precise moment a pedestrian steps into and out of the crosswalk consistently every single time. Nevertheless, the error introduced will be a fraction of a second and the impact that this has on the overall analyses is expected to be minor.

5. Conclusion

5.1. Conclusions & Key Findings

This study proposed three distinct metrics capable of characterizing the severity of pedestrian spatial violations at signalized intersections and examined the spatial violation behaviour of pedestrians at a single signalized intersection. The analysis revealed that 48% of pedestrians committed a spatial violation when crossing. Though the vast majority (86.5%) of spatial violations are minor corner cutting crossings, the most severe spatial violations occur when the pedestrian crosses outside of the crosswalk. The median, mean, and standard deviation of violation severity were all larger for crossing outside of the crosswalk violations compared to corner cutting violations. Extrapolating these observed behaviour tendencies to other locations is not advised due to the limited data used in this study and the hypothesis that spatial violation behaviours are impacted by factors such as intersection geometry, signal control, vehicle volumes and speeds, nearby land uses, and local driver and pedestrian customs.

This study also proposed three distinct metrics capable of characterizing the severity of pedestrian temporal violations at signalized intersections and examined the temporal violation behaviour at a single signalized intersection. The analysis revealed that 7.6% of pedestrians committed a temporal violation when crossings. Though the vast majority (86.7%) of temporal violations are Start in the FDW, the most severe temporal violations occur for Start in SDW violations. The mean, median, and standard deviation of violation severity were all larger for Start in SDW compared to the other three types of temporal violations. Extrapolating these observed behaviour tendencies to other locations is not advised due to hypothesis that temporal violation behaviours are impacted by factors such as intersection geometry, vehicle volumes and speeds, nearby land uses, and local driver and pedestrian customs.

In a case study, SV Metrics 2 and 3 provided very similar measures of the distribution of violation severities (no statistically significant difference), but the distribution resulting from the use of SV Metric 1 was statistically different from both SV Metrics 2 and 3. Practically, any of the three proposed SV metrics could be integrated into existing camera or lidar based automated traffic data collection systems, provided that pedestrian trajectories are recorded.

In a similar case study, all three TV Metrics provided very different distributions of violation severities (statistically significant differences). Practically, any of the three proposed

TV metrics could also be integrated into existing camera or lidar based automated traffic data collection systems, provided that pedestrian crossings times per signal interval and pedestrian entry time into the intersection with respect to the overall signal cycle are recorded. Quantifying pedestrian spatial and temporal violation severities enables future research to analyze the relationship between pedestrian violations and pedestrian-vehicle conflicts or collisions.

5.2. Recommendations

This thesis has proposed a total of seven metrics to quantify the severity of a pedestrian violation and has analyzed six of these metrics. Out of the three SV Metrics, Metric 2 (Total Violation Area) and Metric 3 (Total Time-step) are recommended as the most suitable metrics to quantify pedestrian spatial violations. As mentioned in Section 3.3.3., SV Metric 1 has the higher distribution of severe violations compared to SV Metrics 2 and 3, and there is the possibility that SV Metric 1 overestimates the true severity of a spatial violation. On the contrary, SV Metrics 2 and 3 are very similar to each other (no statistically significant difference), and they also consider more aspects of a pedestrian's crossing behaviour.

While identifying appropriate SV metrics proved to be straightforward, recommending appropriate TV Metric(s) is more challenging. Although two of the proposed SV metrics demonstrated alignment in how they quantified pedestrian spatial violations, statistical analysis of the TV metrics revealed the opposite. Tests indicated statistically significant differences between all three proposed TV metrics. Consequently, the selection of a suitable TV Metric is highly dependent on the definition of a temporal violation. If the purpose is to strictly adhere to formal written traffic regulations, then TV Metric 2 is the most appropriate model. If the focus is to recommend a more practical metric that balances pedestrian behavioural compliance and safety, then TV Metric 3 or 4 may be more suitable since pedestrian crossings during the SDW interval are widely recognized as temporal violations. Although analysis for TV Metric 4 was not completed, the expectation is that the results of TV Metric 3 and 4 are similar, with TV Metric 4 providing further distinguishment for pedestrians that cross during the All-Red interval.

5.3. Future Work

To build upon this foundational methodology, several avenues for future research have been identified. First, future studies should expand the study area and sample size beyond a single intersection and one hour of video footage for spatial violations. Subsequent research should also analyze intersections of different sizes, geometric designs, surrounding land uses, speed limits, traffic volumes and pedestrian population characteristics, to examine the factors that influence pedestrian spatial violation behaviour. Beyond the expanded dataset and study sites, further refinement to the data analysis process should also be completed. Specifically, improving the stitching and gap interpolation process to select the most suitable candidate track rather than using the first suitable candidate track to complete a trajectory. Additionally, if any of the proposed temporal or spatial violation metrics can be integrated into automated data collection technology, this should also be an avenue for future work as this will provide a potentially more accurate dataset and can record pedestrian behaviours over a wide variety of conditions. Similar attention to these issues should be given by other researchers regardless of data collection technology (e.g., camera, lidar, etc.) to ensure analyzed trajectories are representative of real-world behaviours.

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Appendix A: Homography Matrix Calibration & Python Code

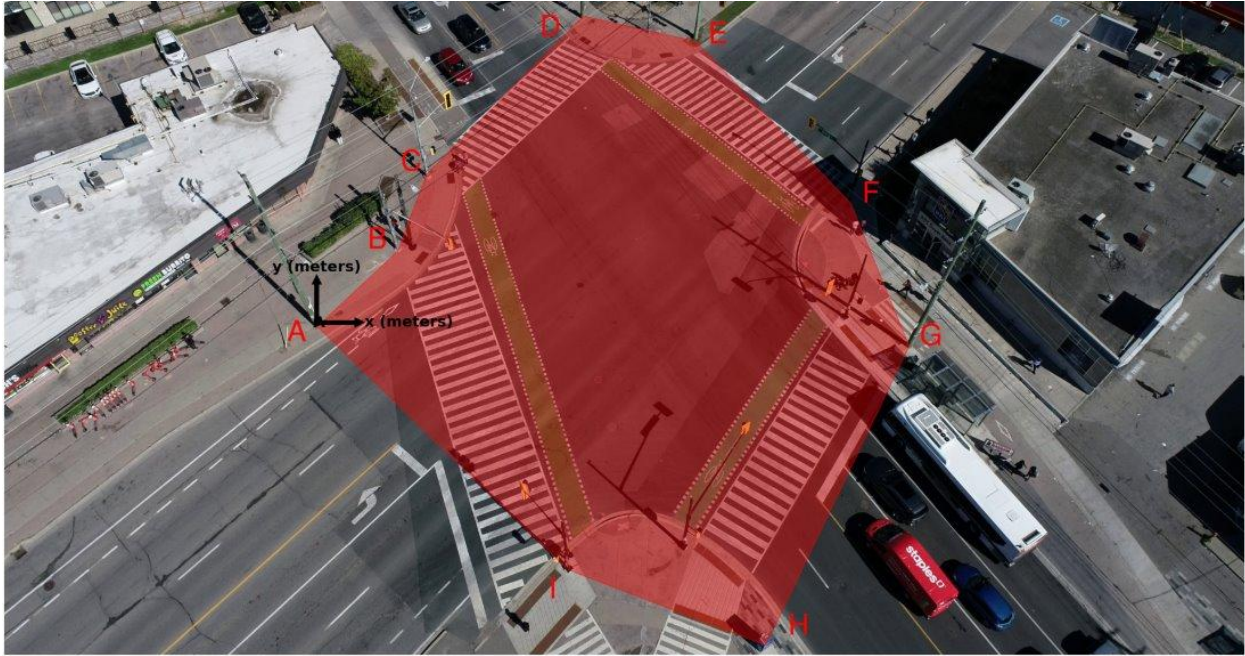


Figure A.1: 9 Points Encompassing Study Area for the first Homography Matrix Calibration

Table A.1: Comparison between Measured Distances and Distances Estimated by the Homography Matrix for the 9 points in Figure B.1

Segment	Measured Distance (m)	Estimated Distance (m)	Absolute Error (m)	Relative Error (%)
A → B	9.0	8.89	0.11	1.22
B → C	8.2	7.93	0.27	3.29
C → D	25.02	24.86	0.16	0.64
D → E	11.34	10.91	0.43	3.79
E → F	24.01	24.69	0.68	2.83
F → G	14.7	14.09	0.61	4.15
G → H	25.16	25.68	0.52	2.07
H → I	13.4	12.8	0.6	4.48
I → A	25.85	26.22	0.37	1.43
Average	----	----	0.42	2.66

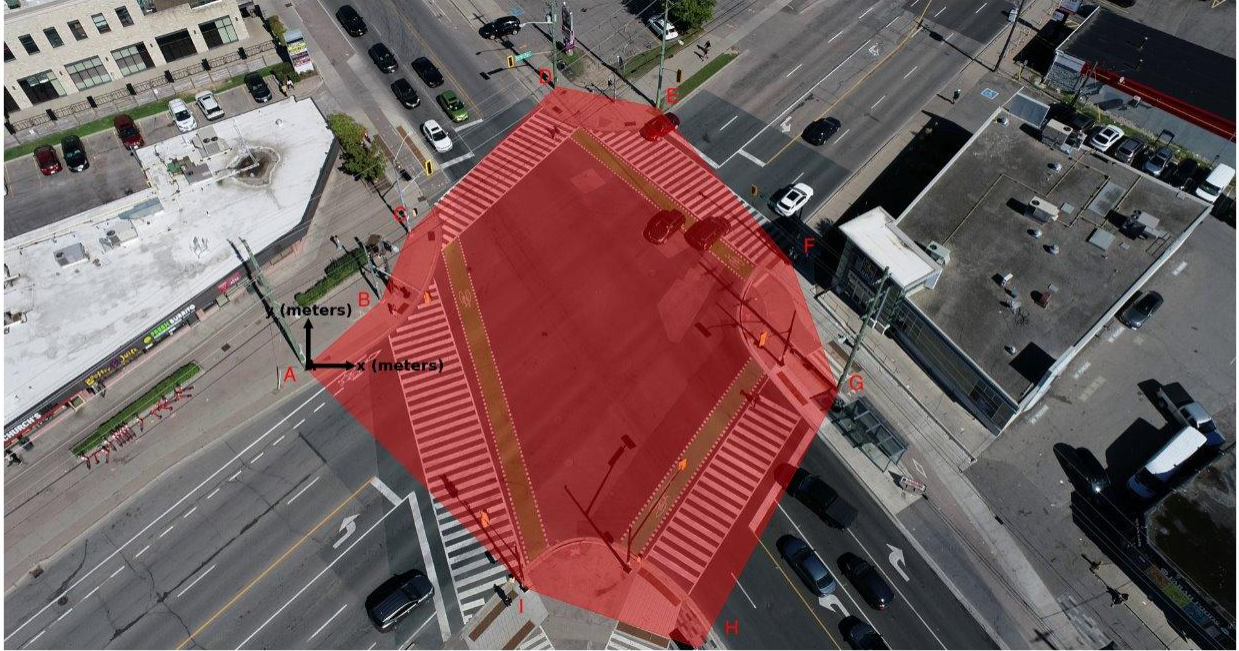


Figure A.2: 9 Points Encompassing Study Area for the second Homography Matrix Calibration

Table A.2: Comparison between Measured Distances and Distances Estimated by the Homography Matrix for the 9 points in Figure B.2

Segment	Measured Distance (m)	Estimated Distance (m)	Absolute Error (m)	Relative Error (%)
A → B	9.0	8.862	0.38	4.22
B → C	8.2	8.16	0.04	0.49
C → D	25.02	24.82	0.20	0.80
D → E	11.34	11.27	0.07	0.62
E → F	24.01	24.13	0.12	0.50
F → G	14.7	14.70	0	0.00
G → H	25.16	25.12	0.04	0.16
H → I	13.4	13.19	0.21	1.57
I → A	25.85	26.11	0.26	1.00
Average	----	----	0.15	1.04

```

import numpy as np
import cv2
import math

# 1. Input Data: (Pixel X, Pixel Y, Lat_DMS, Lon_DMS)
data = [
    (1015, 1234, "43°28'34.27\"N", "80°31'31.06\"W"), # Green Lamppost NW
    (1257, 1009, "43°28'34.37\"N", "80°31'30.66\"W"), # West Traffic Signal NW
    (1347, 784, "43°28'34.65\"N", "80°31'30.51\"W"), # North Traffic Signal NW
    (1830, 304, "43°28'35.13\"N", "80°31'29.62\"W"), # Lamppost NE
    (2175, 370, "43°28'34.89\"N", "80°31'29.26\"W"), # East Traffic Signal NE
    (2604, 874, "43°28'34.12\"N", "80°31'29.10\"W"), # East Traffic Signal SE
    (2766, 1300, "43°28'33.66\"N", "80°31'29.29\"W"), # Lamppost SE
    (2319, 2155, "43°28'33.17\"N", "80°31'30.20\"W"), # Blue traffic signal box
    (1728, 1957, "43°28'33.48\"N", "80°31'30.60\"W") # West Traffic Signal SW
]

# Helper function to convert DMS to Decimal Degrees
def dms_to_dd(dms_str):
    # Strip symbols and split
    clean_str = dms_str.replace('°', ' ').replace("'", ' ').replace("\"", ' ')
    parts = clean_str.split()
    degrees, minutes, seconds = float(parts[0]), float(parts[1]), float(parts[2])
    direction = parts[3]

    dd = degrees + (minutes / 60) + (seconds / 3600)
    if direction in ['S', 'W']:
        dd *= -1
    return dd

# 2. Extract Pixels and Convert GPS to Decimal Degrees
pixels = []
latlons = []
for x, y, lat_str, lon_str in data:
    pixels.append([x, y])
    latlons.append([dms_to_dd(lat_str), dms_to_dd(lon_str)])

pixels = np.array(pixels, dtype=np.float32)

# 3. Convert GPS to a Local Coordinate System (Meters)
# We will use the first point (Green Lamppost NW) as the origin (0, 0) meters
origin_lat, origin_lon = latlons[0]
R = 6378137.0 # Radius of Earth in meters

world_pts = []
for lat, lon in latlons:

```

```

# Convert to radians
lat_rad, lon_rad = math.radians(lat), math.radians(lon)
origin_lat_rad, origin_lon_rad = math.radians(origin_lat), math.radians(origin_lon)

# Equirectangular projection approximation (highly accurate for intersection-scale distances)
x_meters = R * (lon_rad - origin_lon_rad) * math.cos(origin_lat_rad)
y_meters = R * (lat_rad - origin_lat_rad)

world_pts.append([x_meters, y_meters])

world_pts = np.array(world_pts, dtype=np.float32)

# 4. Compute Homography
# Using cv2.RANSAC provides a more robust matrix that ignores minor GPS pinpointing errors
H_MATRIX, mask = cv2.findHomography(pixels, world_pts, cv2.RANSAC)

print("--- NEW CALIBRATED HOMOGRAPHY MATRIX ---")
print("H_MATRIX = np.array([")
for row in H_MATRIX:
    print(f"    [{row[0]:.8e}, {row[1]:.8e}, {row[2]:.8e}],")
print(")])")

```

Appendix B: Pedestrian Trajectory Processing and Spatial Violation (SV)

Analysis Python Code

```
#
=====
# ENVIRONMENT SETUP & DEPENDENCIES
#
=====

import subprocess, sys

# Required packages for processing and Excel handling
pkgs = [
    ("shapely", "shapely"),
    ("opencv-python", "cv2"),
    ("openpyxl", "openpyxl"),
    ("xlsxwriter", "xlsxwriter"),
    ("tqdm", "tqdm"),
    ("pandas", "pandas"),
    ("numpy", "numpy"),
]

print("Installing / verifying packages...")
for pkg_name, import_name in pkgs:
    result = subprocess.run(
        [sys.executable, "-m", "pip", "install", pkg_name, "-q"],
        capture_output=True, text=True
    )
    status = "✅" if result.returncode == 0 else "❌"
    print(f" {status} {pkg_name}")

print("\n✅ All packages ready.")

import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import cv2
from shapely.geometry import Point, Polygon, LineString
from shapely.ops import unary_union
import shapely
from tqdm import tqdm

tqdm.pandas(desc=" Processing rows")
```

```
print("✅ Imports OK")
```

```
#
```

```
=====
```

```
# FILE PATHS
```

```
#
```

```
=====
```

```
INPUT_FILE      = "Trajectory Summaries Part 1.xlsx"
```

```
SUMMARY_OUTPUT  = "Processed Trajectory Summary Part 1_New_Final.xlsx"
```

```
STITCH_LOG_OUTPUT = "Stitch_Log Part 1_New_Final.xlsx"
```

```
TRAJ_OUTPUT     = "Violation_Trajectories_Part 1_New_Final.xlsx"
```

```
#
```

```
=====
```

```
# RECORDING PARAMETERS & THRESHOLDS
```

```
#
```

```
=====
```

```
FPS = 60
```

```
DT = 1.0 / FPS
```

```
# --- TRAJECTORY STITCHING PARAMETERS ---
```

```
STITCH_MAX_GAP_SEC    = 3.0
```

```
STITCH_MAX_DIST_M     = 3.6
```

```
FLICKER_TOLERANCE     = int(FPS * 0.17)
```

```
STITCH_MAX_TRACK_FRAMES = 30.0 * FPS
```

```
STITCH_FLICKER_SEC    = 1.0
```

```
STITCH_FLICKER_DIST_M = 1.2
```

```
STITCH_MAX_ANGLE_DEG  = 30.0 # Creates a 120-degree forward cone match
```

```
MAX_EXTRAPOLATION_M   = 5.0  # Tracks ending > 5m from a curb drop extrapolation
```

```
# --- SPATIAL ANALYSIS FILTERS ---
```

```
SEGMENT_GAP_MERGE_S   = 3.0
```

```
OUTSIDE_THRESHOLD_M   = 0.0
```

```
FULL_OUTSIDE_FRACTION = 1.0
```

```
#
```

```
=====
```

```
# HOMOGRAPHY MATRIX & SPATIAL POLYGONS
```

```
#
```

```

# Camera calibration matrix for pixel-to-meter translation
H_MATRIX = np.array([
    [ 2.54921905e-02, -7.87160531e-03, -1.70739801e+01],
    [-1.04946105e-02, -3.46479746e-02,  4.76862800e+01],
    [-2.57928886e-05,  2.88941308e-04,  1.00000000e+00]
])

try:
    H_INV = np.linalg.inv(H_MATRIX)
except:
    H_INV = None

# Base polygon boundaries (in raw pixel coordinates)
crosswalks_px = {
    'West': Polygon([(1604, 2021), (1815, 1811), (1451, 751), (1289, 985)]),
    'North': Polygon([(1470, 683), (1429, 524), (1824, 165), (1958, 235)]),
    'East': Polygon([(1982, 242), (2199, 225), (2737, 621), (2607, 730)]),
    'South': Polygon([(2667, 1111), (2803, 1274), (2406, 1914), (2240, 1785)]),
}

sidewalks_px = {
    'NW': Polygon([(1, 1943), (547, 1501), (1332, 946), (1473, 760), (1506, 565), (1416, 412),
    (1110, 4), (19, 1)]),
    'NE': Polygon([(2234, 203), (2193, 223), (1956, 227), (1856, 186), (1705, 36), (1839, 4),
    (2429, 33)]),
    'SE': Polygon([(3371, 7), (2802, 568), (2679, 700), (2625, 802), (2616, 892), (2667, 1009),
    (2865, 1228), (3713, 2158), (4085, 2158), (4088, 10)]),
    'SW': Polygon([(1513, 2156), (1615, 2032), (1813, 1835), (1920, 1755), (2027, 1719), (2118,
    1738), (2214, 1781), (2391, 1931), (2560, 2156), (2174, 2154), (1779, 2154)]),
}

INFERRED_OD = {
    'North': {'CW': ('NW', 'NE'), 'CCW': ('NE', 'NW')},
    'South': {'CW': ('SE', 'SW'), 'CCW': ('SW', 'SE')},
    'East': {'CW': ('NE', 'SE'), 'CCW': ('SE', 'NE')},
    'West': {'CW': ('SW', 'NW'), 'CCW': ('NW', 'SW')},
}

VALID_OD_PAIRS = {
    'North': [{'NW', 'NE'}], 'South': [{'SW', 'SE'}],
    'East': [{'NE', 'SE'}], 'West': [{'NW', 'SW'}],
}

# --- Coordinate Transformation Utilities ---
def _apply_homography(poly: Polygon, H: np.ndarray) -> Polygon:
    coords = np.array(poly.exterior.coords, dtype=np.float32).reshape(-1, 1, 2)

```

```

transformed = cv2.perspectiveTransform(coords, H)
return Polygon(transformed.reshape(-1, 2))

def _px_to_m(x_arr: np.ndarray, y_arr: np.ndarray, H: np.ndarray):
    pts = np.column_stack([x_arr, y_arr]).astype(np.float32).reshape(-1, 1, 2)
    out = cv2.perspectiveTransform(pts, H).reshape(-1, 2)
    return out[:, 0], out[:, 1]

def _m_to_px(x_arr: np.ndarray, y_arr: np.ndarray, H_inv: np.ndarray):
    pts = np.column_stack([x_arr, y_arr]).astype(np.float32).reshape(-1, 1, 2)
    out = cv2.perspectiveTransform(pts, H_inv).reshape(-1, 2)
    return out[:, 0], out[:, 1]

def _get_polygon_edges(poly: Polygon):
    coords = list(poly.exterior.coords)
    return [LineString([coords[i], coords[i + 1]]) for i in range(len(coords) - 1)]

# Initialize physical-world polygon structures
crosswalks_m = {n: _apply_homography(p, H_MATRIX) for n, p in crosswalks_px.items()}
sidewalks_m = {n: _apply_homography(p, H_MATRIX) for n, p in sidewalks_px.items()}
crosswalk_edges = {n: _get_polygon_edges(p) for n, p in crosswalks_m.items()}
crosswalk_areas_m2 = {'North': 86.675, 'West': 135.071, 'South': 76.943, 'East': 114.923}

#
=====
# [1/9] LOADING & PROJECTION
#
=====

try:
    xls = pd.ExcelFile(INPUT_FILE)
    sheets = xls.sheet_names

    frames_list = []
    for sheet in tqdm(sheets, desc=" Reading sheets", unit="sheet"):
        tmp = pd.read_excel(xls, sheet_name=sheet)
        tmp['video_title'] = sheet
        frames_list.append(tmp)

    raw_df = pd.concat(frames_list, ignore_index=True)
    raw_df['orig_track_id'] = raw_df['track_id']

    uid_to_video =
    raw_df.drop_duplicates('track_id').set_index('track_id')['video_title'].to_dict()

```

```

uid_to_orig_tid =
raw_df.drop_duplicates('track_id').set_index('track_id')['orig_track_id'].to_dict()

print("   Projecting pixel coords to ground-plane metres...", end=" ")
x_m, y_m = _px_to_m(raw_df['x_center_stabilized_px'].values,
raw_df['y_center_stabilized_px'].values, H_MATRIX)
raw_df['x_m'] = x_m
raw_df['y_m'] = y_m
print("done")

df = raw_df.sort_values(['track_id', 'frame']).reset_index(drop=True)
df['Data_Source'] = 'Original'

print(f" 📁 Total Raw Trajectories loaded: {df['track_id'].nunique()}")

except FileNotFoundError:
    print(f" ❌ Error: Could not find '{INPUT_FILE}'. Please ensure the file is in the correct
folder.")
    sys.exit()

#
=====
=====
# [2/9] STITCHING BROKEN TRACKS & GAP INTERPOLATION
#
=====
=====

def _on_sidewalk_m(x: float, y: float) -> bool:
    pt = Point(x, y)
    return any(poly.contains(pt) for poly in sidewalks_m.values())

track_bounds = df.groupby('track_id').agg(start_frame=('frame', 'min'), end_frame=('frame',
'max')).reset_index()
starts_raw = pd.merge(track_bounds[['track_id', 'start_frame']], df, left_on=['track_id',
'start_frame'], right_on=['track_id', 'frame'])
ends_raw = pd.merge(track_bounds[['track_id', 'end_frame']], df, left_on=['track_id',
'end_frame'], right_on=['track_id', 'frame'])

ends_raw['on_sidewalk'] = ends_raw.apply(lambda r: _on_sidewalk_m(r['x_m'], r['y_m']),
axis=1)
starts_raw['on_sidewalk'] = starts_raw.apply(lambda r: _on_sidewalk_m(r['x_m'], r['y_m']),
axis=1)

broken_ends = ends_raw[~ends_raw['on_sidewalk']].sort_values('end_frame')
broken_starts = starts_raw[~starts_raw['on_sidewalk']]

```

```

track_dur = ((track_bounds.set_index('track_id')['end_frame'] -
track_bounds.set_index('track_id')['start_frame']).to_dict())

stitch_mapping = {}
stitch_gap_meta = {}
claimed_starts = set()
cos_threshold = np.cos(np.radians(STITCH_MAX_ANGLE_DEG))

for _, end_row in tqdm(broken_ends.iterrows(), total=len(broken_ends), desc="    Matching
ends", unit="track"):
    tid_A, end_f = end_row['track_id'], end_row['end_frame']

    track_a_history = df[(df['track_id'] == tid_A) & (df['frame'] <= end_f)].sort_values('frame')
    vec_A = np.array([0.0, 0.0])
    raw_vec_A = np.array([0.0, 0.0])

    lookback = min(int(FPS), len(track_a_history))
    if lookback >= 3:
        pt_past = track_a_history.iloc[-lookback][['x_m', 'y_m']].values.astype(float)
        pt_end = track_a_history.iloc[-1][['x_m', 'y_m']].values.astype(float)
        raw_vec_A = pt_end - pt_past
        norm_A = np.linalg.norm(raw_vec_A)
        if norm_A > 0: vec_A = raw_vec_A / norm_A

    # Trajectory A O/D inference
    pt_A_geom = Point(end_row['x_m'], end_row['y_m'])
    zone_A = None
    for cw_name, cw_poly in crosswalks_m.items():
        if cw_poly.buffer(2.0).contains(pt_A_geom):
            zone_A = cw_name
            break

    prelim_od_A = 'Outside'
    if zone_A and np.linalg.norm(raw_vec_A) > 0:
        dx_A, dy_A = raw_vec_A[0], raw_vec_A[1]
        if zone_A in ['North', 'South']:
            if abs(dx_A) > abs(dy_A):
                dr_A = 'CW' if (dx_A >= 0 if zone_A == 'North' else dx_A <= 0) else 'CCW'
                prelim_od_A = INFERRED_OD[zone_A].get(dr_A)
            else:
                prelim_od_A = 'Perpendicular'
        else:
            if abs(dy_A) > abs(dx_A):
                dr_A = 'CW' if (dy_A >= 0 if zone_A == 'East' else dy_A <= 0) else 'CCW'
                prelim_od_A = INFERRED_OD[zone_A].get(dr_A)

```

```

else:
    prelim_od_A = 'Perpendicular'

candidates = broken_starts[
    (broken_starts['track_id'] != tid_A) &
    (~broken_starts['track_id'].isin(claimed_starts)) &
    (broken_starts['start_frame'] >= end_f - FLICKER_TOLERANCE) &
    (broken_starts['start_frame'] <= end_f + STITCH_MAX_GAP_SEC * FPS)
].copy()

if candidates.empty: continue

candidates['dist_m'] = np.hypot(candidates['x_m'] - end_row['x_m'], candidates['y_m'] -
end_row['y_m'])
candidates['time_gap_s'] = (candidates['start_frame'] - end_f) / FPS

valid_candidates = []

for idx, cand in candidates.iterrows():
    tid_B = cand['track_id']
    track_b_future = df[(df['track_id'] == tid_B) & (df['frame'] >=
cand['start_frame'])].sort_values('frame')
    vec_B = np.array([0.0, 0.0])
    raw_vec_B = np.array([0.0, 0.0])

    lookforward = min(int(FPS), len(track_b_future))
    if lookforward >= 3:
        pt_start = track_b_future.iloc[0][['x_m', 'y_m']].values.astype(float)
        pt_future = track_b_future.iloc[lookforward - 1][['x_m', 'y_m']].values.astype(float)
        raw_vec_B = pt_future - pt_start
        norm_B = np.linalg.norm(raw_vec_B)
        if norm_B > 0: vec_B = raw_vec_B / norm_B

    # Trajectory B O/D inference
    pt_B_geom = Point(cand['x_m'], cand['y_m'])
    zone_B = None
    for cw_name, cw_poly in crosswalks_m.items():
        if cw_poly.buffer(2.0).contains(pt_B_geom):
            zone_B = cw_name
            break

    if zone_A and zone_B and zone_A != zone_B:
        continue

    prelim_od_B = 'Outside'
    if zone_B and np.linalg.norm(raw_vec_B) > 0:

```

```

dx_B, dy_B = raw_vec_B[0], raw_vec_B[1]
if zone_B in ['North', 'South']:
    if abs(dx_B) > abs(dy_B):
        dr_B = 'CW' if (dx_B >= 0 if zone_B == 'North' else dx_B <= 0) else 'CCW'
        prelim_od_B = INFERRED_OD[zone_B].get(dr_B)
    else:
        prelim_od_B = 'Perpendicular'
else:
    if abs(dy_B) > abs(dx_B):
        dr_B = 'CW' if (dy_B >= 0 if zone_B == 'East' else dy_B <= 0) else 'CCW'
        prelim_od_B = INFERRED_OD[zone_B].get(dr_B)
    else:
        prelim_od_B = 'Perpendicular'

if zone_A and zone_B and zone_A == zone_B:
    if prelim_od_A == 'Perpendicular' or prelim_od_B == 'Perpendicular':
        continue
    if prelim_od_A != prelim_od_B:
        continue

if np.linalg.norm(vec_A) > 0 and np.linalg.norm(vec_B) > 0:
    if np.dot(vec_A, vec_B) < 0.0:
        continue

    if cand['time_gap_s'] <= STITCH_FLICKER_SEC and cand['dist_m'] <=
STITCH_FLICKER_DIST_M:
        cand = cand.copy()
        cand['Fix_Type'] = 'Proximity Stitch'
        valid_candidates.append(cand)
        continue

    if cand['dist_m'] <= STITCH_MAX_DIST_M and np.linalg.norm(vec_A) > 0:
        gap_vec = np.array([cand['x_m'] - end_row['x_m'], cand['y_m'] - end_row['y_m']],
dtype=float)
        gap_norm = np.linalg.norm(gap_vec)

        if gap_norm > 0:
            gap_vec = gap_vec / gap_norm
            if np.dot(vec_A, gap_vec) >= cos_threshold:
                cand = cand.copy()
                cand['Fix_Type'] = 'Kinematic Interpolation'
                valid_candidates.append(cand)

valid_df = pd.DataFrame(valid_candidates)
if valid_df.empty: continue

```

```

best = valid_df.sort_values(['start_frame', 'dist_m']).iloc[0]

combined_frames = track_dur.get(tid_A, 0) + track_dur.get(best['track_id'], 0)
if combined_frames <= STITCH_MAX_TRACK_FRAMES:
    stitch_mapping[best['track_id']] = tid_A
    claimed_starts.add(best['track_id'])
    stitch_gap_meta[best['track_id']] = {
        'gap_frames' : int(best['start_frame'] - end_f),
        'gap_duration_s' : round(float(best['time_gap_s']), 4),
        'gap_dist_m' : round(float(best['dist_m']), 4),
        'fix_type' : best.get('Fix_Type', 'Unknown')
    }

# Consolidate cascade mapping
final_mapping = {}
for child, parent in stitch_mapping.items():
    root, seen = parent, {child}
    while root in stitch_mapping:
        if root in seen:
            root = min(seen)
            break
        seen.add(root)
        root = stitch_mapping[root]
    if root != child: final_mapping[child] = root

stitch_log_rows = []
for child_uid, parent_uid in final_mapping.items():
    meta = stitch_gap_meta.get(child_uid, {})
    stitch_log_rows.append({
        'New_Track_ID' : parent_uid, 'Absorbed_Track_ID' : child_uid,
        'New_Track_Orig_ID' : uid_to_orig_tid.get(parent_uid, parent_uid),
        'New_Track_Video' : uid_to_video.get(parent_uid, ""),
        'Absorbed_Orig_ID' : uid_to_orig_tid.get(child_uid, child_uid),
        'Absorbed_Video' : uid_to_video.get(child_uid, ""),
        'Gap_Frames' : meta.get('gap_frames', ""),
        'Gap_Duration_s' : meta.get('gap_duration_s', ""),
        'Gap_Dist_m' : meta.get('gap_dist_m', ""),
        'Fix_Type' : meta.get('fix_type', "")
    })

if stitch_log_rows:
    pd.DataFrame(stitch_log_rows).to_excel(STITCH_LOG_OUTPUT, index=False)
    print(f'  Saved Stitch Log -> {STITCH_LOG_OUTPUT}")

interpolated_track_ids = set()
if final_mapping:

```

```

df['track_id'] = df['track_id'].replace(final_mapping)
df = (df.drop_duplicates(subset=['track_id', 'frame'], keep='first')
      .sort_values(['track_id', 'frame']).reset_index(drop=True))

interpolated_frames = []
parent_ids = set(final_mapping.values())

for tid, grp in df[df['track_id'].isin(parent_ids)].groupby('track_id'):
    grp = grp.sort_values('frame')
    frames = grp['frame'].values
    interpolated_for_this_track = False

    for i in range(len(frames)-1):
        f1, f2 = frames[i], frames[i+1]
        if f2 - f1 > 1:
            row1, row2 = grp.iloc[i], grp.iloc[i+1]
            gap_len = int(f2 - f1)
            interpolated_for_this_track = True

            for step in range(1, gap_len):
                alpha = step / gap_len
                new_row = row1.copy()
                new_row['frame'] = f1 + step
                new_row['x_center_stabilized_px'] = row1['x_center_stabilized_px'] + alpha *
(row2['x_center_stabilized_px'] - row1['x_center_stabilized_px'])
                new_row['y_center_stabilized_px'] = row1['y_center_stabilized_px'] + alpha *
(row2['y_center_stabilized_px'] - row1['y_center_stabilized_px'])
                new_row['x_m'] = row1['x_m'] + alpha * (row2['x_m'] - row1['x_m'])
                new_row['y_m'] = row1['y_m'] + alpha * (row2['y_m'] - row1['y_m'])
                new_row['Data_Source'] = 'Interpolated'
                interpolated_frames.append(new_row)
            if interpolated_for_this_track: interpolated_track_ids.add(tid)

    if interpolated_frames:
        df = pd.concat([df, pd.DataFrame(interpolated_frames)], ignore_index=True)
        df = df.sort_values(['track_id', 'frame']).reset_index(drop=True)

```

```
#
```

```
=====
=====
```

```
# [2.5/9] SIDEWALK EXTRAPOLATION
```

```
#
```

```
=====
=====
```

```

track_bounds = df.groupby('track_id').agg(start_frame=('frame', 'min'), end_frame=('frame',
'max')).reset_index()
starts_raw = pd.merge(track_bounds[['track_id', 'start_frame']], df, left_on=['track_id',
'start_frame'], right_on=['track_id', 'frame'])
ends_raw = pd.merge(track_bounds[['track_id', 'end_frame']], df, left_on=['track_id',
'end_frame'], right_on=['track_id', 'frame'])

ends_raw['on_sidewalk'] = ends_raw.apply(lambda r: _on_sidewalk_m(r['x_m'], r['y_m']),
axis=1)
starts_raw['on_sidewalk'] = starts_raw.apply(lambda r: _on_sidewalk_m(r['x_m'], r['y_m']),
axis=1)

broken_ends = ends_raw[~ends_raw['on_sidewalk']]
broken_starts = starts_raw[~starts_raw['on_sidewalk']]

extrapolated_frames = []

for _, row in tqdm(broken_ends.iterrows(), total=len(broken_ends), desc="    Extending ends",
unit="track"):
    tid, end_f = row['track_id'], row['end_frame']
    t_hist = df[(df['track_id'] == tid) & (df['frame'] <= end_f)].sort_values('frame')

    lookback = min(int(FPS), len(t_hist))
    if lookback < 3: continue

    pt_past = t_hist.iloc[-lookback][['x_m', 'y_m']].values.astype(float)
    pt_end = t_hist.iloc[-1][['x_m', 'y_m']].values.astype(float)
    raw_vec = pt_end - pt_past
    dist_past = np.linalg.norm(raw_vec)

    if dist_past == 0: continue
    vec_norm = raw_vec / dist_past

    speed_m_per_frame = dist_past / lookback
    if speed_m_per_frame < 0.01: speed_m_per_frame = 1.4 * DT

    ext_line = LineString([pt_end, pt_end + vec_norm * MAX_EXTRAPOLATION_M])
    best_hit = None
    best_dist = float('inf')

    for name, poly in sidewalks_m.items():
        if ext_line.intersects(poly):
            inter = ext_line.intersection(poly)
            if hasattr(inter, 'geoms'):
                hit_pt = inter.geoms[0].coords[0] if inter.geoms[0].geom_type == 'LineString' else
(inter.geoms[0].x, inter.geoms[0].y)

```

```

        elif inter.geom_type == 'LineString':
            hit_pt = inter.coords[0]
        elif inter.geom_type == 'Point':
            hit_pt = (inter.x, inter.y)
        else: continue

    dist = np.hypot(hit_pt[0] - pt_end[0], hit_pt[1] - pt_end[1])
    if dist < best_dist:
        best_dist = dist
        best_hit = hit_pt

if best_hit is not None:
    gap_frames = int(best_dist / speed_m_per_frame)
    if gap_frames <= 0: gap_frames = 1

    row_end = t_hist.iloc[-1]
    for step in range(1, gap_frames + 1):
        alpha = step / gap_frames
        new_x_m = pt_end[0] + alpha * (best_hit[0] - pt_end[0])
        new_y_m = pt_end[1] + alpha * (best_hit[1] - pt_end[1])

        new_row = row_end.copy()
        new_row['frame'] = end_f + step
        new_row['x_m'] = new_x_m
        new_row['y_m'] = new_y_m

        if H_INV is not None:
            px, py = _m_to_px(np.array([new_x_m]), np.array([new_y_m]), H_INV)
            new_row['x_center_stabilized_px'] = px[0]
            new_row['y_center_stabilized_px'] = py[0]

        new_row['Extrapolated_To_Curb'] = True
        extrapolated_frames.append(new_row)

for _, row in tqdm(broken_starts.iterrows(), total=len(broken_starts), desc="    Extending
starts", unit="track"):
    tid, start_f = row['track_id'], row['start_frame']
    t_fut = df[(df['track_id'] == tid) & (df['frame'] >= start_f)].sort_values('frame')

    lookfwd = min(int(FPS), len(t_fut))
    if lookfwd < 3: continue

    pt_start = t_fut.iloc[0][['x_m', 'y_m']].values.astype(float)
    pt_fut = t_fut.iloc[lookfwd-1][['x_m', 'y_m']].values.astype(float)
    raw_vec = pt_start - pt_fut
    dist_fut = np.linalg.norm(raw_vec)

```

```

if dist_fut == 0: continue
vec_norm = raw_vec / dist_fut

speed_m_per_frame = dist_fut / lookfwd
if speed_m_per_frame < 0.01: speed_m_per_frame = 1.4 * DT

ext_line = LineString([pt_start, pt_start + vec_norm * MAX_EXTRAPOLATION_M])
best_hit = None
best_dist = float('inf')

for name, poly in sidewalks_m.items():
    if ext_line.intersects(poly):
        inter = ext_line.intersection(poly)
        if hasattr(inter, 'geoms'):
            hit_pt = inter.geoms[0].coords[0] if inter.geoms[0].geom_type == 'LineString' else
(inter.geoms[0].x, inter.geoms[0].y)
            elif inter.geom_type == 'LineString':
                hit_pt = inter.coords[0]
            elif inter.geom_type == 'Point':
                hit_pt = (inter.x, inter.y)
            else: continue

        dist = np.hypot(hit_pt[0] - pt_start[0], hit_pt[1] - pt_start[1])
        if dist < best_dist:
            best_dist = dist
            best_hit = hit_pt

if best_hit is not None:
    gap_frames = int(best_dist / speed_m_per_frame)
    if gap_frames <= 0: gap_frames = 1

    row_start = t_fut.iloc[0]
    for step in range(1, gap_frames + 1):
        alpha = step / gap_frames
        new_x_m = pt_start[0] + alpha * (best_hit[0] - pt_start[0])
        new_y_m = pt_start[1] + alpha * (best_hit[1] - pt_start[1])

        new_row = row_start.copy()
        new_row['frame'] = start_f - step
        new_row['x_m'] = new_x_m
        new_row['y_m'] = new_y_m

    if H_INV is not None:
        px, py = _m_to_px(np.array([new_x_m]), np.array([new_y_m]), H_INV)
        new_row['x_center_stabilized_px'] = px[0]

```

```

        new_row['y_center_stabilized_px'] = py[0]

        new_row['Extrapolated_To_Curb'] = True
        new_row['Data_Source'] = 'Extrapolated'
        extrapolated_frames.append(new_row)

if extrapolated_frames:
    df['Extrapolated_To_Curb'] = False
    df = pd.concat([df, pd.DataFrame(extrapolated_frames)], ignore_index=True)
    df = df.sort_values(['track_id', 'frame']).reset_index(drop=True)
    print(f"   ✓ Bridged gaps to the curb via geometric raycasting!")
else:
    print(f"   ✓ No tracks required curb extrapolation.")

#
=====
# [2.75/9] REMOVE NULL CELLS AND UNRESOLVED FRAGMENTS
#
=====

n_before_purge = df['track_id'].nunique()

def _calc_total_distance(grp):
    grp = grp.sort_values('frame')
    dx = grp['x_m'].diff().fillna(0)
    dy = grp['y_m'].diff().fillna(0)
    return np.sum(np.hypot(dx, dy))

track_lengths = df.groupby('track_id').apply(_calc_total_distance)
MIN_TRACK_LENGTH_M = 5.0
valid_length_ids = track_lengths[track_lengths >= MIN_TRACK_LENGTH_M].index

# Filter downstream dataframe for real tracks
df = df[df['track_id'].isin(valid_length_ids)].reset_index(drop=True)

n_after_purge = df['track_id'].nunique()
print(f"   🗑 Dropped {n_before_purge - n_after_purge} ghost fragments (too short).")
print(f"   ✓ Kept {n_after_purge} substantial pedestrian tracks.")

#
=====
# [3/9] AVERAGE 3S MOVING SPEED

```

```

#
=====

def _get_max_speed(grp):
    grp = grp.sort_values('frame')
    dx, dy = grp['x_m'].diff().fillna(0), grp['y_m'].diff().fillna(0)
    dist = np.hypot(dx, dy)
    window_size = int(3 * FPS)
    roll_dist = dist.rolling(window=window_size, min_periods=int(FPS)).sum()
    roll_time = grp['frame'].diff().fillna(1).rolling(window=window_size,
min_periods=int(FPS)).sum() * DT
    return (roll_dist / roll_time).max()

tqdm.pandas(desc="    Max Speeds")
track_max_speeds =
df.groupby('track_id').progress_apply(_get_max_speed).rename('Max_3s_Speed_m_s')
df = df.merge(track_max_speeds, on='track_id', how='left')

#
=====

# [4/9] ZONE LABELLING
#
=====

def _get_sidewalk_name_buffered(x_m, y_m):
    pt = Point(x_m, y_m)
    for name, poly in sidewalks_m.items():
        if poly.buffer(0.5).contains(pt): return name
    return None

df['sidewalk_name'] = df.apply(lambda r: _get_sidewalk_name_buffered(r['x_m'], r['y_m']),
axis=1)
df['on_sidewalk'] = df['sidewalk_name'].notna()
df['base_segment_id'] = ((df['on_sidewalk'] != df['on_sidewalk'].shift(1)) | (df['track_id'] !=
df['track_id'].shift(1))).cumsum()

road_mask = ~df['on_sidewalk']
cw_names = list(crosswalks_m.keys())
pts = shapely.points(df.loc[road_mask, 'x_m'].values, df.loc[road_mask, 'y_m'].values)
for cw_name, cw_poly in crosswalks_m.items():
    df.loc[road_mask, f'dist_{cw_name}'] = shapely.distance(pts, cw_poly)

dist_cols = [f'dist_{name}' for name in cw_names]

```

```
df.loc[road_mask, 'closest_cw'] = df.loc[road_mask, dist_cols].idxmin(axis=1).apply(lambda x:
x.replace('dist_', '') if pd.notna(x) else x)
```

```
def smooth_crosswalks(cw_series, patience=15):
    smoothed = []
    if cw_series.empty: return smoothed
    current, candidate, count = cw_series.values[0], cw_series.values[0], 0
    for cw in cw_series.values:
        if cw == current: count = 0
        elif cw == candidate: count += 1
        else: candidate, count = cw, 1
        if count >= patience: current, count = candidate, 0
    smoothed.append(current)
    return smoothed
```

```
df['crosswalk'] = np.nan
for (tid, bsid), grp in df[road_mask].groupby(['track_id', 'base_segment_id']):
    df.loc[grp.index, 'crosswalk'] = smooth_crosswalks(grp['closest_cw'], patience=15)
```

```
df['segment_id'] = ((df['base_segment_id'] != df['base_segment_id'].shift(1)) |
(df['crosswalk'].fillna('None') != df['crosswalk'].shift(1).fillna('None'))).cumsum()
```

```
#
```

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```
# [5/9] CONSOLIDATION
```

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#
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```
=====
```

```
road_frames = df[~df['on_sidewalk']].copy()
seg_stats = road_frames.groupby('segment_id')['frame'].agg(['min', 'max'])
valid_seg_ids = set(seg_stats[((seg_stats['max']-seg_stats['min']+1)/FPS) >= 0.5].index)
crossers_df = road_frames[road_frames['segment_id'].isin(valid_seg_ids)].copy()
```

```
print(f' 🚶 Unique Pedestrians entering the asphalt: {crossers_df['track_id'].nunique()}")
```

```
print(f' 🚶 Initial Road Segments (>0.5s exposure): {len(valid_seg_ids)}")
```

```
def _consolidate_segments(group):
    bounds =
    group.groupby('segment_id')['frame'].agg(['min', 'max']).sort_values('min').reset_index()
    if len(bounds) == 1: return group
    merge_map, master = {}, 0
    for i in range(1, len(bounds)):
        if (bounds.loc[i, 'min'] - bounds.loc[0, 'max']) <= SEGMENT_GAP_MERGE_S * FPS:
            merge_map[bounds.loc[i, 'segment_id']] = bounds.loc[0, 'segment_id']
```

```

        bounds.loc[master,'max'] = max(bounds.loc[master,'max'], bounds.loc[i,'max'])
    else: master = i
    if merge_map:
        group = group.copy()
        group['segment_id'] = group['segment_id'].replace(merge_map)
    return group

consolidated = []
for (tid, cw), grp in crossers_df.groupby(['track_id', 'crosswalk']):
    consolidated.append(_consolidate_segments(grp))
crossers_df = pd.concat(consolidated).reset_index(drop=True)

print(f' 🚦 Consolidated into final crossing segments: {crossers_df['segment_id'].nunique()}')

#
=====
=====
# [6/9] U-TURN & DISTANCES & SPEED MATH
#
=====
=====

def _detect_u_turn(grp):
    grp = grp.sort_values('frame')
    if len(grp) < int(FPS * 0.5): return False

    x, y = grp['x_m'].values, grp['y_m'].values
    start_p, end_p = np.array([x[0], y[0]]), np.array([x[-1], y[-1]])
    vec = end_p - start_p
    dist_total = np.linalg.norm(vec)
    if dist_total < 2.0: return False

    vec_norm = vec / dist_total
    pts = np.column_stack((x, y))

    projs = np.dot(pts - start_p, vec_norm)
    max_projs = np.maximum.accumulate(projs)
    rollback = max_projs - projs
    max_forward_progress = np.max(max_projs)

    return bool(np.max(rollback) > (0.50 * max_forward_progress))

uturn_dict = crossers_df.groupby('segment_id').apply(_detect_u_turn).to_dict()
crossers_df['is_u_turn'] = crossers_df['segment_id'].map(uturn_dict)

print("[7/9] Computing per-frame distances to crosswalk boundaries ...")

```

```

crossers_df = crossers_df.sort_values(['segment_id', 'frame'])
crossers_df['step_dist'] = np.hypot(
    crossers_df.groupby('segment_id')['x_m'].diff().fillna(0),
    crossers_df.groupby('segment_id')['y_m'].diff().fillna(0)
)

crossers_df['distance_outside_m'] = 0.0
for cw_name, cw_poly in crosswalks_m.items():
    mask = crossers_df['crosswalk'] == cw_name
    if mask.sum() == 0: continue
    pts = shapely.points(crossers_df.loc[mask, 'x_m'].values, crossers_df.loc[mask, 'y_m'].values)
    crossers_df.loc[mask, 'distance_outside_m'] = shapely.distance(pts, cw_poly)
crossers_df['sv3_step'] = np.where(crossers_df['distance_outside_m'] >
    OUTSIDE_THRESHOLD_M, crossers_df['distance_outside_m'] * DT, 0.0)

#
=====
=====
# [7/9] SUMMARY TABLE
#
=====
=====

summary = (
    crossers_df.groupby(['track_id', 'crosswalk', 'segment_id'])
    .agg(
        total_frames = ('frame', 'count'),
        frames_outside = ('distance_outside_m', lambda x: (x >
    OUTSIDE_THRESHOLD_M).sum()),
        SV_Severity_1_raw = ('distance_outside_m', 'max'),
        SV_Severity_3_raw = ('sv3_step', 'sum'),
        video_title = ('video_title', 'first'),
        Max_3s_Speed = ('Max_3s_Speed_m_s', 'first'),
        U_Turn = ('is_u_turn', 'first'),
        Total_Distance_m = ('step_dist', 'sum')
    ).reset_index()
)
frame_bounds = crossers_df.groupby('segment_id')['frame'].agg(crossing_start_frame='min',
crossing_end_frame='max')
summary = summary.join(frame_bounds, on='segment_id')

```

```

#
=====
# [8/9] O/D LOGIC (WITH 10m LIMIT COMPROMISE)
#
=====

sw_data = df[df['on_sidewalk']][['track_id', 'frame', 'sidewalk_name']]

summary['Total_Crossing_Time_s'] = (summary['total_frames'] / FPS).round(3)
summary['Time_Outside_s'] = (summary['frames_outside'] / FPS).round(3)
summary['Total_Crossing_Time_s'] = summary['Total_Crossing_Time_s'].replace(0, 0.001)
summary['Average_Speed_m_s'] = (summary['Total_Distance_m'] /
summary['Total_Crossing_Time_s']).round(3)

def _direction(row):
    seg = crossers_df[crossers_df['segment_id'] == row['segment_id']]
    if seg.empty: return "
    dx = seg.iloc[-1]['x_center_stabilized_px'] - seg.iloc[0]['x_center_stabilized_px']
    dy = seg.iloc[-1]['y_center_stabilized_px'] - seg.iloc[0]['y_center_stabilized_px']
    cw = str(row.get('crosswalk',''))
    if cw == 'North': return 'CW' if dx >= 0 else 'CCW'
    elif cw == 'South': return 'CW' if dx <= 0 else 'CCW'
    elif cw == 'East': return 'CW' if dy >= 0 else 'CCW'
    elif cw == 'West': return 'CW' if dy <= 0 else 'CCW'
    return "

summary['Direction'] = summary.apply(_direction, axis=1)

def _get_od(row):
    tid, sf, ef = row['track_id'], row['crossing_start_frame'], row['crossing_end_frame']
    past = sw_data[(sw_data['track_id'] == tid) & (sw_data['frame'] < sf)]
    future = sw_data[(sw_data['track_id'] == tid) & (sw_data['frame'] > ef)]
    origin = past.iloc[-1]['sidewalk_name'] if not past.empty else 'Unknown'
    dest = future.iloc[0]['sidewalk_name'] if not future.empty else 'Unknown'
    return pd.Series([origin, dest])

summary[['Origin_SW', 'Dest_SW']] = summary.apply(_get_od, axis=1)

# Apply Inference Dictionary with 10m limit
def _fill_od_with_limit(row):
    o, d = row['Origin_SW'], row['Dest_SW']
    cw, dr = str(row.get('crosswalk','')), str(row['Direction'])

    if o != 'Unknown' and d != 'Unknown':

```

```

    return pd.Series([o, d])

max_inference_gap_m = 10.0

if cw in INFERRED_OD and dr in INFERRED_OD[cw]:
    tid = row['track_id']
    t_df = df[df['track_id'] == tid].sort_values('frame')

    if t_df.empty:
        return pd.Series([o, d])

    if o == 'Unknown' and d != 'Unknown':
        start_pt = Point(t_df.iloc[0]['x_m'], t_df.iloc[0]['y_m'])
        min_orig_dist = min([poly.distance(start_pt) for poly in sidewalks_m.values()])
        if min_orig_dist <= max_inference_gap_m:
            o = INFERRED_OD[cw][dr][0]

    elif d == 'Unknown' and o != 'Unknown':
        end_pt = Point(t_df.iloc[-1]['x_m'], t_df.iloc[-1]['y_m'])
        min_dest_dist = min([poly.distance(end_pt) for poly in sidewalks_m.values()])
        if min_dest_dist <= max_inference_gap_m:
            d = INFERRED_OD[cw][dr][1]

    return pd.Series([o, d])

summary[['Origin_SW', 'Dest_SW']] = summary.apply(_fill_od_with_limit, axis=1)

# Apply basic valid pair check
mask1 = summary.apply(lambda r: {str(r['Origin_SW']), str(r['Dest_SW'])} in
VALID_OD_PAIRS.get(str(r.get('crosswalk', 'None')), []), axis=1)
summary = summary[mask1].copy()

def _classify_crossing(row):
    seg_data = crossers_df[crossers_df['segment_id'] == row['segment_id']]
    if seg_data.empty: return 'Unknown'
    dist = seg_data.sort_values('frame')['distance_outside_m'].values
    if len(dist) == 0: return 'Unknown'
    frac_outside = (dist > OUTSIDE_THRESHOLD_M).sum() / len(dist)
    if frac_outside == 0.0: return 'Crossing Inside the Crosswalk'
    elif frac_outside == 1.0: return 'Crossing Outside the Crosswalk'
    else: return 'Corner Cutting'

summary['Crossing_Type'] = summary.apply(_classify_crossing, axis=1)
summary = summary.sort_values(['track_id', 'crossing_end_frame'])
summary['Crossing_Sequence'] = summary.groupby('track_id').cumcount() + 1
summary['Crosswalk_Area_m2'] = summary['crosswalk'].map(crosswalk_areas_m2).round(3)

```

```

#
=====
# [9/9] EXPANDED MATH (SV Severity) & EXPORT
#
=====

def _project_onto_nearest_edge(pt, edges):
    best_proj, best_dist = None, float('inf')
    for edge in edges:
        d = edge.distance(pt)
        if d < best_dist:
            best_dist, best_proj = d, edge.interpolate(edge.project(pt))
    return best_proj

summary['SV_Severity_1_m'] = 0.0
summary['SV_Severity_2_m2'] = 0.0
summary['SV_Severity_3_m_s'] = 0.0
summary['Time_Outside_s'] = 0.0

for idx, row in tqdm(summary.iterrows(), total=len(summary), desc=" Expanded SV Math"):
    tid = row['track_id']
    cw_name = str(row.get('crosswalk', ''))
    t_df = df[df['track_id'] == tid].sort_values('frame')
    sf, ef = row['crossing_start_frame'], row['crossing_end_frame']

    prev_frame = t_df[t_df['frame'] == sf - 1]
    if not prev_frame.empty and prev_frame.iloc[0]['on_sidewalk']:
        past_sw = t_df[(t_df['frame'] < sf) & (t_df['on_sidewalk'])]
        true_sf = past_sw['frame'].max() + 1 if not past_sw.empty else sf
    else: true_sf = sf

    next_frame = t_df[t_df['frame'] == ef + 1]
    if not next_frame.empty and next_frame.iloc[0]['on_sidewalk']:
        future_sw = t_df[(t_df['frame'] > ef) & (t_df['on_sidewalk'])]
        true_ef = future_sw['frame'].min() - 1 if not future_sw.empty else ef
    else: true_ef = ef

    full_seg = t_df[(t_df['frame'] >= true_sf) & (t_df['frame'] <= true_ef)].copy()
    cw_poly = crosswalks_m.get(cw_name)
    edges = crosswalk_edges.get(cw_name)

```

```

sv1, sv3, time_outside, sv2_area = 0.0, 0.0, 0.0, 0.0

if cw_poly and not full_seg.empty:
    pts = shapely.points(full_seg['x_m'].values, full_seg['y_m'].values)
    dists = shapely.distance(pts, cw_poly)
    full_seg['distance_outside_m'] = dists
    full_seg['sv3_step'] = np.where(dists > OUTSIDE_THRESHOLD_M, dists * DT, 0.0)

sv1 = dists.max() if (dists > OUTSIDE_THRESHOLD_M).any() else 0.0
sv3 = full_seg['sv3_step'].sum()
time_outside = (dists > OUTSIDE_THRESHOLD_M).sum() * DT

# SV2 (Area calculation)
if edges and len(full_seg) >= 2:
    coords = full_seg[['x_m', 'y_m']].values
    quads = []
    for i in range(len(coords)-1):
        if np.array_equal(coords[i], coords[i+1]): continue
        try:
            pt_i, pt_i1 = Point(coords[i]), Point(coords[i+1])
            proj_i, proj_i1 = _project_onto_nearest_edge(pt_i, edges),
            _project_onto_nearest_edge(pt_i1, edges)
            if proj_i is None or proj_i1 is None: continue
            q = Polygon([(coords[i][0], coords[i][1]), (coords[i+1][0], coords[i+1][1]),
            (proj_i1.x, proj_i1.y), (proj_i.x, proj_i.y)]).buffer(0)
            if q.is_valid and not q.is_empty: quads.append(q)
        except: pass
    if quads:
        try:
            union_poly = unary_union(quads).buffer(0)
            violation_geom = union_poly.difference(cw_poly)
            sv2_area = max(violation_geom.area, 0.0)
        except: pass

summary.at[idx, 'SV_Severity_1_m'] = sv1
summary.at[idx, 'SV_Severity_2_m2'] = sv2_area
summary.at[idx, 'SV_Severity_3_m_s'] = sv3
summary.at[idx, 'Time_Outside_s'] = time_outside

# --- Prepare Output Summaries ---
FINAL_COLS = [
    'video_title', 'track_id', 'Crossing_Sequence', 'crosswalk', 'Crosswalk_Area_m2',
    'Direction', 'Origin_SW', 'Dest_SW', 'Total_Crossing_Time_s', 'Average_Speed_m_s',
    'Time_Outside_s', 'Max_3s_Speed', 'U_Turn', 'SV_Severity_1_m', 'SV_Severity_2_m2',
    'SV_Severity_3_m_s', 'Crossing_Type'
]

```

```

final_report = summary[FINAL_COLS].copy()
final_report.columns = [
    'Video Title', 'Trajectory ID', 'Crossing Sequence', 'Crosswalk', 'Crosswalk Area (m²)',
    'Direction (CW/CCW)', 'Origin Sidewalk', 'Destination Sidewalk', 'Total Crossing Time (s)',
    'Average Speed (m/s)', 'Time Outside Crosswalk (s)', 'Max 3s Rolling Speed (m/s)',
    'U-Turn Detected', 'SV Severity 1 (m)', 'SV Severity 2 (m²)', 'SV Severity 3 (m·s)',
    'Crossing Type'
]

for col in ['Crosswalk Area (m²)', 'Total Crossing Time (s)', 'Average Speed (m/s)', 'Time Outside
Crosswalk (s)', 'Max 3s Rolling Speed (m/s)', 'SV Severity 1 (m)', 'SV Severity 2 (m²)', 'SV
Severity 3 (m·s)']:
    final_report[col] = final_report[col].round(4)
final_report.to_excel(SUMMARY_OUTPUT, index=False, sheet_name='Crossing Summary')

ALL_TYPES = {'Crossing Inside the Crosswalk', 'Crossing Outside the Crosswalk', 'Corner
Cutting'}
VIOLATION_TYPES = {'Crossing Outside the Crosswalk', 'Corner Cutting'}

valid_track_ids = set(summary.loc[summary['Crossing_Type'].isin(ALL_TYPES), 'track_id'])
traj_raw = df[df['track_id'].isin(valid_track_ids)].copy()

math_cols = crossers_df[['track_id', 'frame', 'distance_outside_m', 'sv3_step']]
traj = traj_raw.merge(math_cols, on=['track_id', 'frame'], how='left')
traj['distance_outside_m'] = traj['distance_outside_m'].fillna(0.0)
traj['sv3_step'] = traj['sv3_step'].fillna(0.0)
traj = traj.drop(columns=['crosswalk'], errors='ignore')

summary_lookup = summary[['track_id', 'segment_id', 'crosswalk', 'Crossing_Sequence',
'Crossing_Type', 'Direction', 'Origin_SW', 'Dest_SW', 'Total_Crossing_Time_s',
'Average_Speed_m_s', 'Time_Outside_s', 'Max_3s_Speed', 'U_Turn', 'SV_Severity_1_m',
'SV_Severity_2_m2', 'SV_Severity_3_m_s', 'Crosswalk_Area_m2']]
traj_merged = traj.merge(summary_lookup, on=['track_id', 'segment_id'], how='left')
traj = traj.drop(columns=['crosswalk'], errors='ignore')

fill_cols = ['crosswalk', 'Crossing_Sequence', 'Crossing_Type', 'Direction', 'Origin_SW',
'Dest_SW', 'Total_Crossing_Time_s', 'Average_Speed_m_s', 'Time_Outside_s', 'Max_3s_Speed',
'U_Turn', 'SV_Severity_1_m', 'SV_Severity_2_m2', 'SV_Severity_3_m_s',
'Crosswalk_Area_m2']
traj_merged = traj_merged.sort_values(['track_id', 'frame'])

if not traj_merged.empty:
    traj_merged[fill_cols] = traj_merged.groupby('track_id')[fill_cols].transform(lambda x:
x.ffill().bfill())

```

```

traj_out = traj_merged[['video_title','track_id','segment_id',
'Crossing_Sequence','crosswalk','Crossing_Type','Direction', 'Origin_SW','Dest_SW','frame',
'x_center_stabilized_px','y_center_stabilized_px','x_m','y_m','distance_outside_m','sv3_step',
'Total_Crossing_Time_s','Average_Speed_m_s','Time_Outside_s','Max_3s_Speed','U_Turn',
'SV_Severity_1_m','SV_Severity_2_m2','SV_Severity_3_m_s','Crosswalk_Area_m2',
'Data_Source']].copy()

traj_out.rename(columns={
    'video_title': 'Video Title', 'track_id': 'Trajectory ID', 'segment_id': 'Segment ID',
    'Crossing_Sequence': 'Crossing Sequence', 'crosswalk': 'Crosswalk', 'Crossing_Type': 'Crossing
Type',
    'Direction': 'Direction (CW/CCW)', 'Origin_SW': 'Origin Sidewalk', 'Dest_SW': 'Destination
Sidewalk',
    'frame': 'Frame', 'x_center_stabilized_px': 'X Pixel', 'y_center_stabilized_px': 'Y Pixel',
    'x_m': 'X (m)', 'y_m': 'Y (m)', 'distance_outside_m': 'Distance Outside Crosswalk (m)',
    'sv3_step': 'SV3 Step Contribution (m·s)', 'Total_Crossing_Time_s': 'Total Crossing Time (s)',
    'Average_Speed_m_s': 'Average Speed (m/s)', 'Time_Outside_s': 'Time Outside Crosswalk
(s)',
    'Max_3s_Speed': 'Max 3s Speed (m/s)', 'U_Turn': 'U-Turn Detected',
    'SV_Severity_1_m': 'SV Severity 1 (m)', 'SV_Severity_2_m2': 'SV Severity 2 (m²)',
    'SV_Severity_3_m_s': 'SV Severity 3 (m·s)', 'Crosswalk_Area_m2': 'Crosswalk Area (m²)',
    'Data_Source': 'Data Source',
}, inplace=True)

for col in ['X (m)','Y (m)','Distance Outside Crosswalk (m)', 'SV3 Step Contribution (m·s)','Total
Crossing Time (s)', 'Average Speed (m/s)', 'Time Outside Crosswalk (s)','SV Severity 1 (m)',
'Max 3s Speed (m/s)', 'SV Severity 2 (m²)','SV Severity 3 (m·s)','Crosswalk Area (m²)']:
    if col in traj_out.columns: traj_out[col] = traj_out[col].round(6)

sheets_to_write = [
    ('All Trajectories', traj_out),
    ('All Violations', traj_out[traj_out['Crossing Type'].isin(VIOLATION_TYPES)]),
]
for vtype in sorted(ALL_TYPES):
    sd = traj_out[traj_out

```