EXPLORING LATENT PATTERNS IN U-TURN CRASHES: A DUAL-MODEL APPROACH USING ASSOCIATION RULES MINING AND CLUSTER CORRESPONDENCE ANALYSIS

by

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A thesis submitted to the Graduate Council of

Texas State University in partial fulfillment

of the requirements for the degree of

Master of Science

with a Major in Engineering

August 2025

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**ACKNOWLEDGMENTS**

Praise be to Allah, the beneficent, the merciful. I would like to sincerely thank the Department of Civil and Environmental Engineering at Texas State University for providing me with a supportive academic environment and the resources necessary to complete my thesis. My academic journey at Texas State University has been a transformative experience, deepening my knowledge and skills and strengthening my passion for transportation safety research.

I am profoundly grateful to my advisor, Dr. Subasish Das, for his invaluable guidance, encouragement, and unwavering support throughout my research. His insightful feedback, patient mentorship, and leadership of the Artificial Intelligence in Transportation (AIT) Lab have been essential in shaping this work and providing a collaborative research environment. I am equally thankful to my committee members, Dr. Feng Hong and Dr. Jung Yeon, for their thoughtful suggestions, constructive critiques, and generosity with their time and expertise, which have significantly enhanced the quality of this thesis.

I also extend my gratitude to the faculty and staff of the Civil and Environmental Engineering Department for their dedication to student success. Special thanks go to my colleagues and fellow researchers at the AIT Lab for their collaboration, insightful discussions, and technical support, which have enriched my academic experience. I would also like to thank Mr. Marcus Brewer for the opportunity to work with him on TxDOT projects during my graduate studies.

Most importantly, I am deeply appreciative of my wife, Sonia Akter, for her unwavering love, patience, and understanding throughout this journey. Her support has been my greatest source of strength and motivation. I am equally grateful to my family for their continuous encouragement and sacrifices that made this accomplishment possible.

TABLE OF CONTENTS

**Page**

[LIST OF TABLES vii](#_Toc201161983)

[LIST OF FIGURES ix](#_Toc201161984)

[LIST OF ABBREVIATIONS xi](#_Toc201161985)

[ABSTRACT xiii](#_Toc201161986)

CHAPTER

[I. INTRODUCTION 1](#_Toc201161987)

[1.1 Background 1](#_Toc201161988)

[1.2 Importance of U-turn Safety Analysis 3](#_Toc201161989)

[1.3 Research Gaps 5](#_Toc201161990)

[1.4 Research Objectives and Scope 7](#_Toc201161991)

[1.5 Thesis Organization 8](#_Toc201161992)

[II. LITERATURE REVIEW 10](#_Toc201161993)

[2.1 Overview of U-turn Maneuvers and Safety Concerns 10](#_Toc201161994)

[2.2 U-turns in Alternative Intersection Designs 12](#_Toc201161995)

[2.2.1 Median U-Turn Intersection 12](#_Toc201161996)

[2.2.2 Restricted Crossing U-Turn (RCUT) Intersection 18](#_Toc201161997)

[2.2.3 Diverging Diamond Interchange (DDI) 24](#_Toc201161998)

[2.2.4 Jughandle Intersection 30](#_Toc201161999)

[2.2.5 Thru-Cut Intersection 34](#_Toc201162000)

[2.2.6 Bowtie Intersection 37](#_Toc201162001)

[2.2.7 Teardrop Intersection 40](#_Toc201162002)

[2.2.8 Displaced Left-Turn (DLT) Intersection 43](#_Toc201162003)

[2.2.9 Quadrant Roadway (QR) Intersection 46](#_Toc201162004)

[2.2.10 Continuous Green-T (CGT) Intersection 49](#_Toc201162005)

[2.3 Crash Severity Studies Involving U-turns 53](#_Toc201162006)

[2.3.1 Overview of U-turn Crash Research 53](#_Toc201162007)

[2.3.2 U-Turn Crash Characteristics and Contributing Factors 55](#_Toc201162008)

[2.3.3 Safety and Operations 56](#_Toc201162009)

[2.3.4 Driver Behavior 59](#_Toc201162010)

[2.3.5 Design Interventions 61](#_Toc201162011)

[2.3.6 Technological Innovations 64](#_Toc201162012)

[2.3.7 Integrated Strategies 66](#_Toc201162013)

[2.4 Research Gaps and Summary 68](#_Toc201162014)

[III. ASSOCIATION RULE MINING WITH LIFT INCREASE CRITERIA 71](#_Toc201162015)

[3.1 Introduction 71](#_Toc201162016)

[3.1.1 Crash Risk at U-Turn Facilities 73](#_Toc201162017)

[3.1.2 ARM in Transportation Safety Research 76](#_Toc201162018)

[3.2 Data 78](#_Toc201162019)

[3.2.1 Exploratory Data Analysis 78](#_Toc201162020)

[3.2.2 Spatial Distribution 85](#_Toc201162021)

[3.3 Methodology 86](#_Toc201162022)

[3.3.1 Association Rules Mining 86](#_Toc201162023)

[3.3.2 The Apriori Algorithm 88](#_Toc201162024)

[3.3.3 Research Framework 90](#_Toc201162025)

[3.4 Results and Discussions 91](#_Toc201162026)

[3.4.1 Crash Patterns Associated with KA-Level Injuries 92](#_Toc201162027)

[3.4.2 Crash Patterns Associated with BC-Level Injuries 95](#_Toc201162028)

[3.4.3 Crash Patterns Associated with O-Level Injuries 99](#_Toc201162029)

[3.4.4 Severity-Based Analysis of U-Turn Crash Patterns 102](#_Toc201162030)

[3.4.5 Crash Narrative Review for Contextual Analysis 108](#_Toc201162031)

[3.4.6 Major Findings 113](#_Toc201162032)

[3.5 Conclusions 114](#_Toc201162033)

[IV. CLUSTER CORRESPONDENCE ANALYSIS 117](#_Toc201162034)

[4.1 Introduction 117](#_Toc201162035)

[4.1.1 U-Turn Safety Challenges 119](#_Toc201162036)

[4.1.2 CCA in Transportation Safety Research 123](#_Toc201162037)

[4.2 Data 125](#_Toc201162038)

[4.2.1 Exploratory Data Analysis 125](#_Toc201162039)

[4.2.2 Spatial Distribution 131](#_Toc201162040)

[4.3 Methodology 133](#_Toc201162041)

[4.3.1 Research Framework 135](#_Toc201162042)

[4.4 Results and Discussions 136](#_Toc201162043)

[4.4.1 Variable Importance Analysis 136](#_Toc201162044)

[4.4.2 CCA Results 139](#_Toc201162045)

[4.4.3 Cluster C1: Moderate Speed Multi- Lane Roadways 144](#_Toc201162046)

[4.4.4 Cluster C2: Low-Speed Non-Arterial Roadways 145](#_Toc201162047)

[4.4.5 Cluster C3: High-Speed Locations with No Lighting at Dark 146](#_Toc201162048)

[4.4.6 Cluster C4: Single-Vehicle Fixed Object Collisions and   
Driver Impairment 148](#_Toc201162049)

[4.4.7 Cluster C5: Commercial Motor Vehicle Run-off-Road   
Crashes 149](#_Toc201162050)

[4.4.8 Cluster C6: Parked Vehicles and Low-Speed Conditions 151](#_Toc201162051)

[4.4.9 Policy Implications 152](#_Toc201162052)

[4.5 Conclusions 154](#_Toc201162053)

[V. CONCLUSIONS 157](#_Toc201162054)

[5.1 Summary of Findings 157](#_Toc201162055)

[5.2 Practical Implications 158](#_Toc201162056)

[5.3 Limitations 159](#_Toc201162057)

[5.4 Recommendations for Future Research 161](#_Toc201162058)

[REFERENCES 163](#_Toc201162059)

# LIST OF TABLES

**Page**

[Table 2.1. Safety Performance of MUT Intersections (Reid et al., 2014). 14](#_Toc200626645)

[Table 2.2. CMF for MUT. 15](#_Toc200626646)

[Table 2.3. Safety Performance of RCUT Intersections (Hummer et al., 2010). 20](#_Toc200626647)

[Table 2.4. CMFs for RCUT Intersections. 22](#_Toc200626648)

[Table 2.5. Safety Performance of RCUT Intersections (Abdel-Aty et al., 2020)​. 26](#_Toc200626649)

[Table 2.6. CMFs for DDI Intersections. 28](#_Toc200626650)

[Table 2.7. Safety Performance of Jughandle Intersections (Abdel-Aty et al., 2020). 31](#_Toc200626651)

[Table 2.8. CMFs for Jughandle Intersections (Abdel-Aty et al., 2020). 33](#_Toc200626652)

[Table 2.9. Safety Performance of DLT Intersections (Abdel-Aty et al., 2020). 44](#_Toc200626653)

[Table 2.10. Safety Performance of CGT Intersections (Abdel-Aty et al., 2020). 51](#_Toc200626654)

[Table 2.11. CMFs for CGT Intersections (Wood and Donnell, 2016). 52](#_Toc200626655)

[Table 3.1. Crash Attribute Distributions Categorized by Severity Level. 80](#_Toc200626656)

[Table 3.2. Example Database with Six Crash Records and Selected Traffic Attributes. 89](#_Toc200626657)

[Table 3.3. Frequent Patterns Associated with KA Injuries in U-Turn Crashes. 92](#_Toc200626658)

[Table 3.4. Frequent Patterns Associated with BC Injuries in U-Turn Crashes. 96](#_Toc200626659)

[Table 3.5. Frequent Patterns Associated with O-Level U-Turn Crashes. 99](#_Toc200626660)

[Table 3.6. Visualization of Factors Linked to KA Injuries. 103](#_Toc200626661)

[Table 3.7. Visualization of Factors Linked to BC Injuries. 104](#_Toc200626662)

[Table 3.8. Visualization of Factors Linked to O No Injuries. 106](#_Toc200626663)

[Table 3.9. Narrative-Based Summary of U-Turn Crashes by Severity. 109](#_Toc200626664)

[Table 4.1. Distribution of Variable Categories by Severity Group. 127](#_Toc200626665)

[Table 4.2. Centroids and Size of the Clusters. 142](#_Toc200626666)

[Table 4.3. Summary of Cluster Characteristics Based on Positively Influencing Variables. 143](#_Toc200626667)

# LIST OF FIGURES

**Page**

[Figure 2.1. Illustration of MUT Left-Turn Traffic Movements. 13](#_Toc200626668)

[Figure 2.2. Vehicle-to-Vehicle Conflict Points at MUT Intersection. 15](#_Toc200626669)

[Figure 2.3. Divided Highway Level of Service and Throughput Comparison   
(Reid et al., 2014). 17](#_Toc200626670)

[Figure 2.4. Typical Phasing Scheme at a RCUT. 19](#_Toc200626671)

[Figure 2.5. Vehicular Conflict Points at Four-Approach RCUT Intersection. 22](#_Toc200626672)

[Figure 2.6. Typical Phasing Scheme at a DDI. 25](#_Toc200626673)

[Figure 2.7. Vehicle-To-Vehicle Conflict Points at DDI Intersection. 27](#_Toc200626674)

[Figure 2.8. Typical Phasing Scheme at Jughandle Intersection. 30](#_Toc200626675)

[Figure 2.9. Number of Conflicts at Jughandle Intersection. 32](#_Toc200626676)

[Figure 2.10. Typical Phasing Scheme at Thru-Cut Intersection. 35](#_Toc200626677)

[Figure 2.11. Number of Conflicts at Thru-Cut Intersection. 36](#_Toc200626678)

[Figure 2.12. Typical Phasing Scheme at Bowtie Intersection. 38](#_Toc200626679)

[Figure 2.13. Conflict Points in a Typical Bowtie Intersection. 39](#_Toc200626680)

[Figure 2.14. Typical Phasing Scheme at Teardrop Intersection. 41](#_Toc200626681)

[Figure 2.15. Conflict Points in a Typical Teardrop Intersection. 42](#_Toc200626682)

[Figure 2.16. Typical Phasing Scheme at a DLT Intersection. 43](#_Toc200626683)

[Figure 2.17. Number of Conflict Points at a DLT Intersection*.* 45](#_Toc200626684)

[Figure 2.18. Typical Phasing Scheme at an QR intersection. 47](#_Toc200626685)

[Figure 2.19. Number of Conflict Points at an QR intersection. 48](#_Toc200626686)

[Figure 2.20. Typical Phasing Scheme at CGT Intersection. 50](#_Toc200626687)

[Figure 2.21. Number of Conflicts at CGT. 52](#_Toc200626688)

[Figure 3.1. Density Visualization of U-turn Crash Events in Ohio by Severity Classification. 86](#_Toc200626689)

[Figure 3.2. Framework for U-turn Crash Pattern Analysis. 91](#_Toc200626690)

[Figure 4.1. Density Maps of U-turn Crashes in Ohio by Crash Severity Level. 132](#_Toc200626691)

[Figure 4.2. Cramer’s V Correlation Plot. 133](#_Toc200626692)

[Figure 4.3. Research Framework for U-turn Crash Analysis. 136](#_Toc200626693)

[Figure 4.4. Ranked Importance of Variables in Crash Severity. 138](#_Toc200626694)

[Figure 4.5. Optimum Number of Clusters Utilizing Silhouette Score. 139](#_Toc200626695)

[Figure 4.6. Clusters Developed from U-turn Crash Data. 141](#_Toc200626696)

[Figure 4.7. Top 20 Residual Representations in Cluster C1. 145](#_Toc200626697)

[Figure 4.8. Top 20 Residual Representations in Cluster C2. 146](#_Toc200626698)

[Figure 4.9. Top 20 Residual Representations in Cluster C3. 148](#_Toc200626699)

[Figure 4.10. Top 20 Residual Representations in Cluster C4. 149](#_Toc200626700)

[Figure 4.11. Top 20 Residual Representations in Cluster C5. 150](#_Toc200626701)

[Figure 4.12. Top 20 Residual Representations in Cluster C6. 152](#_Toc200626702)

# LIST OF ABBREVIATIONS

**Abbreviation Description**

ARM Association Rule Mining

BC Minor Injury

CCA Cluster Correspondence Analysis

CGT Continuous Green-T Intersection

CMF Crash Modification Factor

DDI Diverging Diamond Interchange

DLT Displaced Left Turn

FHWA Federal Highway Administration

GBM Gradient Boosting Machine

INAFOGA Influence Area for Gap Acceptance

KA Fatal or Severe Injury

LIC Lift Increase Criterion

LOS Level of Service

MI Minor Injury

MUT Median U-Turn

NI No Injury

O No Injury

PDO Property Damage Only

QR Quadrant Roadway

RCUT Restricted Crossing U-Turn

SI Severe Injury

SPF Safety Performance Function

UMU Unconventional Median U-turn

# ABSTRACT

U-turns are essential maneuvers in modern roadway networks, enabling vehicles to reverse direction and improve network connectivity. Despite their operational benefits, U-turns are often associated with elevated crash risks due to their complex interactions with opposing traffic, geometric design, driver behavior, technological challenges, and environmental conditions. Existing research frequently aggregates U-turn crashes within broader intersection studies, limiting the understanding of maneuver-specific crash severity. This thesis addresses this gap by applying advanced data-driven analytical methods to examine U-turn crash patterns and contributing factors using Ohio crash data from 2017 to 2021. Association Rule Mining with Lift Increase Criterion (ARM-LIC) was employed to identify significant combinations of factors associated with higher crash severity, highlighting key interactions among risk elements. Notably, multi-vehicle involvement, high posted speed limits (65–70 mph), commercial motor vehicle presence, and poor lighting conditions were found to elevate crash severity with lift values exceeding 40.5 in the most severe scenarios. Cluster Correspondence Analysis (CCA) further classified crash records into six clusters with distinct severity profiles. Clusters characterized by factors such as high posted speed limits, driver impairment, and multi-vehicle involvement consistently demonstrated higher severity risks, while others emphasized environmental contributors like dark, unlit roads. These findings demonstrate the multifactorial nature of U-turn crash risks and underscore the importance of utilizing both ARM-LIC and CCA as complementary analytical tools. The combined use of ARM-LIC and CCA provided comprehensive insights into risk patterns, enabling a solid foundation for developing targeted safety interventions and informed design practices aimed at improving U-turn facility safety.

# INTRODUCTION

**I.**

## Background

U-turns are an essential maneuver in modern roadway networks, enabling vehicles to reverse direction with a 180-degree turn. They are widely implemented to support flexible route choice, improve corridor-level circulation, and reduce out-of-direction travel, especially along divided highways and access-managed arterials. In operational terms, they help reduce the need for signalized intersections and left-turn bays, thereby contributing to improved traffic flow and space efficiency. However, their growing use has also introduced safety concerns, particularly in environments characterized by high speeds, limited visibility, or inadequate geometric control. Executing a U-turn is operationally and cognitively complex. The maneuver requires drivers to decelerate, change lanes or diverge from the current path, and merge back into fast-moving traffic after identifying a sufficient gap. In many cases, this sequence also involves a complete stop and heightened situational awareness to avoid collisions. Successfully completing the turn demands attention, patience, and alertness, especially in conditions involving congestion, unfamiliar geometry, or inconsistent signage. Poorly managed U-turns can disrupt traffic flow and introduce risks for all road users (Fan et al., 2013; Zhou et al., 2008). These challenges are further compounded under real-world driving conditions involving multiple vehicle types, low visibility, driver fatigue, and time pressure. Despite their mobility advantages, U-turns pose a heightened risk of conflict with opposing traffic, particularly when roadway design or situational awareness is compromised. The maneuver often requires judgment of tight time and space gaps in oncoming traffic, exposing drivers to elevated crash risk when visibility or reaction time is inadequate.

Crash statistics further underscore the importance of closely examining U-turn safety. According to the Federal Highway Administration (FHWA), the average crash rate for U-turn and left-turn maneuvers at unsignalized median openings is 0.41 crashes per opening per year in urban areas and 0.20 in rural areas (FHWA, 2023). While these per-site rates may appear modest, their cumulative effect across extensive road networks contributes significantly to urban and suburban crash frequencies. Moreover, U-turn crashes often result in severe outcomes. Many U-turn collisions are head-on or angle crashes, crash types known to cause the highest injury severity at intersections. These risks are particularly prevalent where U-turning vehicles must navigate across multilane roads, merge under pressure, or contend with limited acceleration space. Improper U-turns have also been identified as a critical pre-crash factor in approximately 14% of road crashes (NHTSA, 2015). This suggests that while U-turns are less frequent than other turning movements such as left-turns, they may contribute disproportionately to crash risk. The maneuver often involves more complex interaction zones, limited visibility, and greater driver uncertainty, particularly in uncontrolled or signal-free environments. These characteristics, combined with their expanding role in modern roadway design, underscore the need for focused safety research that treats U-turns as a distinct category of risk.

In response to the limitations of traditional intersections, many transportation agencies have adopted innovative intersection designs, including the Median U-Turn (MUT), Restricted Crossing U-Turn (RCUT), Diverging Diamond Interchange (DDI), Jughandle, and other indirect left-turn configurations, that reduce or eliminate direct left-turns by rerouting traffic through U-turns or alternate trajectories. Empirical research supports the effectiveness of these designs. MUT intersections have been shown to reduce total crashes by up to 60%, with angle crashes dropping by as much as 96%, primarily due to the elimination of direct left-turn conflicts and a reduction in overall conflict points (Hughes et al., 2010). Similarly, RCUT intersections have demonstrated a reduction in total crashes by 44% to 53%, with fatal and injury crashes decreasing by as much as 63%, particularly in high-speed rural settings (Hochstein et al., 2009; Hummer et al., 2010; Inman and Haas, 2012). These safety benefits stem largely from a reduction in the number of conflict points, a standard four-leg intersection has 32 conflict points, while a well-designed RCUT or MUT layout can reduce that number to 14 or fewer (Hughes et al., 2010; Reid et al., 2014).

However, while these designs significantly reduce left-turn crash risks, they also shift a substantial portion of conflict exposure to the U-turn maneuver itself. U-turns now carry the operational load of redirected traffic, often under constrained spatial and temporal conditions. Poorly designed U-turn bays, insufficient signage, or high-speed approach conditions can create new safety hazards, particularly involving rear-end, side-swipe, or merging crashes. Despite their expanded use in modern intersection configurations, U-turns remain underrepresented in empirical crash research. Most studies prioritize left-turn behavior, phase timing, and geometric optimizations, with U-turns typically treated as secondary or grouped under left-turn categories. This has left a knowledge gap concerning the distinct behavioral, environmental, and contextual factors that influence U-turn crash risk. In light of this evolving traffic landscape, it is increasingly critical to adopt data-driven methods capable of uncovering multidimensional crash patterns involving U-turns. Understanding how crash severity is influenced by roadway design, driver demographics, lighting conditions, and environmental factors can support the development of more effective countermeasures and informed design guidance. This thesis responds to that need by applying advanced analytical frameworks to explore U-turn crash patterns in depth and to support safer roadway design and policy decisions.

## Importance of U-turn Safety Analysis

The growing prevalence of U-turn maneuvers in modern roadway systems has shifted the nature of intersection operations, requiring not only re-evaluation of geometric design but also a deeper understanding of how crash patterns emerge under evolving traffic conditions. As agencies increasingly implement indirect left-turn strategies and alternative intersection forms, U-turns have transitioned from being incidental movements to critical components of traffic flow. Despite this transformation, the safety implications of U-turns remain insufficiently addressed in both research and practice. A key issue lies in the analytical framing of crash data. Conventional safety evaluations tend to assess intersections holistically, aggregating crash types without distinguishing between maneuver-specific risks. U-turns, in particular, are frequently subsumed within broader left-turn or “other” categories, making it difficult to isolate their behavioral dynamics and contributory risk factors. This lack of maneuver-level resolution obscures the interaction of roadway design, traffic control, driver characteristics, and environmental conditions that uniquely influence U-turn outcomes. Additionally, most existing studies rely on traditional statistical approaches, often linear models or frequency-based summaries, that may not fully capture the multifactorial and interdependent nature of crash risk. U-turn crashes often arise from combinations of factors, such as poor lighting, adverse weather, misjudged gaps, or complex lane configurations. Understanding these co-occurrences requires analytical techniques that can detect patterns beyond single-variable correlations.

In this context, data mining methods such as Association Rule Mining (ARM) and Cluster Correspondence Analysis (CCA) offer promising pathways to uncover hidden structures within crash datasets. These methods are capable of identifying conditional rules and latent groups that would be difficult to detect using conventional modeling. By applying such techniques to U-turn crash data, this research aims to generate actionable insights into crash severity patterns, high-risk configurations, and vulnerable user profiles. Furthermore, a deeper understanding of U-turn safety is essential for informing engineering decisions, traffic control strategies, and policy development. As transportation agencies commit to systemic safety goals—such as those embedded in Vision Zero initiatives or Strategic Highway Safety Plans—there is a pressing need for evidence-based guidance that addresses emerging risk categories. U-turn maneuvers, now central to many intersection treatments, must be evaluated with the same analytical rigor historically applied to more established movements like left-turns and rear-end interactions.

## Research Gaps

Existing research on U-turn safety remains limited in both scope and analytical depth, despite the increasing role of U-turn maneuvers in modern traffic operations. While numerous studies have evaluated overall intersection safety and geometric configurations—particularly in the context of alternative intersection designs such as RCUTs and MUTs, very few have treated U-turns as a distinct focus of investigation. As a result, the specific crash mechanisms, risk factors, and severity profiles associated with U-turn movements remain underexplored and poorly understood in comparison to more extensively studied maneuvers like left-turns or rear-end collisions.

A major shortcoming in current literature is the overwhelming emphasis on geometric parameters, such as median width, turn radii, and offset distance, often at the expense of deeper behavioral and environmental insights. While these geometric elements influence U-turn performance, they do not fully account for the contextual complexity in which crashes occur, such as driver misjudgment, lighting conditions, gap acceptance behavior, traffic speed variations, or the presence of heavy vehicles. Many of these factors operate in combination, yet they are rarely analyzed together in existing studies. Another critical limitation is the analytical framing of crash data. U-turn crashes are frequently aggregated with other maneuvers, most often left-turns, making it difficult to extract maneuver-specific insights. Even when U-turns are analyzed separately, findings are often limited to descriptive statistics or crash frequency summaries. These approaches lack the capacity to uncover nonlinear relationships, co-occurring risk factors, or patterns that emerge only under specific conditions (e.g., night-time, wet pavement, high-volume multilane roads). As a result, current analyses offer a fragmented understanding of what makes U-turns particularly hazardous in certain settings.

Furthermore, most studies continue to rely on traditional statistical tools, such as logistic regression or simple before-and-after comparisons, that are not well-suited for high-dimensional, categorical datasets. These methods often assume variable independence and linearity, which may obscure important patterns in crash severity outcomes. The absence of data-driven and pattern-mining techniques further limits the ability to generate actionable insights for practitioners and policymakers. Again, there is limited effort to develop generalizable models of U-turn safety that account for diverse site conditions, driver populations, and roadway types. Much of the available research is context-specific, with findings tied to isolated case studies or corridor-level evaluations. This lack of transferability makes it difficult to establish broadly applicable design guidance or to anticipate U-turn safety outcomes in varied implementation scenarios.

In light of these limitations, there is a clear need for research that:

* Recognizes U-turns as a distinct and analytically relevant maneuver.
* Moves beyond geometry-focused evaluations to consider behavioral, environmental, and contextual factors.
* Applies advanced methods, such as ARM and CCA, to reveal hidden relationships and risk clusters, and
* Generates interpretable, data-driven findings to support targeted safety improvements in both conventional and innovative roadway designs.

## Research Objectives and Scope

This thesis aims to address the pressing need for maneuver-specific safety research by focusing on U-turn crashes as a distinct and underexplored category within roadway safety analysis. U-turns are increasingly relied upon in both conventional and innovative intersection designs to improve operational efficiency and access management. However, the associated crash risks, particularly those arising from complex driver behavior, varying site conditions, and unstructured merging environments, are not yet fully understood. Given the limitations of prior studies, there is a need for advanced analytical approaches capable of uncovering multidimensional patterns in U-turn crash data. The primary objective of this thesis is to extract meaningful, interpretable insights into U-turn crash severity and contributing factors by applying two complementary data mining techniques: ARM with a Lift Increase Criterion (LIC), and CCA. These methods allow for the detection of frequent crash factor combinations and the identification of context-specific clusters that are not easily captured using traditional statistical approaches.

The research is guided by the following objectives:

1. To identify and isolate U-turn-related crashes from a comprehensive crash dataset, ensuring that the analysis captures maneuver-specific safety patterns.
2. To apply ARM to discover frequent combinations of crash attributes and to evaluate their influence on crash severity using the LIC.
3. To implement CCA to classify U-turn crashes into meaningful clusters based on the correspondence between crash factors and severity outcomes.
4. To compare and interpret the findings from both ARM and CCA to determine how different methodological perspectives contribute to a deeper understanding of U-turn safety.
5. To translate data-driven insights into practical implications for roadway design, traffic control strategies, and policy recommendations aimed at reducing U-turn-related crashes.

The scope of this thesis is limited to the analysis of U-turn crashes occurring on roadways in the state of Ohio, using the most recent available statewide crash datasets. The study focuses on variables such as crash severity, environmental conditions, lighting, roadway geometry, vehicle type, and driver demographics. While the methods are applied to a regional dataset, the analytical frameworks developed here are generalizable and can be adapted for broader applications in other states or roadway contexts. By focusing on the interaction between crash conditions and severity through modern, interpretable data-mining approaches, this thesis contributes both to the academic literature on traffic safety analytics and to the practical advancement of safer U-turn design and regulation.

## Thesis Organization

This thesis is structured in a paper-based format and consists of five chapters. Each chapter contributes to the overall goal of understanding and improving U-turn safety through focused analysis and data-driven methods.

* **Chapter 1 – Introduction**

Establishes the background and motivation for studying U-turn safety, identifies key research gaps, and presents the objectives and scope of the thesis.

* **Chapter 2 – Literature Review**

Reviews existing studies related to U-turn crash patterns, alternative intersection designs, and methodological approaches to crash severity analysis. This chapter provides the theoretical foundation and highlights areas requiring further exploration.

* **Chapter 3 – U-turn Crash Severity Analysis Using ARM with LIC**

Presents the first paper, which applies ARM with a Lift Increase Criterion to uncover frequent and high-impact crash factor combinations. The results highlight interpretable rule-based patterns associated with increased crash severity.

* **Chapter 4 – U-turn Crash Pattern Clustering Using CCA**

Presents the second paper, which uses CCA to identify crash clusters based on correspondence between crash attributes and severity levels. The analysis reveals distinct patterns of risk and informs context-sensitive safety strategies.

* **Chapter 5 – Conclusion and Recommendations**

Summarizes the key findings from Chapters 3 and 4, discusses their practical implications, and outlines limitations and future research directions.

# LITERATURE REVIEW

**II.**

## Overview of U-turn Maneuvers and Safety Concerns

U-turns are a fundamental yet complex maneuver within roadway networks, commonly used to reverse direction and regain access to missed destinations or realign travel routes along divided highways. In many jurisdictions, particularly those emphasizing access management principles, U-turns are increasingly favored over direct left turns to reduce the number of conflict points at intersections and improve traffic flow efficiency. Their operational value lies in facilitating continuous movement along the arterial corridors and minimizing the need for signalized cross-street access. However, from a safety perspective, the maneuver introduces distinct risks that differ from conventional turning or merging movements. Executing a U-turn requires significant driver cognitive and motor control. The maneuver typically involves decelerating within a median opening or designated bay, judging a suitable gap in opposing traffic, turning sharply across multiple lanes, and accelerating into the new direction of travel. This process introduces high cognitive load, especially under conditions of limited sight distance, fast-moving traffic, or heavy congestion. Drivers may also misjudge time gaps or fail to recognize vehicle speeds, especially at night or in unfamiliar roadway environments. These conditions make U-turns particularly prone to severe crash types such as angle or head-on collisions.

The safety concerns associated with U-turns are compounded by a variety of real-world operational factors. These include inconsistent geometric standards across jurisdictions, poorly signed or improperly designed U-turn bays, and varying driver behavior. For example, in multi-lane arterial settings, U-turning drivers often interact with both through and turning vehicles simultaneously, increasing the complexity and potential for miscommunication. Additionally, vehicle type plays a significant role: larger vehicles such as trucks, buses, or vehicles with trailers may require multiple attempts or encroach into adjacent lanes, disrupting surrounding traffic and creating exposure to side-swipe or rear-end collisions. Crash data from various jurisdictions have shown that while U-turns are less frequent than other maneuvers, they are disproportionately represented in severe crash outcomes. The mechanics of U-turn crashes typically involve high-speed angle impacts, limited escape options, and short decision windows. Unlike typical left-turn scenarios, where drivers have a dedicated turn phase or protected signal, U-turns are often executed under permissive or uncontrolled conditions, increasing reliance on driver judgment. The maneuver’s embedded vulnerability is particularly evident at unsignalized median openings or indirect left-turn configurations, where protective control measures are minimal or absent. U-turns also play a critical role in alternative intersection designs, such as MUT or RCUT intersections. These layouts intentionally shift turning movements to downstream U-turn locations to simplify the main intersection and reduce crossing conflict points. While such designs have demonstrated reductions in total crashes and improved operational efficiency, they also redistribute turning conflict exposure to U-turn areas. As a result, U-turns now serve as a core operational element in network design, making their safety implications more relevant than ever.

Despite the increasing reliance on U-turns as a design and operational strategy, they continue to receive limited focused attention in mainstream traffic safety research. While intersection safety studies frequently address left-turn behavior, signal phasing, or geometric control, U-turns are often underrepresented or grouped with broader turning movements. This lack of maneuver-specific attention impedes the development of targeted safety interventions and design guidelines. In light of their operational necessity and crash risk profile, U-turns represent a unique challenge in traffic safety, demanding a more nuanced understanding of the behavioral, geometric, and environmental conditions that shape their performance. Addressing this challenge requires analytical frameworks that go beyond surface-level analysis to uncover the interaction effects and latent patterns associated with crash occurrence and severity.

## U-turns in Alternative Intersection Designs

Alternative intersections are designed to improve traffic flow and safety by reconfiguring traditional conflict points and rerouting left-turns through U-turn maneuvers. Designs such as the MUT, RCUT, DDI, and Jughandle commonly employ U-turns as operational substitutes for direct left-turns. While these designs are effective in reducing intersection delays and angle crashes, they also increase reliance on U-turn locations, making their safety performance an important research concern. The following subsections briefly summarize each intersection type with a focus on U-turn implications.

### Median U-Turn Intersection

The MUT intersection, also known as the Michigan Left, Boulevard Left, Indirect, Left Turn, ThrU Turn, or P-Turn is an innovative intersection design that modifies left-turn movements to improve safety and efficiency. Instead of allowing direct left turns at the main intersection, left-turning vehicles must proceed straight through the intersection, execute a U-turn at a designated median opening, and then turn right onto the cross street. Figure 2.1 illustrates the MUT design, highlighting the rerouting of left-turning vehicles to improve operational efficiency​.

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Figure 2.1. Illustration of MUT Left-Turn Traffic Movements.

This design eliminates traditional left-turn conflicts, which are a significant cause of angle and left-turn crashes and enables more efficient signal phasing by removing dedicated left-turn phases. The MUT intersection has been widely implemented in Michigan, Florida, and Louisiana, with increasing adoption in other states due to its proven safety and operational benefits (Schroeder et al., 2024). The primary objectives of the MUT intersection design are to:

* Reduce conflict points and minimize crash risks, particularly severe angle crashes.
* Improve intersection efficiency by enabling two-phase signal control, reducing wait times for through movements.
* Enhance capacity by separating left-turn traffic from the primary intersection.
* Lower construction costs compared to grade-separated interchanges while maintaining high operational efficiency.

#### Safety Benefits

The safety benefits of the MUT intersection stem from its ability to eliminate direct left turns, which are a major cause of angle and left-turn crashes. Table 2.1 summarizes key safety improvements observed by (Reid et al., 2014).

Table 2.1. Safety Performance of MUT Intersections (Reid et al., 2014).

|  |  |
| --- | --- |
| **Crash Type** | **Reduction (%)** |
| Total Crashes | 60% |
| Injury Crashes | 75% |
| Angle Crashes | 96% |
| Rear-End Crashes | 17% |
| Sideswipe Crashes | 61% |

The reduction in conflict points further enhances safety. A conventional four-leg signalized intersection has 32 conflict points, whereas an MUT intersection has only 16 conflict points, cutting potential vehicle-to-vehicle conflicts by 50% (Reid et al., 2014). Figure 2.2 illustrates the conflict points in a conventional four-leg signalized intersection compared to an MUT intersection, highlighting the reduction in potential vehicle-to-vehicle conflicts.

A graphic of a road intersection

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Figure 2.2. Vehicle-to-Vehicle Conflict Points at MUT Intersection.

The separation distances between driveway exits and downstream U-turn locations influence safety (Liu et al., 2008a). Their findings revealed that increasing separation distances significantly improved safety performance, with a 10 percent increase in distance leading to a 3.3 percent reduction in total crashes and a 4.5 percent decrease in total crash severity. The Crash modification factor (CMF) for MUT is shown in Table 2.2.

Table 2.2. CMF for MUT.

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Crash Type** | **CMF** | **Roadway Condition** |
| (Kay et al., 2022) | Fatal and injury crashes | 0.438 | Undivided (two-lane two-way) |
| Property damage only crashes | 0.035 | Undivided (two-lane two-way) |
| Fatal and injury crashes | - | Divided (four-lane boulevard) |
| Property damage only crashes | 1.325 | Divided (four-lane boulevard) |
| (Al-Omari et al., 2020) | All | [0.633](https://cmfclearinghouse.fhwa.dot.gov/detail.php?facid=10851) | Urban and suburban |
| K, A, B, C | 0.773 | Urban and Suburban |
| A, B, C | 0.755 | Urban and Suburban |
| O | 0.598 | Urban and Suburban |
| Angle | 0.683 | Urban and Suburban |
| Rear-End | 0.526 | Urban and Suburban |

Note: K = Fatal Injury, A =Incapacitating Injury, B = Non-incapacitating Injury, C = Possible Injury

The FHWA's information guide (Reid et al., 2014) highlighted several safety considerations unique to the operational characteristics of MUT intersections, which are absent in conventional signalized intersections. These include:

* Conflicts between right-turn and U-turn movements,
* Risks associated with potential wrong-way movements,
* Weaving maneuvers on the major roadway,
* Possibility of drivers violating left-turn restrictions,
* Challenges for trucks navigating crossovers, and
* Ensuring adequate intersection sight distance.

#### Operational Characteristics

MUT intersections enhance corridor throughput by combining shorter clearance intervals, reduced cycle lengths, and improved signal progression along the corridor compared to conventional signalized intersections. Figure 2.3 illustrates how the MUT design improves performance, typically achieving a higher level of service (LOS) grade (C, D, E) on average. The major street through movement benefits from a larger share of green time at MUT intersections, increasing the likelihood of vehicles arriving during the green phase compared to conventional intersections.

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Figure 2.3. Divided Highway Level of Service and Throughput Comparison (Reid et al., 2014).

Several advantages and disadvantages of MUT intersections, compared to conventional signalized intersections, focus on their operational and safety impacts (Hummer and Reid, 2000).

Advantages

* Through arterial traffic delays is reduced.
* Through arterial traffic progression is more efficient.
* Through traffic has fewer stops.
* Crossing pedestrians encounter fewer conflicts.
* Traffic conflict points are reduced.

Disadvantages

* Left turning traffic delay is increased.
* Left turning traffic travel distance is increased.
* Left turning traffic stops are increased.
* Driver confusion.
* Drivers may neglect the prohibition of left turns on the main intersection.
* Right of way must be larger along the arterial.
* Increase in operational cost due to extra signalization needed.
* Cross-street minimum green times may need to be longer.

### Restricted Crossing U-Turn (RCUT) Intersection

The RCUT intersection, also known as Superstreet, J-Turn, Reduced Conflict Intersection, or High-T Intersection, is an innovative intersection design that restricts direct left turns and through movements from minor streets. Instead, vehicles on the minor street must turn right onto the major road, travel to a designated U-turn location, and then proceed in the desired direction. This design is effective in reducing conflict points, improving safety, and increasing traffic flow efficiency. Figure 2.4 shows a typical RCUT layout.

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Figure 2.4. Typical Phasing Scheme at a RCUT.

The RCUT intersection is particularly beneficial on high-speed divided highways and suburban corridors, where minor street traffic conflicts with major road operations. It has been implemented in several states, including North Carolina, Texas, and Michigan, with proven safety and operational benefits​. The primary objectives of the RCUT intersection design are to:

* Reduce conflict points and minimize crash risks, particularly severe angle crashes, by eliminating direct left turns and through movements from minor roads.
* Improve traffic flow and signal efficiency by optimizing signal timing, reducing delays, and enhancing the capacity of major roadways.
* Enhance operational performance by prioritizing major road traffic and allowing higher traffic volumes with fewer delays.
* Lower construction costs compared to grade-separated interchanges while maintaining high levels of safety and operational efficiency.

#### Safety Benefits

The RCUT intersection significantly improves safety by eliminating direct left turns and through movements from minor roads, reducing the risk of severe right-angle crashes. Table 2.3 summarizes key safety improvements observed by Hummer (Hummer et al., 2010).

Table 2.3. Safety Performance of RCUT Intersections (Hummer et al., 2010).

|  |  |
| --- | --- |
| **Crash Type** | **Reduction (%)** |
| Total Crashes | 46% |
| Fatal & Injury Crashes | 63% |
| Angle Crashes | 75% |
| Left turn crashes | 76% |

Hochstein et al. analyzed before-and-after crash data at the intersection of US-23/74 and SR-1527/1449, which was converted to an RCUT design (Hochstein et al., 2009). Their findings showed a 53% reduction in total crashes, including a complete elimination (100% reduction) of right-angle collisions after the conversion. They also performed a nave before-and-after analysis at the junction of US-64 and Mark’s Creek Road, which underwent a similar conversion. The results revealed a 48% reduction in total crashes, with decreases observed across all severity levels. Right-angle crashes, which previously accounted for 57% of collisions, were reduced by 92%, with far-side right-angle crashes eliminated. Inman and Haas conducted a crash analysis for eight intersections in Maryland that were converted from conventional signalized designs to RCUT configurations (Inman and Haas, 2012). Their study found an overall 44% reduction in crashes, including a 70% decrease in fatal crashes and a 42% reduction in injury crashes over the three-year study period. Similarly, five intersections in Missouri using both simple comparison and the Empirical Bayes (EB) method (Edara et al., 2013). The simple comparison showed a 51% reduction in total crashes and an 86% reduction in disabling injury crashes. The EB analysis further confirmed these results, demonstrating a 53.7% reduction in crash frequency, which was statistically significant at the 95% confidence level.

According to an FHWA report by Hughes et al. a four-legged RCUT intersection has 14 conflict points, significantly fewer than the 32 conflict points found in a conventional intersection (Hughes et al., 2010). Beyond reducing the overall number of conflict points, RCUT intersections specifically minimize crossing conflicts, which are a primary cause of severe angle crashes. The FHWA information guide indicated that implementing unsignalized RCUT intersections in environments similar to those in North Carolina, Maryland, and Missouri could lead to a one-third reduction in total crashes and a 50% reduction in injury crashes (Hummer et al., 2014). In a related study, Ott et al. examined the safety benefits of unsignalized superstreets (RCUTs) in North Carolina, finding that this design significantly reduced total, angle, right-turn, and left-turn collisions (Ott et al., 2012). North Carolina RCUT intersections revealed notable safety improvements, including a 17% reduction in total crashes, a 31% decline in the total crash rate, a 41% decrease in fatal and injury crashes, and a 51% reduction in the fatal injury crash rate (Bared, 2009). Additional insights into RCUT intersections are presented in Figure 2.5.

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Figure 2.5. Vehicular Conflict Points at Four-Approach RCUT Intersection.

CMFs provide valuable insights into the safety performance of RCUT intersections under various roadway conditions and crash types. Studies have shown that RCUT intersections significantly reduce crash frequencies and severities across multiple crash categories and environments. Table 2.4 summarizes the CMFs reported on key studies.

Table 2.4. CMFs for RCUT Intersections.

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Crash Type** | **CMF** | **Roadway Condition** |
| (Mishra and Pulugurtha, 2021) | All | 0.301 | Rural |
| K, A, B, C | 0.212 | Rural |
| All | 0.351 | Suburban |
| K, A, B, C | 0.266 | Suburban |
| (Sun et al., 2019b) | All | 0.42 | All |
| (Al-Omari et al., 2020) | All | 0.7632 | Urban and Suburban |
| K, A, B, C | 0.5669 | Urban and Suburban |
| Angle | 0.5854 | Urban and Suburban |
| Head on | 0.0667 | Urban and Suburban |
| Rear end | 0.7511 | Urban and Suburban |
| O | 0.8414 | Urban and Suburban |

#### Operational Performance

The RCUT design has been found to be more efficient than conventional signalized intersections, largely due to its single U-turn lane configuration and its ability to handle high traffic volumes (Kim et al., 2006). A study conducted in Michigan during peak traffic conditions revealed that RCUT crossovers reduced travel time on corridors by 10% (Hummer and Reid, 2000). Additionally, Hummer et al. outlined the operational benefits and challenges associated with RCUT intersections (Hummer et al., 2014).

Advantages

* Enables the widest possible progression bands for both directions of arterial traffic at any speed and signal spacing.
* Reduces overall travel time at signalized locations.
* Lowers delays and travel times for arterial through traffic at signalized intersections.
* Supports shorter signal cycle lengths.
* Allows a greater portion of the signal cycle to be dedicated to arterial through movements.
* Minimizes the need for signalization on rural high-speed divided highways.

Disadvantages

* Increase travel distance and potentially travel time for minor street left-turn and through movements.
* Experiences high demand, which can strain capacity.
* May lead to spillback from the crossover storage lane.
* Requires minor street left-turn and through drivers to perform unconventional maneuvers, often necessitating additional guidance.

### Diverging Diamond Interchange (DDI)

The DDI, also known as the Double Crossover Diamond Interchange, is an innovative interchange design that enhances traffic efficiency and safety by temporarily shifting traffic to the left side of the road between ramp terminals. This configuration eliminates left-turn conflicts and reduces the number of conflict points, thereby improving overall traffic flow. Figure 2.6 presents a typical DDI layout.

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Figure 2.6. Typical Phasing Scheme at a DDI.

The primary advantage of the DDI design is that it allows vehicles to turn left onto freeway ramps without crossing opposing through traffic, which simplifies signal phasing and increases intersection capacity (Abdel-Aty et al., 2020)​. Since its first U.S. implementation in Springfield, Missouri, in 2009, DDIs have been widely adopted across multiple states, including Florida, Georgia, North Carolina, and Utah, due to their proven safety and operational benefits (Schroeder et al., 2024). The primary objectives of the DDI intersection design are to:

* Reduce conflict points and improve safety by eliminating left-turn conflicts at intersections, reducing the total number of conflict points, and minimizing crash risks, particularly severe angle crashes.
* Enhance traffic flow and operational efficiency by optimizing signal phasing, reducing delays, and improving capacity for both left-turning and through traffic.
* Lower construction and retrofit costs compared to traditional interchange designs, as the DDI requires a smaller bridge footprint and fewer additional lanes.
* Accommodate multimodal users by providing safe and accessible pathways for pedestrians and cyclists, including median refuges and separated bike lanes.

#### Safety Benefits

The DDI intersection significantly improves safety by reducing conflict points and eliminating left-turn conflicts, which lowers the likelihood of severe crashes, particularly angle collisions. Table 2.5 summarizes key safety improvements observed from various studies evaluating DDIs.

Table 2.5. Safety Performance of RCUT Intersections (Abdel-Aty et al., 2020)​.

|  |  |  |
| --- | --- | --- |
| **Crash Type** | **Reduction (%) - Before-and-After Method** | **Reduction (%) - Empirical Bayes (EB) Method** |
| Total Crashes | 26% | 14% |
| Fatal & Injury Crashes | 49% | 44% |
| Property Damage Only (PDO) Crashes | 19% | 8% |
| Rear-End Crashes | 18% | 11% |
| Angle/Left-Turn Crashes | 68% | 55% |

DDIs improve safety by reducing the number of vehicle conflict points compared to conventional designs. Figure 2.7 illustrates the number and types of conflicts present in a DDI. In this layout, traffic briefly crosses over to the opposite side of the road to facilitate direct left-turn access to freeway ramps without conflicting with opposing flows. This configuration results in 18 total conflict points, comprising 8 diverging, 8 merging, and only 2 crossing conflicts. The sharp reduction in crossing conflicts, often associated with the most severe crash types, demonstrates the safety benefits of the DDI over traditional diamond interchanges.

A diagram of a road with arrows and lines

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Figure 2.7. Vehicle-To-Vehicle Conflict Points at DDI Intersection.

CMFs offer valuable insights into the safety performance of DDI intersections by quantifying their effectiveness in reducing crash frequencies and severities under various roadway conditions and traffic scenarios. Studies have demonstrated that DDI intersections significantly lower the likelihood of crashes, particularly angle and left-turn collisions, by minimizing conflict points and improving traffic flow. Table 2.6 summarizes the CMFs reported in key studies evaluating the safety benefits of DDIs.

Table 2.6. CMFs for DDI Intersections.

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Crash Type** | **CMF** | **Roadway Condition** |
| (Walls et al., 2018) | All | 0.42 | -- |
| (Zlatkovic, 2019) | All | 0.755 | -- |
| (Abdelrahman, 2012) | K/A/B/C | 0.558 | Urban and Suburban |
| PDO | 0.92 | Urban and Suburban |
| Rear | 0.887 | Urban and Suburban |
| Angle/Left | 0.448 | Urban and Suburban |
| Single Veh | 0.845 | Urban and Suburban |
| Sideswipe | 1.241 | Urban and Suburban |
| Head-on | 0.643 | Urban and Suburban |
| (Claros et al., 2015) | K/A/B/C | 0.686 | Urban and Suburban |
| (Nye et al., 2019) | Angle | 0.441 | Urban and Suburban |
| Rear End | 0.549 | Urban and Suburban |
| Sideswipe | 1.139 | Urban and Suburban |
| K/A/B/C | 0.461 | Urban and Suburban |
| O | 0.695 | Urban and Suburban |

The FHWA informational guide identified key safety concerns commonly recognized by transportation professionals (Schroeder et al., 2014). These concerns are associated with exit ramp movements, heavy vehicles, bicyclists, pedestrians, and emergency vehicles. The specific issues include:

* 1. Right turns at exit ramps,
  2. Left turns at exit ramps,
  3. Heavy vehicle operations,
  4. Wrong-way maneuvers,
  5. Pedestrian safety, and
  6. Bicyclist safety.

#### Operational Performance

Abou-Senna et al. summarized the operational strengths and weaknesses of the DDI design (Abou-Senna et al., 2015).

Advantages

* Requires fewer signal phases.
* Reduces the number of conflict points.
* Enables left turns without crossing opposing traffic lanes.
* Allows flexible lane assignments without altering signal phases.
* Performs efficiently in scenarios with significant left-turn and right-turn volumes.

Disadvantages

* Causes driver confusion, particularly if signage is inadequate.
* Struggles to perform effectively when ramp volumes exceed the capacity of mainline through traffic.
* Involves higher costs due to the need for wider medians, larger bridges, and ramp adjustments to minimize confusion.
* Presents challenges with driveway access for nearby residents and businesses.

### Jughandle Intersection

The Jughandle intersection, also known as a Jersey Left, Forward Jughandle, Near-Side Jughandle, Reverse Jughandle, or Far-Side Jughandle, is an at-grade intersection design that reroutes left-turning and U-turn traffic through a ramp located on the right side of the road. Unlike conventional intersections where left turns occur directly from the left lane, jughandle designs require vehicles to turn right onto a ramp before executing a left or U-turn. There are three main types of jughandle intersections: forward jughandle (near-side entry before the intersection), reverse jughandle (far-side entry after the intersection), and a combination of both. Figure 2.8 illustrates the typical jughandle intersection layout, showing rerouted left-turn movements and simplified signal phases to improve traffic flow.

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Figure 2.8. Typical Phasing Scheme at Jughandle Intersection.

The primary objectives of the Jughandle intersection design are to:

* Reduce conflict points and improve safety by rerouting left-turn and U-turn movements to designated ramps, minimizing severe angle crashes and reducing the total number of conflict points from 32 to 24 compared to conventional intersections.
* Enhance traffic flow and operational efficiency by separating turning movements from the main intersection, allowing shorter signal cycle lengths, reducing congestion, and improving overall traffic progression.
* Lower construction and retrofit costs compared to grade-separated designs by utilizing at-grade ramps and requiring minimal additional infrastructure.
* Accommodate multimodal users by providing safe and accessible pedestrian crossings at the main intersection and incorporating shared-use paths or marked crossings for cyclists.

#### Safety Benefits

Jughandle intersections significantly impact safety performance by rerouting left-turn and U-turn movements, effectively reducing the likelihood of severe angle crashes. However, their implementation may result in increases in certain crash types, such as rear-end and non-motorized crashes, due to changes in traffic flow patterns and pedestrian interactions. Table 2.7 presents the safety performance of Jughandle intersections, highlighting crash type reductions and increases based on the Cross-Sectional Method (Abdel-Aty et al., 2020).

Table 2.7. Safety Performance of Jughandle Intersections (Abdel-Aty et al., 2020).

|  |  |
| --- | --- |
| **Crash Type** | **Reduction (%) - Cross-Sectional Method** |
| Same-Direction Sideswipe | 31% |
| Left/U-Turn Crashes | 81% |
| Angle Crashes | 45% |
| Rear-End Crashes | 219% Increase |
| Non-Motorized Crashes | 120% Increase |

Jughandle intersections are designed to reduce conflict points and improve safety by rerouting left-turn and U-turn movements through dedicated ramps, thereby minimizing direct conflicts at the main intersection. This innovative design decreases the number of crossing and merging conflict points, which are common sources of severe crashes in conventional intersections. Figure 2.9 illustrates the distribution of conflict points in a typical jughandle intersection.

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Figure 2.9. Number of Conflicts at Jughandle Intersection.

CMFs provide valuable insights into the safety performance of jughandle intersections by quantifying their effectiveness in reducing crash frequencies and severities across various crash types and roadway conditions. Studies have shown that jughandle intersections significantly reduce certain crash types, such as left-turn and U-turn collisions, while slightly increasing the likelihood of non-motorized crashes due to changes in vehicle-pedestrian interactions. Table 2.8 summarizes the CMFs reported in key studies evaluating the safety performance of jughandle intersections.

Table 2.8. CMFs for Jughandle Intersections (Abdel-Aty et al., 2020).

|  |  |
| --- | --- |
| **Crash Type** | **CMF** |
| Total Crashes | 0.8552 |
| Injury Crashes | 0.8340 |
| Fatal-and-Injury Crashes | 0.8320 |
| PDO Crashes | 0.8704 |
| Same-Direction Sideswipe | 0.6909 |
| Left/U-Turn Crashes | 0.1860 |
| Non-Motorized Crashes | 1.0863 |

Jughandle intersections have fewer conflict points compared to conventional intersections (Smith, 2013). A comparative study found that jughandles experienced lower rates of head-on collisions than conventional intersections. Additionally, most crashes at jughandle intersections were rear-end or property-damage-only incidents, as opposed to more severe left-turn crashes (Jagannathan et al., 2006).

#### Operational Performance

The operational advantages and disadvantages of jughandle intersections are as follows:

Advantages

* Reduces the likelihood of left-turn crashes.
* Decreases travel time and the number of stops.

Disadvantages

* Left-turning vehicles experience more stops and longer travel times.
* May require additional right-of-way acquisition.
* Transit stops need to be relocated outside the intersection's influence area.
* Increases risk for pedestrians crossing at the ramp terminal.

### Thru-Cut Intersection

A Thru-Cut intersection is an innovative intersection design that restricts through movements from side streets, instead requiring drivers to turn right or left and then make another turn at an adjacent opening to cross the major roadway. This design is particularly beneficial at locations where side street through movements is minimal and can be efficiently rerouted. Thru-cut intersections improve safety and reduce congestion by eliminating direct side-street through traffic, leading to fewer conflict points and optimized traffic signal timing (VDOT, 2023). Table 2.9 illustrates a typical Thru-Cut intersection layout, demonstrating how side-street through movements is redirected via right turns and connecting roadways, improving both safety and traffic flow efficiency.

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Figure 2.10. Typical Phasing Scheme at Thru-Cut Intersection.

Primary Objectives of the Thru-Cut Intersection Design

* Improve safety by reducing the number of conflict points where vehicles cross paths, particularly side-street through movements that can contribute to severe right-angle crashes.
* Enhance operational efficiency by eliminating side-street through movements, allowing for fewer or shorter traffic signal phases, reducing delays, and increasing intersection capacity.
* Minimize travel delays by optimizing signal phasing, leading to shorter waiting times for vehicles traveling on both the major and minor streets.
* Offer a cost-effective solution by using existing roadway infrastructure without the need for extensive geometric modifications, making it a viable innovative to adding lanes or grade-separating intersections.

#### Safety Benefits

Thru-cuts remove through movement conflicts on minor streets, which can help decrease the likelihood of right-angle crashes (Schroeder et al., 2024). Additionally, the reduction in delays may lead to fewer rear-end collisions at minor street approaches. However, rerouted traffic increases right-turn volumes, potentially creating conflicts with pedestrians. To address this, designers can implement measures such as restricting the right turns on red. By removing minor-street through movements, Thru-Cut intersections minimize conflict points and improve traffic efficiency. This design reduces crossing, merging, and diverging conflicts, which are common sources of severe crashes in conventional intersections. Thru-Cut intersections effectively reduce the total number of conflict points from 32 to 20, enhancing overall safety while maintaining efficient traffic operations. Figure 2.11 illustrates the distribution of conflict points in a typical Thru-Cut intersection.

A screenshot of a video game

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Figure 2.11. Number of Conflicts at Thru-Cut Intersection.

Thru-Cut intersections have fewer conflict points compared to conventional intersections. Studies have shown that Thru-Cut designs reduce right-angle crashes by eliminating minor-street through movements (Schroeder et al., 2024). Additionally, these intersections enhance traffic efficiency by reducing intersection delays and simplifying signal phasing. However, the shift in vehicle movements may lead to an increase in right-turn volumes, which can introduce new merging and pedestrian conflicts.

#### Operational Performance

The operational advantages and disadvantages of Thru-Cut intersections are as follows:

Advantages

* Reduces the likelihood of right-angle crashes.
* Improves traffic flow by eliminating unnecessary signal phases.
* Minimizes delays for major street traffic.

Disadvantages

* Increases right-turn volumes, which may lead to pedestrian conflicts.
* Requires additional signage and driver awareness to ensure proper navigation.
* May cause minor travel time increases for vehicles redirected through adjacent openings.

### Bowtie Intersection

The Bowtie intersection is an innovative design that directs left-turning movements away from the main intersection, rerouting them through small roundabouts located on either side of the intersection (Cunningham et al., 2023). This design eliminates direct left turns at the main intersection, thereby improving traffic flow and reducing the number of conflict points compared to conventional intersections. The bowtie intersection is particularly effective in areas with moderate too high through traffic and relatively low left-turn volumes. Figure 2.12 illustrates a typical Bowtie intersection layout.

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Figure 2.12. Typical Phasing Scheme at Bowtie Intersection.

The operational advantages and disadvantages of Bowtie intersections are as follows:

* Left-turn movements are redirected via adjacent roundabouts, eliminating direct left turns at the main intersection.
* Improved traffic flow due to simplified signal phasing and fewer critical movements.
* Enhanced safety by reducing the number of crossing conflicts, which are a primary cause of severe crashes.
* Accommodates multimodal users, including pedestrians and cyclists, with dedicated crossings and shared-use paths.

#### Safety Benefits

Bowtie intersections are designed to reduce conflict points and enhance safety by replacing direct left-turn movements with compact roundabouts, thereby eliminating left-turn conflicts at the main intersection. This innovative design decreases the number of crossing and merging conflict points, which are common sources of severe crashes in conventional intersections. Figure 2.13 illustrates the distribution of conflict points in a typical Bowtie intersection.

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Figure 2.13. Conflict Points in a Typical Bowtie Intersection.

Bowtie intersections provide notable safety advantages by reducing conflict points and minimizing severe crash risks. However, they introduce additional considerations:

Advantages

* Eliminates left-turn conflicts, reducing severe crashes.
* Shortens signal cycle lengths, leading to improved traffic flow.
* Enhances pedestrian and bicycle safety through controlled crossings and dedicated paths.

Disadvantages

* Increased travel distance for left-turning vehicles due to the need to use roundabouts.
* Potential for higher pedestrian conflicts at roundabout crossings.
* Requires additional right-of-way for roundabout construction​

### Teardrop Intersection

The Teardrop intersection is a variation of the Bowtie design, featuring two closely spaced roundabouts that manage left-turning movements (Cunningham et al., 2023). Unlike the Bowtie, which uses full roundabouts for all left-turning traffic, the Teardrop design limits certain movements, making it more suitable for locations with low left-turn demand. Figure 2.14 illustrates a typical Teardrop intersection layout.

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Figure 2.14. Typical Phasing Scheme at Teardrop Intersection.

#### Safety Benefits

The Teardrop intersection has fewer total conflict points than both conventional intersections and Bowtie designs. Figure 2.15 illustrates the distribution of conflict points in a typical Teardrop intersection.

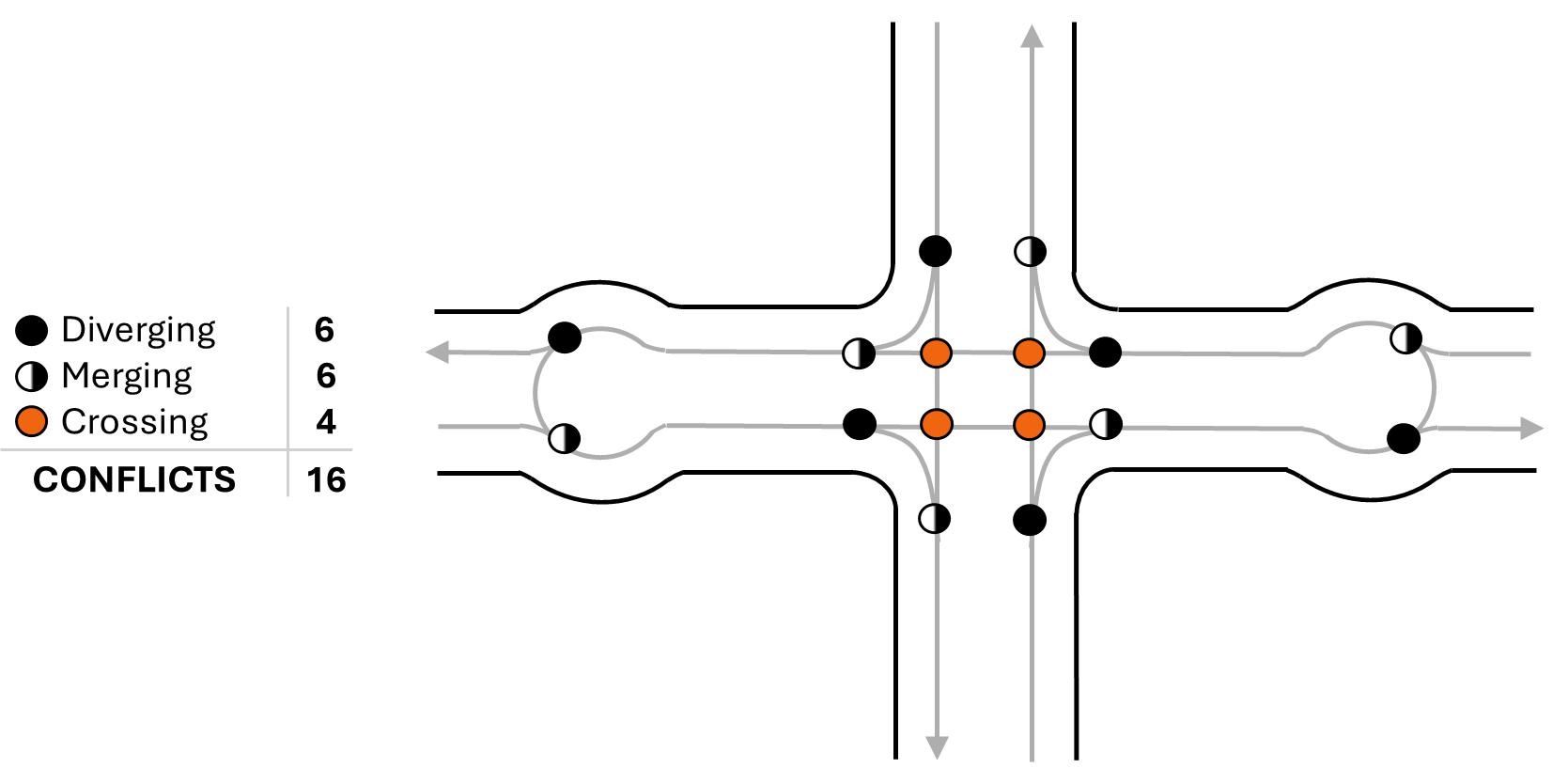
**

Figure 2.15. Conflict Points in a Typical Teardrop Intersection.

#### Operational Performance

While Teardrop intersections offer safety benefits, they also introduce unique operational challenges:

Advantages

* Further reduces conflict points compared to Bowtie and conventional intersections.
* Enhances operational efficiency with smoother left-turn transitions.
* Reduces crossing conflicts, leading to fewer severe crashes.

Disadvantages

* Not suitable for intersections with high left-turn demand.
* Can introduce additional pedestrian conflicts due to increased right-turning traffic.
* Requires more precise spacing of roundabouts to prevent queue spillback.

### Displaced Left-Turn (DLT) Intersection

The DLT intersection, also known as the Continuous Flow Intersection or Crossover Displaced Left-Turn, is an innovative design that relocates left-turn movements to the opposite side of the roadway before the main intersection (Cunningham et al., 2023; Schroeder et al., 2024). This configuration allows left turns and opposing through movements to occur simultaneously, eliminating the need for a dedicated left-turn phase at the primary intersection. The DLT is particularly beneficial in locations with high left-turn volumes and aims to improve both safety and traffic flow efficiency​. Figure 2.16 illustrates a typical Bowtie DLT intersection layout.

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Figure 2.16. Typical Phasing Scheme at a DLT Intersection.

The primary objectives of the DLT intersection design are to:

* Reduce conflict points and improve safety by relocating left-turn movements away from the main intersection, decreasing the likelihood of severe crashes.
* Enhance traffic flow and operational efficiency by eliminating the left-turn phase at the main intersection, allowing for shorter signal cycle lengths and improved progression.
* Support multimodal users through dedicated pedestrian crosswalks at the displaced left-turn locations.
* Accommodate heavy traffic volumes efficiently by optimizing lane usage and intersection signalization​

#### Safety Benefits

DLT intersections significantly impact safety performance by redistributing conflict points and reducing severe crashes. Studies have shown that DLT intersections reduce total crashes by approximately 24%, with fatal and injury crashes declining by 19%. However, the design introduces unique safety challenges, including increased merging conflicts at the crossover points and potential driver unfamiliarity with displaced left-turn movements​. Table 2.9 presents the safety performance of DLT intersections. The overall CMF for DLT intersections ranges between 0.71 and 0.89 (Cunningham et al., 2023).

Table 2.9. Safety Performance of DLT Intersections (Abdel-Aty et al., 2020).

|  |  |
| --- | --- |
| **Crash Type** | **Reduction (%)** |
| Total Crashes | 24% |
| Fatal & Injury Crashes | 19% |

The DLT intersection reduces the total number of conflict points compared to conventional four-leg intersections. By shifting left-turn movements away from the main intersection, the DLT decreases the number of high-risk crossing conflicts. However, the design introduces additional merging and diverging conflicts at the upstream crossover locations. Figure 2.17 illustrates the distribution of conflict points in a typical DLT intersection.

A map of a road with orange dots and arrows

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Figure 2.17. Number of Conflict Points at a DLT Intersection*.*

Advantages

* Reduces the likelihood of severe left-turn crashes.
* Eliminates the left-turn phase at the main intersection, improving signal efficiency.
* Enhances progression along the arterial by synchronizing traffic signals at crossovers.
* Accommodates heavy left-turn volumes with minimal right-of-way expansion.

Disadvantages

* Requires additional space for crossover lanes and medians.
* Increased merging and diverging conflicts at crossover points.
* Potential driver confusion due to unfamiliar intersection design.
* Requires coordinated signal timing for optimal operation.

### Quadrant Roadway (QR) Intersection

A QR intersection is an innovative design aimed at improving the efficiency and safety of high-volume suburban and urban roadways (Abdel-Aty et al., 2020). The main feature of this intersection is the rerouting of left-turn movements onto a separate connector road within one or more quadrants of the intersection. By eliminating direct left turns at the main intersection, QR designs help reduce congestion, minimize conflicts, and improve signal timing efficiency. Figure 2.18 illustrates a typical QR intersection layout.

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AI-generated content may be incorrect.

Figure 2.18. Typical Phasing Scheme at an QR intersection.

Primary Objectives of the QR Intersection Design are to:

* Enhance traffic flow by eliminating left-turn movements at the main intersection, reducing signal phases and overall delay.
* Improve safety by reducing the number of conflict points associated with left-turning vehicles.
* Support multimodal access by allowing for better pedestrian and cyclist movement due to fewer vehicle conflicts.
* Provide a cost-effective innovative to grade-separated interchanges, requiring fewer geometric changes while still improving operational performance.

#### Safety Benefits

QR intersections significantly improve traffic operations and safety by reducing intersection delays and total system travel time. Studies have shown that QR intersections experience fewer crashes compared to conventional four-legged intersections due to the removal of left-turn conflicts​. Figure 2.19 illustrates the distribution of conflict points in a typical QR intersection.

A black and white map of a road

AI-generated content may be incorrect.

Figure 2.19. Number of Conflict Points at an QR intersection.

#### Operational Performance

QR intersections have been shown to reduce the likelihood of severe crashes by rerouting left turns away from the main intersection. The design also improves pedestrian and bicycle safety by reducing the number of lanes they must cross. However, increased right-turn volumes may introduce new merging conflicts that require proper signage and roadway markings.

Advantages

* Improves traffic progression by reducing signal phases.
* Decreases intersection congestion and travel time.
* Reduces severe crash types, particularly right-angle collisions.

Disadvantages

* Requires additional right-of-way for the connector road.
* May cause driver confusion due to the rerouted left-turn movements.
* Can increase left-turn travel distance depending on the connector road layout.

### Continuous Green-T (CGT) Intersection

The CGT intersection, also referred to as a Seagull Intersection, High-T or Turbo T-Intersection, is an innovative intersection design that allows free-flow through movement in one direction on the major road (Abdel-Aty et al., 2020). This is achieved by channelizing left-turn movements from the minor street while permitting uninterrupted through movement for one major street approach. The CGT intersection typically operates with three signal phases, optimizing traffic flow by reducing the number of stopped approach movements​. Figure 2.20 illustrates a typical CGT intersection layout.

A black and white map

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Figure 2.20. Typical Phasing Scheme at CGT Intersection.

Primary Objectives of the CGT Intersection Design are to:

* Enhance traffic efficiency by allowing continuous flow for the mainline through movement, reducing unnecessary delays.
* Improve safety by reducing vehicle stops, minimizing rear-end collisions, and optimizing left-turn maneuvers from the minor street.
* Reduce signal phasing complexity, requiring only three major signal phases for optimal operation.
* Support multimodal access, allowing safe integration of pedestrian and cyclist movements with clearly marked crossings.

#### Safety Benefits

The CGT intersection has been shown to reduce total crashes by 46% and significantly decrease injury-related and angle crashes after implementation. The most significant crash reduction was observed for CGT-related crashes, which saw a 64% reduction. However, there was no significant change for single-vehicle, non-motorized, and elderly driver-involved crashes (Abdel-Aty et al., 2020)​. A technical report by FHWA analyzed the impact of converting three-leg intersections to CGT intersections in Colorado (Hughes et al., 2010). The findings revealed a significant reduction in total crashes, injury crashes, and angle crashes following the conversion. Sando et al investigated the safety performance of CGT intersections using paired t-tests and an ordered probit model (Sando et al., 2010). Their study identified three common crash types at CGT intersections: sideswipe, angle, and rear-end crashes. Among these, angle crashes and those involving lane-changing maneuvers were found to be considerably more severe than rear-end crashes. Table 2.10 presents key safety performance improvements associated with CGT intersections.

Table 2.10. Safety Performance of CGT Intersections (Abdel-Aty et al., 2020).

|  |  |
| --- | --- |
| **Crash Type** | **Reduction (%) – Before-and-After Method** |
| Total Crashes | 46% |
| Injury Crashes | 56% |
| PDO Crashes | 44% |
| Rear-End Crashes | 61% |
| CGT-Related Crashes | 64% |

A key advantage of CGT intersections is the reduction in the number of conflict points compared to conventional intersections. By eliminating direct left-turn movements on the major road, the design significantly reduces crossing conflicts, which are a primary cause of severe crashes. Figure 2.21 shows the Conflicts of at CGT intersection.

A black and white map of a road

AI-generated content may be incorrect.

Figure 2.21. Number of Conflicts at CGT.

CGT intersections Table 2.11 summarizes the CMFs from a before-and-after study with a comparison group.

Table 2.11. CMFs for CGT Intersections (Wood and Donnell, 2016).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Crash Type** | **Severity** | **CMF** | **No. of Intersections** | **Location** |
| Total Crashes | All | 0.958 | 46 | FL & SC |
| Fatal-and-Injury Crashes | KABC | 0.846 | 46 | FL & SC |
| Angle, Rear-End, Sideswipe Crashes | All | 0.92 | 46 | FL & SC |

#### Operational Performance

CGT intersections offer significant safety and operational benefits, but they also require proper design considerations.

Advantages

* Increases capacity and improves traffic progression on major roads.
* Reduces intersection delay by eliminating unnecessary signal phases.
* Enhances safety by reducing conflict points and left-turn-related crashes.

Disadvantages

* Potentially higher speeds on the major road may increase the severity of crashes if they occur.
* Requires clear signage and driver education to ensure proper usage, especially for minor-street drivers.
* Limited applicability in locations where major-road left-turn demand is extremely high.

## Crash Severity Studies Involving U-turns

Research on U-turn safety has expanded over the past two decades, with studies exploring various aspects of crash risk, geometric design, driver behavior, and environmental influences. While U-turns have historically received less focused attention than left-turns or rear-end collisions, their growing role in modern intersection and corridor design has prompted more targeted investigations. This section synthesizes existing studies that have analyzed U-turn crash severity and contributing factors, highlighting key findings, methodological approaches, and research gaps relevant to this thesis.

### Overview of U-turn Crash Research

Studies examining U-turn safety have emphasized the role of geometric design, operational characteristics, and driver behavior in influencing crash risk. NCHRP (2004) reported that unsignalized median openings on urban arterials experienced relatively low average crash rates—approximately 0.41 crashes per median opening annually, yet these sites can still pose significant safety concerns depending on geometric and operational conditions. Fan et al., (2013) and Zhou et al. (2008) highlighted that U-turn maneuvers, while less frequent than left-turns, often involve severe conflict types, such as angle and merging collisions, particularly at high-speed arterial roadways. These studies emphasize the importance of understanding the unique risks posed by U-turns, which frequently require drivers to judge time gaps in opposing traffic under challenging conditions.

Research on alternative intersection configurations has further highlighted the significance of U-turns in modern traffic design. Abdel-Aty et al. (2020) examined the safety performance of MUT and RCUT intersections, finding substantial crash reductions, up to 70.63% in total crashes and 76.10% in injury and fatal crashes, particularly in high-speed rural settings. Kay et al. (2022) corroborated the safety benefits of median U-turn designs, reporting a 41% reduction in severe crashes by separating turning movements and reducing conflict points. However, these studies also acknowledged that shifting turning movements to downstream U-turn locations introduces new operational challenges and potential conflict points, underscoring the need for comprehensive safety evaluations of these maneuvers.

Beyond geometric configurations, driver behavior plays a critical role in U-turn safety. Mishra and Pulugurtha (2022) noted that improper gap acceptance and aggressive lane-changing maneuvers contribute significantly to crash risk, especially in areas with limited enforcement and complex traffic environments. Lu and Dissanayake (2002) similarly emphasized the impact of speed behavior and driver decision-making on crash occurrence during U-turns.

### U-Turn Crash Characteristics and Contributing Factors

A thorough review of literature identifies several categories of factors contributing to U-turn crashes, namely geometric characteristics, operational features, driver behaviors, technological tools, and integrated intersection management strategies.

Geometric characteristics such as median widths, turning radii, and dedicated lanes for acceleration and deceleration significantly influence safety and maneuverability. Studies evaluating RCUT intersections identified median width and extended acceleration spaces as crucial elements for safer U-turn maneuvers, reducing crash frequencies and facilitating smoother vehicle transitions (Schroeder et al., 2024).

Operational conditions, including intersection signalization and traffic flow dynamics, have been extensively studied. For instance, RCUT intersections evaluated using empirical Bayes methods showed notable operational benefits, including substantial reductions in crashes and improved traffic flow efficiency due to optimized signal timing and reduced conflicting movements (Hochstein et al., 2009).

Driver behaviors, particularly gap acceptance, lane-changing decisions, and compliance with traffic rules, were found critical in determining U-turn crash outcomes. Studies from Karachi and similar regions emphasized that aggressive driving behaviors and improper gap selection significantly contributed to higher crash risks at U-turn facilities, especially when combined with inadequate enforcement and unclear infrastructure design (Mishra and Pulugurtha, 2022).

Technological innovations, including IoT-based warning systems and adaptive signal controls, have also demonstrated effectiveness. Crash prevention systems employing real-time sensors significantly enhanced driver awareness and reduced collisions at blind curves and challenging U-turn locations (Abdel-Aty et al., 2020).

Lastly, integrated strategies incorporating geometric improvements, data-driven analytical tools, and stakeholder engagement offer comprehensive approaches to intersection safety. For example, the integration of CMFs with regional traffic management strategies provided actionable insights for planners, effectively reducing crash frequencies and severities across broader intersection networks (Hochstein et al., 2009; Schroeder et al., 2024).

### Safety and Operations

Safety and operational performance are critical factors in evaluating and designing U-turn and alternative intersection configurations. Geometric reconfigurations such as RCUT, MUT, and J-turn intersections significantly influence crash frequencies, conflict points, and traffic flow dynamics. Studies on RCUT intersections have demonstrated their effectiveness in reducing conflict points, reporting reductions of 34.8% in total crashes and 53.7% in injury and fatal crashes (Sun et al., 2019a). Additional analyses have validated even greater crash reductions at unsignalized RCUT intersections, showing a 70.63% decrease in total crashes and a 76.10% reduction in fatal and injury crashes, particularly under rural high-speed conditions (Mishra and Pulugurtha, 2022). Similarly, evaluations of J-turn intersections in Missouri documented reductions of 46.6% in fatal and injury crashes and 44.4% in total crashes using comparison group methods, further corroborated by empirical Bayes analyses reporting reductions of 51.4% and 40.3%, respectively (Edara, 2024). These safety improvements have largely been attributed to critical geometric elements such as deceleration and acceleration lanes, splitter islands, and loons.

MUT intersections have also consistently demonstrated safety advantages. Evaluations in Michigan revealed a 41% reduction in severe crashes attributed to the separation of turning movements from through traffic, which substantially reduced conflict points (Kay et al., 2022). CMFs for MUT designs further highlight their effectiveness, showing CMFs as low as 0.30 for severe angle crashes and CMFs of 0.25 for injury crashes at RCUT intersections (FHWA, 2017; NCHRP, 2004). Directional median openings spaced between 400 and 600 feet downstream have also been identified as optimal for balancing safety and traffic flow, significantly reducing midblock crash risks (Reid et al., 2014).

Operational studies complement these safety evaluations by underscoring improvements in traffic flow and delay reduction through geometric refinements. Analyses of Texas U-turn configurations at diamond interchanges reported substantial operational benefits, notably the elimination of up to two conflicting left-turn maneuvers, significantly reducing congestion and improving overall mobility (Dixon et al., 2018). Likewise, RTUT (Right-Turn followed by U-Turn) configurations at at-grade intersections consistently showed reduced delays, fewer conflict points, and approximately 25% lower crash frequencies compared to direct left-turn movements, emphasizing the importance of adequate spacing and strategic access management, such as directional median openings (Lu et al., 2005; Pirinccioglu et al., 2006). Studies in Kentucky demonstrated that signalized U-turn facilities improved overall corridor performance, especially during peak periods, by enhancing downstream intersection operations (Stamatiadis et al., 2004).

Research on rural restricted U-turn intersections further indicated that increased traffic volumes intensified merging conflicts, highlighting the need for well-designed merging zones to enhance operational safety (Olarte et al., 2011). Comparative studies emphasized significant benefits from replacing DLT configurations with RTUT intersections, documenting approximately a 39% reduction in conflict rates and noticeable decreases in crash severity during peak hours (Lu et al., 2001; Lu and Dissanayake, 2002). Non-traversable medians equipped with unsignalized U-turn openings have consistently been found superior in safety performance to undivided roadways by effectively reducing conflict points and improving operational efficiency (NCHRP, 2004; Phillips et al., 2004).

International studies have contributed valuable context-specific insights. Evaluations of MUT intersections in Thailand identified optimal offset distances, significantly reducing lane-changing conflicts, improving travel times by up to 15%, and minimizing side-swipe crash likelihood near median openings (Kronprasert et al., 2021). Conversely, research on a roundabout in Romania highlighted operational trade-offs, noting that heavy U-turn traffic led to significant delays in opposing movements, emphasizing the need for careful operational balancing in high-demand scenarios (Lobază, 2022). Similarly, analyses of unconventional U-turn configurations in Tehran observed an overall crash increase of approximately 13%, yet emphasized the importance of optimized weaving lengths and median designs in specifically reducing severe angle crashes (Azizi and Sheikholeslami, 2013). Signalized RCUT intersections also demonstrated effectiveness with a CMF of 0.78 for injury crashes, reinforcing their suitability for enhancing traffic safety internationally (FHWA, 2017). Furthermore, evaluations of J-turn intersections in Minnesota reported significant reductions in fatal and serious injury crashes due to their optimized geometric layouts, highlighting their potential in diverse regional contexts (Moreland et al., 2024).

Finally, context-specific studies further underline the importance of local conditions. U-turn facilities in Karachi highlighted challenges arising from cultural behaviors and infrastructural deficiencies, significantly increasing crash occurrences due to infrastructure misuse and poor compliance with traffic regulations (Zubair and Shaikh, 2015). These findings emphasize the critical role of enforcement measures and locally adapted geometric solutions. Additionally, the importance of tailoring Safety Performance Functions (SPFs) to accommodate regional traffic characteristics and geometric constraints was underscored, enhancing the effectiveness of RCUT implementations in diverse contexts (Ulak et al., 2020). Studies on signalized intersections accommodating U-turns generally reported minimal operational impacts, with minor saturation flow reductions (approximately 1.8% per 10% increase in U-turn volume), though intersections with high opposing traffic volumes experienced increased collision risks, necessitating optimized signal timing (Carter et al., 2005). Near-miss crash analyses at channelized junctions also stressed integrating advanced traffic monitoring systems to proactively manage conflict scenarios (Siregar et al., 2018). Overall, unsignalized median openings exhibited relatively low average crash frequencies of approximately 0.41 crashes per median opening annually, reinforcing the effectiveness of appropriate access management strategies (Levinson et al., 2005; Liu et al., 2005).

### **Driver** Behavior

Understanding driver behavior is critical to addressing the safety and operational challenges of U-turn maneuvers. Studies have highlighted several key behavioral aspects influencing crash outcomes, including gap acceptance, lane-changing maneuvers, speed compliance, and evasive actions. These behaviors are influenced significantly by factors such as roadway infrastructure, enforcement intensity, and localized driving culture.

Research on driver decision-making at U-turn facilities, emphasized that poor infrastructure and inadequate enforcement measures contributed substantially to hazardous driving behaviors, including abrupt lane changes, aggressive driving, and non-compliance with traffic rules (Ulak et al., 2020; Zubair and Shaikh, 2015). Similar behavioral issues were observed in studies evaluating RTUT configurations, where weaving maneuvers and gap selection along the roadway segment leading to U-turn facilities posed notable risks, particularly in areas with insufficient signage or poor design clarity (Dissanayake et al., 2002). Findings consistently underscored the critical role of intuitive infrastructure design, clear lane markings, and adequate signage in alleviating driver confusion and promoting safer driving decisions.

The relationship between geometric design and behavioral challenges has also been widely documented. Raised medians, while effective in reducing direct conflict points, require precise lane-change execution—a skill inconsistently mastered by drivers, thereby often leading to operational inefficiencies and minor conflicts (Phillips et al., 2004). Studies utilizing traffic simulation methods explored the role of speed humps at unconventional U-turn intersections, revealing that moderate-speed humps (approximately 12.5 mph) effectively reduced severe traffic conflicts by 11–20%, highlighting how strategic speed management interventions can significantly enhance driver compliance and overall intersection safety (Shahdah and Azam, 2021). Furthermore, near-miss crash analyses at channelized U-turn junctions revealed that severe conflicts frequently resulted from driver misjudgments regarding speed and gap selection, underlining the necessity of proactive interventions to address such behavioral risks (Siregar et al., 2018).

Alternative intersection configurations also significantly influence driver behavior. Comparative analyses between DLT and RTUT intersections demonstrated that drivers engaged in RTUT maneuvers exhibited improved gap acceptance and safer lane transitions, with conflict rates decreasing by approximately 39–50%, especially during peak periods (Lu et al., 2001; Lu and Dissanayake, 2002). Signalized intersections with dedicated U-turn lanes similarly encouraged better adherence to traffic controls, although studies noted persistent challenges at higher-speed locations where drivers sometimes attempted unprotected U-turns, indicating the need for continued optimization of intersection controls and driver guidance measures (Stamatiadis et al., 2004).

International studies further illustrate the importance of localized behavioral adaptations. Lane-changing behaviors at U-turn segments in Malaysia identified critical determinants of safety, including driver reaction times, vehicle speeds, and inter-vehicular distances. Models developed from these studies suggested that increased reaction times and safer following distances substantially reduced conflict likelihood during lane changes (Shafie and Rahman, 2016). Simulator-based investigations reinforced these findings, showing drivers often exceeded speed limits by up to 40%, especially near high-speed U-turn facilities, exacerbating collision risks during merging and lane-changing maneuvers (Nemmang et al., 2017). Similarly, gap acceptance behaviors at U-turn median openings in Hanoi, Vietnam, were significantly influenced by local driving culture and geometric characteristics. Narrower medians and longer opening distances generally increased gap acceptance; however, drivers frequently rejected adequate gaps if they perceived any collision risks, emphasizing the complex interplay between driver perception and geometric configurations (Dung and Hoi, 2022).

### Design Interventions

Design interventions play a critical role in optimizing the geometric and operational characteristics of U-turn facilities, aiming to enhance maneuverability, minimize conflict exposure, and improve overall traffic efficiency. Key design modifications frequently studied include adjustments in median widths, turning radii, acceleration and deceleration lanes, weaving sections, and effective access management strategies.

Evaluations of RCUT configurations have demonstrated that adjustments to median widths, offset distances, and lane alignments significantly facilitate smoother transitions, particularly on rural arterials, by providing extended acceleration spaces and clearer turning trajectories (Sun et al., 2019a). Studies comparing geometric treatments at signalized versus unsignalized RCUTs have emphasized dedicated turn bays, channelized islands, and lane segregation as critical features enhancing intersection clarity and vehicle guidance (Mishra and Pulugurtha, 2022). Similarly, analyses of RTUT designs as alternatives to DLT configurations highlighted their streamlined layouts, promoting predictable vehicle paths, reducing lane-change complexity, and effectively managing spatial constraints in dense urban environments (Lu et al., 2001; Pirinccioglu et al., 2006).

Detailed geometric evaluations of MUT intersections have underscored essential design elements such as adequately sized storage lanes, appropriately spaced crossover distances, and strategically designed weaving sections, all contributing significantly to safer vehicle merging and reduced lane-change disruptions (Kay et al., 2022). Investigations into parallel U-turn designs at congested urban intersections further supported these findings, demonstrating that refined geometric configurations, including reduced turning radii, optimal spacing between U-turn bays and mainline lanes, and minimized conflict zones, substantially improved traffic flow and decreased vehicular delays during peak conditions (Shi et al., 2023).

Research on unsignalized median openings has shown these U-turn accommodations can be flexibly adapted across varying traffic environments by adjusting opening widths and sight distances, thus enhancing operational comfort and vehicle maneuvering efficiency (Levinson et al., 2005). Studies examining the influence of separation distances between driveways and downstream U-turn facilities concluded that optimal spacing significantly reduced vehicle weaving lengths and facilitated smoother integration into mainline flows (Liu et al., 2008a). Specific design guidance for unsignalized median openings has recommended standards for spacing, median widths, and sight distances, advocating that properly designed midblock openings generally provided superior traffic accommodation compared to intersection-based alternatives (NCHRP, 2004).

Additional analyses have emphasized the operational importance of incorporating extended acceleration and deceleration lanes. Extended acceleration lanes within RCUT intersections have been demonstrated to facilitate vehicle merging, effectively reducing bottlenecks and improving operational fluidity (Inman et al., 2013). Extended weaving sections in rural RCUT intersections similarly contribute to distributing traffic density more evenly and mitigating localized congestion at merge points (Olarte et al., 2011). Evaluations of auxiliary lanes downstream of U-turn facilities indicated that their inclusion supported smoother merging behaviors, reduced maneuver ambiguity, and improved traffic transitions (Meel et al., 2017). Moreover, research has consistently highlighted that appropriately designed deceleration lanes, with adequate lengths and curvature, allow safer vehicle speed transitions into U-turn areas, significantly enhancing operational safety (Meel et al., 2016).

Strategic use of speed modulation features such as speed humps has been examined within unconventional median U-turn (UMU) designs. Findings suggest moderate-speed hump profiles effectively balance conflict mitigation and operational delays by influencing vehicle speed modulation and approach behaviors (Shahdah and Azam, 2021). Geometric analyses of Texas U-turn configurations at diamond interchanges further reinforced the importance of carefully planned design factors, including turning radii, driveway spacing, and dedicated turning bays, in achieving efficient traffic redistribution and reduced congestion at adjacent intersections (Dixon et al., 2018).

Context-specific evaluations, particularly in urban and regional settings, underscored the necessity of site-adaptive geometric configurations. Median widths, opening lengths, and lane allocations were identified as critical determinants of safe traffic circulation and functional performance, emphasizing the importance of aligning intersection designs closely with local traffic demands and roadway conditions (Ulak et al., 2020).

### Technological Innovations

Technological innovations provide essential complementary solutions to geometric interventions by leveraging intelligent transportation systems, real-time monitoring capabilities, and predictive analytics to enhance U-turn safety and operational efficiency. Recent studies have explored diverse technologies such as IoT-based driver warning systems, machine learning frameworks for predicting safety performance, adaptive signal control systems, and sophisticated conflict analysis tools, demonstrating their substantial impacts on intersection safety and efficiency.

IoT-based crash prevention technologies have been investigated for their potential to improve driver awareness, especially in challenging visibility scenarios such as sharp curves and mountainous U-turns. For instance, one system utilized ultrasonic sensors and auditory alerts to provide proactive warnings to drivers, successfully demonstrating technical feasibility, although challenges regarding real-world deployment, infrastructure integration, and maintenance have been identified as areas needing further exploration (Sivaprakash and John, 2024). Similarly, another crash prevention system employed Arduino-based technology integrating infrared sensors and auditory buzzers, showing promising results in reducing collision risks at blind curves by providing real-time alerts and enhancing driver situational awareness (Mullani et al., 2022). Additionally, a Smart Roads initiative employing ultrasonic sensors combined with LED alerts was tested for its ability to mitigate head-on collision risks at blind U-turn curves, particularly in low-visibility environments such as hilly terrains (Johnson et al., 2023). These systems collectively highlight the potential of embedded roadway technologies to enhance driver response and proactively mitigate crash risks.

Machine learning frameworks have also gained attention for their predictive capabilities in safety planning and design. One notable example involved the development of a data-driven framework that leveraged historical crash data, traffic volume metrics, and geometric design parameters to predict safety performance at RCUT intersections. This analytical approach demonstrated a substantial potential, predicting reductions in conflict points of up to 30% under optimized intersection designs, thereby providing transportation planners with quantifiable insights to proactively improve intersection safety (Molan et al., 2022).

Evaluations of signalized RCUT intersections using empirical Bayes methods further validated the utility of integrating technological solutions, highlighting crash reductions of 15% in total crashes and 22% in injury crashes post-deployment, accompanied by a favorable benefit-cost ratio of 3.6:1. This economic evaluation underscores the financial justification and operational effectiveness of technology-enhanced intersection designs (Hummer and Rao, 2017).

Adaptive signal systems represent another critical technological advancement in intersection safety. Investigations into adaptive signal control demonstrated significant benefits for pedestrian and bicyclist safety at U-turn facilities. By dynamically adjusting signal timings based on real-time sensor data, these adaptive systems effectively reduced pedestrian-vehicle conflicts, especially in high-traffic environments (Kittelson and Associates, 2021). Additional studies evaluating advanced signalization technologies at alternative intersections reported notable operational improvements, including an 18% reduction in vehicle queue lengths during peak periods and significant reductions in severe crash types through optimized traffic flow and improved queue management (Abdel-Aty et al., 2020).

Moreover, advanced conflict analysis tools leveraging video surveillance technologies have been utilized to evaluate intersection safety, specifically in J-turn configurations. Real-time monitoring enabled the identification of critical conflict zones, providing actionable insights to refine intersection designs and enhance operational safety outcomes (Edara et al., 2013).

Collectively, these studies illustrate how technological innovations substantially complement traditional geometric and operational interventions, offering robust predictive, analytical, and real-time monitoring capabilities. Their integration into intersection designs enhances overall safety, reduces conflict severity, and significantly improves traffic operational efficiency, reinforcing the importance of technology-based solutions within comprehensive U-turn safety management strategies.

### Integrated Strategies

Integrated strategies represent a comprehensive approach that merges geometric design improvements, traffic management practices, and advanced data-driven analytical tools to enhance intersection safety and operational performance holistically. These strategies often include integration of CMFs, microsimulation modeling, predictive analytics, and systematic stakeholder engagement, allowing planners to proactively identify and prioritize intersections for targeted interventions.

Research into holistic safety evaluation frameworks has demonstrated the effectiveness of combining traffic patterns, crash histories, and geometric variables into unified evaluations for intersection redesigns. For example, a detailed framework introduced for assessing the future safety and operational impacts of RCUT intersections highlighted the importance of such integrative analyses in helping planners prioritize intersection redesigns effectively (Molan et al., 2022). Similarly, microsimulation-based evaluations have been utilized to optimize median U-turn offset placements, emphasizing the critical need for integrating detailed geometric designs with traffic flow analyses to balance intersection safety with operational mobility (Kronprasert et al., 2021). Further, studies examining the integration of speed humps within UMU corridors demonstrated their contribution to comprehensive safety strategies, complementing signal optimization and other traffic management interventions to enhance overall operational efficiency and reduce conflict occurrences (Shahdah and Azam, 2021).

Strategically planned network-wide interventions involving unsignalized median U-turn intersections have also underscored their potential to significantly enhance corridor-level safety. Evaluations have shown how individual intersection improvements collectively support broader regional safety objectives by reducing cumulative crash rates and enhancing operational efficiencies across interconnected traffic networks (Kay et al., 2022). Likewise, coordinated implementations of J-turn intersections across regional networks have consistently demonstrated substantial safety benefits, notably reducing crash severity and supporting rural transportation safety goals through before-and-after analyses (Moreland et al., 2024). Moreover, studies have emphasized integrating operational guidelines for strategic U-turn placement within broader traffic systems, revealing how carefully designed U-turn configurations effectively reduce congestion and maintain safety standards, especially at intersections featuring raised medians (Carter et al., 2005).

The practical integration of CMFs into planning tools has provided quantifiable metrics for evaluating safety improvements across various intersection configurations, including MUT and RCUT designs. Notably, such integrative planning approaches have proven particularly beneficial in regions with high crash densities, explicitly linking CMF applications to broader traffic management strategies and offering planners actionable safety insights (Al-Omari et al., 2020). Similarly, data-driven frameworks employing empirical Bayesian models have successfully predicted crash trends following U-turn conversions, facilitating proactive design refinements and informed intersection strategy adjustments (Azizi and Sheikholeslami, 2013).

Stakeholder engagement has also emerged as a critical component in integrated safety strategies. Operational evaluations of J-turn intersections in Missouri demonstrated how incorporating public feedback into the design and implementation process significantly enhanced acceptance, effectiveness, and overall operational performance of intersection treatments (Edara et al., 2013). Additionally, a synthesis of MUT intersections has positioned these configurations as foundational components within comprehensive access management strategies. These designs were particularly emphasized for their ability to accommodate large vehicles through strategically designed loons, ensuring compatibility with existing regional traffic infrastructure and enhancing overall functional performance (FHWA, 2017).

Finally, predictive analytics through tailored SPFs have been effectively integrated into RCUT intersection evaluations, enabling planners to precisely adapt intersection designs to specific roadway conditions and regional traffic characteristics (El-Urfali, 2019). Deployments of extended acceleration lanes within RCUT corridors have been specifically emphasized for supporting smoother merging operations, significantly reducing system-wide bottlenecks when implemented alongside coordinated signal systems and corridor-level operational improvements (Inman et al., 2013).

## Research Gaps and Summary

The preceding literature review identified several critical gaps in the current understanding of U-turn crash safety. Although many studies have documented the benefits of geometric interventions, such as median widths, turning radii, and acceleration and deceleration lanes, these improvements often shift conflict exposure downstream to U-turn locations, where specific crash patterns and severity levels remain underexplored. Most existing research aggregates U-turn crashes within broader left-turn or general intersection analyses, overlooking the unique operational demands and conflict scenarios associated with dedicated U-turn maneuvers.

Furthermore, while alternative intersection configurations, including MUTs and RCUTs, have demonstrated overall crash reductions, few studies have systematically examined the influence of these configurations on downstream U-turn performance and associated crash severity. This knowledge gap limits the development of targeted safety interventions that address the operational complexities of U-turn movements within diverse traffic environments.

Behavioral factors, such as gap acceptance decisions, lane-changing behaviors, and speed compliance, also contribute significantly to U-turn crash risks, yet remain insufficiently integrated into current analytical frameworks. Although some studies highlight the importance of driver behavior in crash outcomes, comprehensive analyses that combine geometric, behavioral, and operational factors are scarce.

Moreover, while technological solutions, including IoT-based driver warning systems and adaptive signal controls, have shown promise in enhancing intersection safety, their application to U-turn-specific scenarios remains limited. Region-specific influences, such as local driving culture and enforcement practices, are also underexplored, hindering the transferability of existing findings to different contexts.

Finally, existing literature predominantly relies on traditional statistical techniques to analyze crash data, limiting the ability to uncover complex, multifactorial relationships among contributing factors. Advanced data-driven methods, such as ARM-LIC and CCA, offer promising tools to extract nuanced patterns and classify crash severities based on interrelated factors. However, their application to U-turn crash analyses remains largely untapped.

In response to these gaps, this study employs advanced analytical approaches, including ARM-LIC and CCA, to develop a comprehensive understanding of U-turn crash risks. By integrating geometric, behavioral, operational, and technological factors into the analysis, this research aims to provide data-driven insights that can inform safer intersection designs and targeted safety countermeasures.

# ASSOCIATION RULE MINING WITH LIFT INCREASE CRITERIA

**III.**

## Introduction

Crashes involving U-turn maneuvers represent a substantial safety concern, particularly in high-traffic environments where drivers must make quick judgments regarding the speed and distance of opposing vehicles. U-turns, especially those performed in unsignalized or congested areas, often create complex traffic interactions that elevate the likelihood of severe crashes (Schneider et al., 2019). According to the Federal Highway Administration (FHWA), the average crash rate for U-turn and left-turn maneuvers at unsignalized median openings is approximately 0.41 crashes per opening annually in urban settings and 0.20 in rural areas, reflecting the recurring nature of these incidents (FHWA, 2023).

As urban development intensifies and traffic demands grow, U-turn maneuvers have become increasingly integral to roadway operations, necessitating a deeper understanding of their safety implications. To mitigate crash risks associated with U-turns, transportation engineers have explored innovative intersection designs that restructure traditional vehicle movements. Research by Lu et al. (2001) showed that substituting direct left-turns with right-turn-plus-U-turn strategies can reduce overall crash rates by 17.8% and lower injury and fatal crash rates by 27.3% on major arterials. Building on this foundation, Edara et al. (2015) employed the Empirical Bayes method to evaluate the safety performance of intersection redesigns, offering stronger causal inferences by controlling for regression-to-the-mean effects. Complementary simulation-based analyses have further demonstrated the operational benefits of alternative designs; for example, Olarte et al. (2011) found that rural Restricted Crossing U-Turn (RCUT) intersections reorganize conflict points under high-volume conditions, enhancing safety through improved merging and weaving patterns. Empirical assessments by Mishra and Pulugurtha (2022) validated these benefits, documenting significant reductions in fatal and injury crashes at unsignalized RCUT intersections. A broader systematic review by Javed et al. (2025) reinforced the effectiveness of RCUT and Median U-Turn (MUT) designs in improving both safety and traffic flow outcomes. Despite these advances, much of the existing research remains centered on geometric and operational improvements, often overlooking the multifaceted interactions among driver behavior, roadway conditions, environmental factors, and temporal variations that contribute to crash severity under real-world conditions.

To address these gaps, this study applied Association Rule Mining (ARM) to systematically uncover hidden patterns within categorical crash data. ARM is a robust data mining technique designed to explore complex, multi-attribute relationships without relying on strict distributional assumptions, making it particularly well-suited for analyzing the multifaceted dynamics of U-turn crashes. By mining association rules among roadway features, environmental conditions, driver behaviors, and temporal factors, ARM provides a data-driven approach to reveal how specific combinations of attributes influence crash severity outcomes. U-turn crashes often arise from intricate interactions where drivers, especially in high-traffic or high-speed environments, may misjudge critical elements such as opposing vehicle speed and distance, leading to severe collisions. Additional challenges such as inadequate geometric designs, poor lighting, and limited sight distance further exacerbate crash risks, often resulting in multi-vehicle incidents with serious consequences. Unlike traditional statistical methods that may overlook subtle and multidimensional interactions, ARM enables the discovery of nuanced relationships, highlighting critical factor combinations that might remain undetected through conventional analyses. In addition, a qualitative review of police-reported crash narratives was conducted to provide real-world context and deeper insight into the circumstances surrounding U-turn crashes. This comprehensive understanding is essential for developing evidence-based roadway safety improvements, optimizing intersection and median designs, and informing targeted public safety initiatives. By leveraging ARM to analyze these underlying dynamics, this study seeks to support data-driven policymaking, guide intersection safety enhancements, and ultimately reduce crash risks associated with U-turn maneuvers.

### Crash Risk at U-Turn Facilities

Research efforts have long focused on understanding the conflict risks and safety challenges associated with U-turn maneuvers at median openings, aiming to inform better design and operational practices. Sharma et al. (2017) investigated U-turns at uncontrolled median openings, emphasizing the complexities of critical gap acceptance shaped by factors such as driver frustration, traffic volume, and varying vehicle types. Using data from six median openings, they evaluated critical gap estimations across traditional, Influence Area for Gap Acceptance (INAFOGA), and Modified Raff’s methods to compare their effectiveness. Similarly, Khan et al. (2021) highlighted that smaller available gaps at mid-block median openings contribute to unpredictable driver behavior and increased crash potential, recommending minimum safe gaps through methods like Modified Raff, Ashworth, Occupancy Time, and Binary Logit modeling. In the context of J-turn safety, Sun et al. (2017) used driving simulation to demonstrate that incorporating acceleration–deceleration lanes can lower critical event occurrences by 66.3% compared to configurations with only deceleration lanes, although reduced U-turn spacing was found to exacerbate lane-change conflicts. Dung and Hoi (2022) further showed that factors like gap size, median width, and opening distance influenced collision risks, while Liu et al. (2007) found that narrow medians and limited turning spaces elevated crash likelihoods at unsignalized intersections. Zhang et al. (2024) extended this discussion by optimizing speed limits at unsignalized U-turn left-turn intersections using VISSIM and SSAM, concluding that a 10% speed limit reduction effectively balances traffic delays, conflicts, and emissions.

Beyond individual gap acceptance issues, researchers have explored how U-turn maneuvers influence broader traffic safety and congestion dynamics. Fan et al. (2013) applied a cellular automaton modeling approach to examine the impacts of U-turning vehicles on intersection operations, finding that U-turn activities often lead to increased control delay and rear-end crash risks due to abrupt braking patterns. Using VISSIM and SSAM, Olarte et al. (2011) utilized VISSIM and SSAM simulations to show that rural RCUT intersections experience amplified merging and weaving conflicts under higher volumes. Al-Omari et al. (2020) demonstrated through empirical Bayes and cross-sectional studies that RCUT and MUT intersections relocate conflict points and reduce severe crashes, although issues related to single-vehicle and non-motorized crashes persist due to inadequate crosswalks. Mishra and Pulugurtha (2022) strengthened this evidence by documenting significant reductions in fatal and injury crashes at rural unsignalized RCUT intersections, while suburban RCUTs also showed notable improvements. Molan et al. (2022) proposed a framework combining empirical Bayes and surrogate safety analysis to forecast RCUT safety benefits at constrained rural intersections, and Howard et al. (2023) showed that RCUT designs effectively eliminated severe conflicts even under scenarios involving connected and autonomous vehicles. Inman et al. (2013) similarly observed a 28% to 44% crash reduction after RCUT implementation compared to conventional two-way stop-controlled intersections. Supporting broader safety evaluations, Javed et al. (2025) conducted a systematic review using PRISMA guidelines, highlighting the role of innovative designs like RCUTs and MUTs in improving U-turn safety and traffic flow.

Safety benefits associated with J-turn and MUT intersections have also been extensively reported. Moreland et al. (2024) analyzed 83 J-turn intersections in Minnesota, identifying significant reductions in fatal, serious injury, and angle crashes compared to conventional intersections. Edara et al. (2024) similarly evaluated 47 J-turn sites in Missouri using comparison group and empirical Bayes methods, revealing 40% to 50% reductions in crash rates and emphasizing the role of design elements such as loons and acceleration lanes in safety outcomes. Pannela and Bhuyan (2017) compared different critical gap estimation methods at U-turn median openings in India, concluding that modified INAFOGA methods better captured driver behaviors in mixed traffic environments. (Lobază, 2022) highlighted operational challenges when replacing left-turns with U-turns at roundabouts, where delays and intersection capacity concerns emerged. Kay et al. (2022) also contributed by evaluating 95 unsignalized intersections, recommending CMFs that support safer conversions to median U-turn designs, particularly for two-lane and four-lane major roadways. Khavarian and Sahebi (2025) introduced a robust case-control resampling method to improve CMF estimation for U-turn elimination, demonstrating the sensitivity of CMF distributions to stratification approaches.

Analyzing U-turn safety and intersection configurations remains vital for understanding and mitigating conflicts and the risks associated with vehicle interactions, congestion, and collision potential. Xu et al. (2017) demonstrated through VISSIM and SSAM simulations that inadequate U-turn offset lengths substantially raise lane-change conflicts. Wu et al. (2020) found that longer U-turn waiting times without cooperative behavior increase risky interactions, especially at high arrival rates. Holzem et al. (2015) discussed risks for vulnerable users at unconventional crossings within Superstreet designs, where side-swipe and rear-end collisions are more likely. Al-Sahili et al. (2018) analyzed citation data for illegal U-turns on limited-access roads, revealing that misjudged gaps and high-speed maneuvers frequently led to rear-end, sideswipe, and head-on crashes.

### ARM in Transportation Safety Research

ARM has emerged as a powerful method in transportation safety research, enabling the identification of complex relationships between crash characteristics and outcomes, which helps in developing targeted countermeasures to improve road safety. In one study, ARM was applied to explore the relationship between crash severity and roadway deficiencies identified during safety inspections on two roads in Spain, revealing strong associations between vulnerable road users and severe outcomes, particularly linked to poor shoulder conditions, outdated barriers, and inadequate signage (Gutiérrez-Rodríguez et al., 2025). Similarly, ARM was used to analyze injury and fatal crash data involving vulnerable road users in Tehran, identifying critical risk factors such as adverse weather conditions, non-working days, and alcohol use, and proposing systematic countermeasures through mathematical optimization frameworks (Nadimi et al., 2025). Focusing on environmental and demographic risk factors, rainy weather crash patterns were analyzed using ARM, which revealed a dominance of single-vehicle run-off crashes on curved or grade-aligned roads with poor nighttime lighting, especially for drivers aged 15–44 (Das et al., 2020b). A related study employed a priori supervised ARM to explore pedestrian crash severity and found that alcohol presence, inadequate lighting, and vulnerable demographic groups such as male pedestrians and younger female drivers contributed significantly to severe outcomes (Das et al., 2019). Building on this work, national fatal pedestrian crashes at intersections were examined using lift-based rule mining, showing heightened risks under poor lighting, vehicle turning movements, and pedestrian violations of crosswalk boundaries (Das et al., 2021c). Similar associations were found in nighttime crashes involving older pedestrians on high-speed or complex roadway environments (Mimi et al., 2025). ARM was also applied to hit-and-run crash data to identify that single-vehicle crashes and dark lighting were jointly associated with severe crash outcomes, particularly in urban, segment-related settings (Das et al., 2021b).

Behavioral crash typologies have also been explored through rule mining approaches. In the context of wrong-way driving, fatal crash records were analyzed to reveal that intoxication, urban conditions, and nighttime hours elevated risk for local drivers, while rural and unlit roads posed greater threats for non-local drivers (Abbaszadeh Lima et al., 2024). Another study used the Eclat algorithm to differentiate between freeway exit ramp and median crossover WWD crashes, showing that driver impairment, male drivers, and peak nighttime hours were recurrent risk contributors (Das et al., 2018b). Speeding-related patterns were analyzed using a hybrid clustering and ARM approach, which found that fatal motorcycle crashes were concentrated on weekends and on dark, unlit roads (Rahman et al., 2025). A complementary investigation applied classification-based association rule mining to naturalistic driving data and identified that longer trips, higher functional class roads, absence of medians, and pre-event congestion conditions were linked with elevated speeding risk (Kong et al., 2020). In addition, a study combining ARM with a random parameters model demonstrated that alcohol use, surface conditions, and demographic traits significantly affected single-vehicle motorcycle crash severity (Wei et al., 2024).

Although extensive research has examined U-turn safety through critical gap acceptance, intersection design, and traffic flow impacts, particularly using simulation tools like VISSIM and SSAM, most prior studies have emphasized operational performance or geometric alternatives such as RCUTs, MUTs, and J-turns. While these efforts have yielded valuable insights into crash reductions and conflict mitigation, they often overlook the complex, multifactorial nature of crash severity. Specifically, limited attention has been given to how combinations of roadway, vehicle, environmental, and behavioral attributes jointly influence injury outcomes in U-turn crashes. Moreover, existing approaches typically rely on traditional statistical or simulation models that may not capture hidden interaction patterns among categorical variables. Although ARM has recently been applied in broader traffic safety contexts, such as speeding or vulnerable road user crashes, it has not yet been used to explore severity-linked risk patterns in U-turn-related crashes. This study introduces the use of a Lift Increase Criterion (LIC) within ARM to evaluate multi-factor association rules in the traffic safety domain. This approach ensures that each additional condition in a rule meaningfully increases the rule’s predictive power (lift), thereby filtering out spurious or coincidental patterns and enhancing the robustness of the findings. This presents a critical opportunity for applying ARM with application of LIC to reveal latent, multi-attribute relationships that support more targeted and effective safety interventions. In addition, crash narrative analysis provides additional contexts.

## Data

### Exploratory Data Analysis

The dataset used in this study includes 2,716 U-turn-related crash records from Ohio, U.S., spanning the years 2017 to 2021. Crash severity was initially categorized based on the KABCO scale and later consolidated into three broader groups: severe injuries (KA), minor to moderate injuries (BC), and no injuries (O). Before applying association rule mining, the crash data were carefully preprocessed and examined through exploratory analysis. Categorical variables such as crash type, road class, lighting condition, weather, vehicle type, and driver actions were checked for consistency and cleaned (e.g. ensuring uniform naming of categories, handling missing or unknown entries by treating them as separate categories). This study also conducted basic significance tests (chi-square tests for independence) across the three severity groups to identify which factors vary statistically with crash severity. This preliminary step helped identify variables that are likely meaningful for severity outcomes and thus worthy of inclusion in the pattern mining. Table 3.1 presents the distribution of key crash characteristics across these categories, with 67 cases classified as KA, 633 as BC, and 2,016 as O. Crash type showed a notable association with severity, where angle crashes accounted for 37.3% of KA outcomes but only 26.7% of O cases, whereas sideswipe crashes were more common among BC (57.7%) and O (48.7%) crashes. Road facility types also influenced severity, with 64.2% of KA crashes occurring on two-way roadways. The functional class variable indicated that severe crashes were relatively concentrated on major collector roads (22.4%), whereas no-injury crashes were more dispersed across local roads (22.8%), minor roads (26.7%), and other functional classes (28.6%). Commercial motor vehicles were involved in 22.4% of severe crashes compared to 12.5% of no-injury crashes, showing a strong association with higher severity outcomes. Lighting conditions also played an important role; crashes under dark, unlit roadway conditions were more frequently associated with KA crashes (13.4%) than O crashes (9.03%), although daylight remained dominant across all severities. In terms of vehicle involvement, two-vehicle crashes were predominant across all severity levels, while single-vehicle crashes were more common in no-injury cases (18.4%). Four-way intersections appeared slightly more often in severe injury crashes (19.4%) compared to no-injury crashes (16.0%), indicating the risk associated with intersection complexity. Surface conditions further revealed that crashes on dry roadways were dominant across all severities, but wet surfaces were more commonly involved in no-injury crashes (19.7%). Regarding speed limits, crashes occurring in 45–60 mph zones contributed to 50.7% of KA crashes but only 25.1% of O crashes, underscoring the elevated risk associated with higher-speed environments. Driver-related factors such as gender also exhibited disparities, with male drivers accounting for 67.2% of KA crashes compared to 57.0% of O cases. Although driver impairment remained relatively low, it was slightly more frequent among severe injuries (4.48%) than no-injury crashes (2.03%). Vehicle type analysis showed a higher presence of semi-tractors and other vehicle types in KA crashes, while passenger cars were more common in BC and O cases.

The p-values associated with each variable were derived from chi-square tests, indicating whether the distribution of attributes significantly differed across the three severity categories. A p-value less than 0.05 suggests that the variable has a statistically significant relationship with crash severity and merits further investigation. Variables such as commercial motor vehicle involvement, roadway facility type, lighting conditions, and driver gender demonstrated statistically significant differences and were prioritized for further exploration using ARM techniques.

Table 3.1. Crash Attribute Distributions Categorized by Severity Level.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable Category** | **KA (Fatal/Severe) N=67** | **BC (Moderate/Minor) N=633** | **O**  **(No Injury) N=2016** | **p-val** |
| **Crash Type (CrType)** |  |  |  | . |
| Angle | 25 (37.3%) | 194 (30.6%) | 539 (26.7%) |  |
| Fixed Object | 2 (2.99%) | 30 (4.74%) | 281 (13.9%) |  |
| Other | 10 (14.9%) | 38 (6.00%) | 141 (6.99%) |  |
| Parked Vehicle | 0 (0.00%) | 6 (0.95%) | 73 (3.62%) |  |
| Sideswipe | 30 (44.8%) | 365 (57.7%) | 982 (48.7%) |  |
| **Road facility type (Facility)** |  |  |  | 0.043 |
| One Way Roadway | 0 (0.00%) | 4 (0.63%) | 13 (0.64%) |  |
| Other | 24 (35.8%) | 350 (55.3%) | 1114 (55.3%) |  |
| Ramp | 0 (0.00%) | 5 (0.79%) | 22 (1.09%) |  |
| Two Way Roadway | 43 (64.2%) | 274 (43.3%) | 867 (43.0%) |  |
| **Functional class** |  |  |  | . |
| Interstate Route | 4 (5.97%) | 23 (3.63%) | 72 (3.57%) |  |
| Local Roads | 9 (13.4%) | 110 (17.4%) | 459 (22.8%) |  |
| Major Collector Roads | 15 (22.4%) | 114 (18.0%) | 369 (18.3%) |  |
| Minor Roads | 15 (22.4%) | 194 (30.6%) | 539 (26.7%) |  |
| Other | 24 (35.8%) | 192 (30.3%) | 577 (28.6%) |  |
| **Commercial Motor Vehicle** |  |  |  | <0.001 |
| No | 52 (77.6%) | 586 (92.6%) | 1764 (87.5%) |  |
| Yes | 15 (22.4%) | 47 (7.42%) | 252 (12.5%) |  |
| **Lighting Condition** |  |  |  | . |
| Dark - Lighted Roadway | 12 (17.9%) | 123 (19.4%) | 322 (16.0%) |  |
| Dark - Roadway Not Lighted | 9 (13.4%) | 40 (6.32%) | 182 (9.03%) |  |
| Dawn/Dusk | 1 (1.49%) | 25 (3.95%) | 82 (4.07%) |  |
| Daylight | 45 (67.2%) | 444 (70.1%) | 1418 (70.3%) |  |
| Other / Unknown | 0 (0.00%) | 1 (0.16%) | 12 (0.60%) |  |
| **Number of vehicles (NumVeh)** |  |  |  | . |
| Multi | 4 (5.97%) | 21 (3.32%) | 41 (2.03%) |  |
| Single | 8 (11.9%) | 39 (6.16%) | 370 (18.4%) |  |
| Two | 55 (82.1%) | 573 (90.5%) | 1605 (79.6%) |  |
| **Location** |  |  |  | . |
| Four-Way Intersection | 13 (19.4%) | 109 (17.2%) | 322 (16.0%) |  |
| Not An Intersection | 47 (70.1%) | 424 (67.0%) | 1397 (69.3%) |  |
| Other | 3 (4.48%) | 22 (3.48%) | 96 (4.76%) |  |
| T-Intersection | 4 (5.97%) | 78 (12.3%) | 201 (9.97%) |  |
| **Surface Condition (Surface\_Cond)** |  |  |  | . |
| Dry | 65 (97.0%) | 512 (80.9%) | 1569 (77.8%) |  |
| Other / Unknown | 0 (0.00%) | 3 (0.47%) | 13 (0.64%) |  |
| Snow | 0 (0.00%) | 9 (1.42%) | 37 (1.84%) |  |
| Wet | 2 (2.99%) | 109 (17.2%) | 397 (19.7%) |  |
| **Road Condition (Road\_Conition)** |  |  |  | . |
| Curve Grade | 3 (4.48%) | 17 (2.69%) | 63 (3.12%) |  |
| Curve Level | 1 (1.49%) | 19 (3.00%) | 45 (2.23%) |  |
| Other / Unknown | 0 (0.00%) | 0 (0.00%) | 3 (0.15%) |  |
| Straight Grade | 17 (25.4%) | 117 (18.5%) | 337 (16.7%) |  |
| Straight Level | 46 (68.7%) | 480 (75.8%) | 1568 (77.8%) |  |
| **Contributing Factors (Contri\_Fac)** |  |  |  | . |
| Drove Off Road | 0 (0.00%) | 12 (1.90%) | 104 (5.16%) |  |
| Failure To Yield | 13 (19.4%) | 106 (16.7%) | 300 (14.9%) |  |
| Improper Lane Change | 4 (5.97%) | 52 (8.21%) | 179 (8.88%) |  |
| Improper Turn | 33 (49.3%) | 322 (50.9%) | 939 (46.6%) |  |
| Other | 17 (25.4%) | 141 (22.3%) | 494 (24.5%) |  |
| **Driver Gender (DrGen)** |  |  |  | <0.001 |
| Female | 18 (26.9%) | 214 (33.8%) | 629 (31.2%) |  |
| Male | 45 (67.2%) | 393 (62.1%) | 1150 (57.0%) |  |
| Unknwon | 4 (5.97%) | 26 (4.11%) | 237 (11.8%) |  |
| **Driver impairment (DrImp)** |  |  |  | 0.221 |
| No | 64 (95.5%) | 617 (97.5%) | 1975 (98.0%) |  |
| Yes | 3 (4.48%) | 16 (2.53%) | 41 (2.03%) |  |
| **Number of Through Lanes (ThruLn)** |  |  |  | . |
| Multi | 12 (17.9%) | 197 (31.1%) | 465 (23.1%) |  |
| One | 2 (2.99%) | 19 (3.00%) | 68 (3.37%) |  |
| Two | 53 (79.1%) | 417 (65.9%) | 1483 (73.6%) |  |
| **Object Struck** |  |  |  | . |
| Ditch | 1 (1.49%) | 5 (0.79%) | 80 (3.97%) |  |
| Nothing Struck | 60 (89.6%) | 581 (91.8%) | 1709 (84.8%) |  |
| Other | 6 (8.96%) | 34 (5.37%) | 162 (8.04%) |  |
| Traffic Sign Post | 0 (0.00%) | 3 (0.47%) | 42 (2.08%) |  |
| Utility Pole | 0 (0.00%) | 10 (1.58%) | 23 (1.14%) |  |
| **Posted speed limit (PSL)** |  |  |  | . |
| 25 MPH or less | 11 (16.4%) | 159 (25.1%) | 683 (33.9%) |  |
| 30-40 MPH | 17 (25.4%) | 260 (41.1%) | 765 (37.9%) |  |
| 45-60 MPH | 34 (50.7%) | 195 (30.8%) | 507 (25.1%) |  |
| 65-70 MPH | 5 (7.46%) | 19 (3.00%) | 61 (3.03%) |  |
| **Sequence of events (Seq\_Event)** |  |  |  | . |
| Cross Centerline OD of Travel | 7 (10.4%) | 24 (3.79%) | 70 (3.47%) |  |
| Motor Vehicle in Transport | 44 (65.7%) | 534 (84.4%) | 1462 (72.5%) |  |
| Other | 13 (19.4%) | 45 (7.11%) | 178 (8.83%) |  |
| Parked Motor Vehicle | 0 (0.00%) | 4 (0.63%) | 72 (3.57%) |  |
| Ran Off Road | 3 (4.48%) | 26 (4.11%) | 234 (11.6%) |  |
| **Vehicle type (VehTyp)** |  |  |  | . |
| Other | 22 (32.8%) | 82 (13.0%) | 247 (12.3%) |  |
| Passenger Car | 31 (46.3%) | 363 (57.3%) | 1036 (51.4%) |  |
| Pick Up | 4 (5.97%) | 46 (7.27%) | 180 (8.93%) |  |
| Semi-Tractor | 5 (7.46%) | 10 (1.58%) | 130 (6.45%) |  |
| Sport Utility Vehicle | 5 (7.46%) | 132 (20.9%) | 423 (21.0%) |  |
| **Weather condition (Wthr\_Cond)** |  |  |  | . |
| Clear | 55 (82.1%) | 414 (65.4%) | 1254 (62.2%) |  |
| Cloudy | 12 (17.9%) | 144 (22.7%) | 486 (24.1%) |  |
| Other | 0 (0.00%) | 2 (0.32%) | 20 (0.99%) |  |
| Rain | 0 (0.00%) | 59 (9.32%) | 210 (10.4%) |  |
| Snow | 0 (0.00%) | 14 (2.21%) | 46 (2.28%) |  |

### Spatial Distribution

Figure 3.1 illustrates the spatial distribution and density of U-turn-related crashes across Ohio between 2017 and 2021, categorized by crash severity levels: KA, BC, and O. The distribution of KA crashes shows localized clustering primarily in the northeastern and southwestern parts of the state, suggesting that fatal and severe injuries tend to occur in regions with potentially complex traffic environments or insufficient safety infrastructure. In contrast, BC crashes exhibit a broader dispersion pattern across mid-sized urban areas and surrounding regions, reflecting moderate crash risks in more varied roadway settings. The O category demonstrates the most extensive spatial spread, with dense clusters concentrated around major metropolitan centers, particularly in Columbus, Cleveland, and Cincinnati. This pattern suggests that while everyday minor fender-benders during U-turns are common in busy urban settings (likely due to the sheer volume of traffic and turning movements), the most severe U-turn crashes are somewhat more localized; potentially pointing to specific problematic locations or corridors. Such location-based insights can be valuable for policymakers to identify hotspots for intervention (for example, specific intersections or stretches of road that might benefit from a redesign or enhanced traffic control to accommodate U-turns more safely).

A screenshot of a graph

AI-generated content may be incorrect.

Figure 3.1. Density Visualization of U-turn Crash Events in Ohio by Severity Classification.

## Methodology

### Association Rules Mining

ARM is a widely adopted data mining technique for uncovering hidden patterns and correlations among attributes within large datasets. First introduced by Agrawal et al. (1993), ARM aims to identify strong relationships between disjoint sets of items based on their co-occurrence within a transactional database. Let represent the set of all items, and let *T* be a set of transactions where each transaction is a subset of *I*. An association rule takes the form , where and , indicating that the presence of *X* implies the presence of *Y.* The quality of association rules is assessed using three principal metrics: support, confidence, and lift. These measures determine the statistical significance, strength, and relevance of the identified relationships.

Support is defined as the frequency or the number of times an itemset appears in a given transactional database (Agrawal et al., 1993). Support measures the relative frequency with which an itemset appears in the dataset, reflecting its statistical relevance within the transactional database. For instance, a support value of 0.05% implies that the corresponding itemset is present in only 0.05% of all recorded transactions. Itemsets with such low support may arise due to random variation and are generally considered less meaningful for further analysis. To focus on significant patterns, itemsets are typically filtered by applying a minimum support threshold. Support is mathematically expressed as,

|  |  |
| --- | --- |
|  | (3.1) |

While support reflects the statistical significance of a rule, confidence measures its strength (Agrawal et al., 1993). Confidence is defined as the conditional probability , which represents the likelihood of both *X* and *Y* occurring together, given that the transaction includes *X*. For example, a confidence value of 90% implies that 90% of the transactions involving *X* also include *Y*, indicating a strong association between the two itemsets. A confidence value of 1, or 100%, signifies that the antecedent and consequent consistently occur together across all relevant transactions. The formula for calculating confidence is given as,

|  |  |
| --- | --- |
|  | (3.2) |

Lift is a measure of the importance of a rule (Brin, 1997). It represents the ratio between the observed confidence of a rule and the confidence expected under the assumption of statistical independence between the antecedent and consequent. It evaluates how much more frequently the antecedent and consequent occur together than would be anticipated if no association existed between them. The lift for a given rule is calculated as,

|  |  |
| --- | --- |
|  | (3.3) |

A lift value exceeding 1 indicates that the antecedent and consequent co-occur more frequently than would be expected under conditions of independence, suggesting a positive association between the two itemsets. Conversely, a lift value below 1 implies that the items appear together less often than anticipated, reflecting a negative association. A lift value exactly equal to 1 denotes that the antecedent and consequent occur together at a rate consistent with statistical independence, indicating no meaningful relationship between them.

In this study, rules containing more than two itemsets were assessed using the LIC to ensure their reliability. Specifically, it was important to confirm that the addition of each variable category to the antecedent led to a meaningful increase in the lift value (Gu et al., 2022; Montella et al., 2021). This process involves evaluating a base rule (referred to as the parent rule) with a single item and corresponding lift value . When a new item is added, the updated rule’s lift value ​ is compared against ​. The difference between these two values quantifies the LIC, as expressed in Equation (3.4).

|  |  |
| --- | --- |
|  | (3.4) |

### The Apriori Algorithm

ARM encompasses two primary sub-tasks: first, the identification of itemsets that occur with a frequency exceeding a specified support threshold, known as frequent or large itemsets; and second, the generation of association rules from these itemsets based on minimum confidence constraints (Agrawal et al., 1993). Once frequent itemsets are established, deriving association rules becomes a relatively straightforward process, leading most ARM approaches to focus primarily on the first sub-task. One of the most commonly adopted and efficient algorithms for discovering frequent itemsets is the Apriori algorithm, developed by Agrawal and Srikant (1994). The first sub-task is further divided into two stages: generating candidate itemsets and subsequently determining which of these candidates meet the minimum support threshold (Zhao and Bhowmick, 2003). Itemsets that satisfy or exceed the support threshold are classified as frequent itemsets.

The Apriori algorithm operates through a two-step iterative process to identify all frequent itemsets within a given dataset *D*. Initially, candidate itemsets are generated, and the database is scanned to compute the support count for each candidate. In the first scan, the algorithm evaluates individual items, generating large 1-itemsets by removing items whose support falls below the minimum threshold. In subsequent iterations, candidate itemsets of size *k* are generated by joining frequent *(k−1)*-itemsets, and their supports are evaluated. According to the Apriori property, if any *(k−1)*-subset of a candidate *k*-itemset is infrequent, then the *k*-itemset itself must also be infrequent and can be excluded from further consideration, thereby improving computational efficiency. Table 3.2 illustrates a sample dataset consisting of six crash records with multiple attributes, provided to clarify the computation and interpretation of support, confidence, and lift within the context of ARM.

Table 3.2. Example Database with Six Crash Records and Selected Traffic Attributes.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Crash Id | Light | Speed Limit | Driver Distraction | Cloudy Weather | Signalized Intersection | Fatal |
| 1000 | 0 | 1 | 0 | 0 | 1 | 1 |
| 1001 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1002 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1003 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1004 | 1 | 0 | 1 | 0 | 1 | 1 |
| 1005 | 1 | 0 | 1 | 1 | 1 | 0 |

* The itemset has a support of 4/6 = 0.67, indicating that this combination occurs in 67% of all crashes.
* The rule has a confidence of , meaning that when both light and alcohol impairment are present, a fatal crash occurs 75% of the time.
* For example, the rule has a lift of , which indicates a direct relationship between the purchase of Light, Alcohol Impairment and Fatal.

### Research Framework

The study framework, depicted in Figure 3.2, outlines the analytical process applied to examine U-turn-related crashes in Ohio from 2017 to 2021. The process begins with the extraction of raw crash records from the Ohio crash database, followed by a targeted selection of U-turn-related incidents. The selected crash data is then organized and standardized through a data preprocessing stage, where variables are reformatted, missing values are handled, and attribute consistency is ensured to prepare the dataset for analysis. Subsequently, the structured dataset undergoes advanced data processing, allowing for the identification of key attributes relevant to U-turn crash severity patterns. ARM is then applied to uncover hidden relationships among crash factors and to generate robust association rules. These mined patterns provide insights into the combinations of roadway, driver, environmental, and vehicular factors associated with varying crash severities. Finally, the insights derived from the ARM analysis are synthesized into actionable safety recommendations aimed at informing targeted interventions and enhancing road safety at U-turn locations.

A screenshot of a video game

AI-generated content may be incorrect.

Figure 3.2. Framework for U-turn Crash Pattern Analysis.

## Results and Discussions

This section presents the findings of an association rule mining analysis applied to U-turn-related crash data, structured by injury severity level: KA, BC, and O. To ensure statistical relevance, only rules with lift values greater than 1.00 were considered for interpretation, indicating that the observed combinations of factors occurred more frequently than would be expected by chance. Rules exhibiting a notable increase in LIC values, along with those involving critical crash-related attributes, were emphasized in the analysis to highlight meaningful patterns. The results are presented by severity level to illustrate how the interaction of these factors varies across different crash outcomes.

### Crash Patterns Associated with KA-Level Injuries

This section presents the association rules for KA injury outcomes in U-turn-related crashes. Table 3.3 includes 15 rules that illustrate the patterns contributing to high-severity injuries, emphasizing interactions between vehicle involvement, driver behavior, environmental factors, and road characteristics. Major contributing factors include multi-vehicle crashes (KA1–KA3), high posted speed limits (KA4–KA6), commercial motor vehicle involvement (KA7–KA11), poor lighting (KA12–KA13), and semi-tractor presence (KA14–KA15). These rules highlight combinations of risk factors that significantly elevate the likelihood of fatal or severe crash outcomes during U-turn maneuvers.

Table 3.3. Frequent Patterns Associated with KA Injuries in U-Turn Crashes.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **ID** | **Antecedent** | **S** | **C** | **L** | **LIC** |
| n/a | {NumVeh=Multi} | 0.001 | 0.06 | 2.46 | NA |
| KA1 | {NumVeh=Multi, Contri\_Fac=Improper Turn} | 0.001 | 0.10 | 4.05 | 1.65 |
| KA2 | {NumVeh=Multi, Contri\_Fac=Improper Turn, Commercial\_Motor\_Vehicle=Yes} | 0.001 | 1.00 | 40.5 | 10 |
| KA3 | {NumVeh=Multi, Commercial\_Motor\_Vehicle=Yes} | 0.001 | 0.43 | 17.4 | 7.07 |
| n/a | {PSL=65-70 MPH} | 0.002 | 0.06 | 2.38 | NA |
| KA4 | {PSL=65-70 MPH, Commercial\_Motor\_Vehicle=Yes} | 0.001 | 0.13 | 5.07 | 2.13 |
| KA5 | {PSL=65-70 MPH, Contri\_Fac=Improper Turn} | 0.001 | 0.12 | 4.77 | 2.00 |
| KA6 | {PSL=65-70 MPH, Contri\_Fac=Improper Turn, Seq\_Event=Other} | 0.001 | 0.30 | 12.16 | 2.55 |
| n/a | {Commercial\_Motor\_Vehicle=Yes} | 0.006 | 0.05 | 1.94 | NA |
| KA7 | {Commercial\_Motor\_Vehicle=Yes, Location=Four-Way Intersection} | 0.002 | 0.14 | 5.63 | 2.91 |
| KA8 | {Commercial\_Motor\_Vehicle=Yes, DrGen=Female} | 0.002 | 0.12 | 4.96 | 2.56 |
| KA9 | {Commercial\_Motor\_Vehicle=Yes, DrGen=Female, Functional\_Class=Interstate Route} | 0.001 | 0.38 | 15.20 | 3.06 |
| KA10 | {Commercial\_Motor\_Vehicle=Yes, VehTyp=Passenger Car} | 0.003 | 0.12 | 4.89 | 2.53 |
| KA11 | {Commercial\_Motor\_Vehicle=Yes, VehTyp=Passenger Car, Functional\_Class=Interstate Route} | 0.001 | 0.33 | 13.51 | 2.76 |
| n/a | {Lighting\_Condition=Dark - Roadway Not Lighted} | 0.003 | 0.04 | 1.58 | NA |
| KA12 | {Lighting\_Condition=Dark - Roadway Not Lighted, Location=Four-Way Intersection} | 0.001 | 0.13 | 5.07 | 3.20 |
| KA13 | {Lighting\_Condition=Dark - Roadway Not Lighted, Location=Four-Way Intersection, CrType=Angle} | 0.001 | 0.50 | 20.27 | 4.00 |
| n/a | {VehTyp=Semi-Tractor} | 0.002 | 0.03 | 1.40 | NA |
| KA14 | {VehTyp=Semi-Tractor, Location=Four-Way Intersection} | 0.001 | 0.27 | 11.06 | 7.91 |
| KA15 | {VehTyp=Semi-Tractor, Seq\_Event=Motor Vehicle In Transport} | 0.001 | 0.16 | 6.49 | 4.64 |

*Note: S = Support, C = Confidence, L = Lift, LIC = Lift Increase Criterion*

Multi-vehicle involvement was found to be a key factor associated with KA injuries in U-turn-related crashes. The basic association *{Number of Vehicles = Multi → Injury Severity = KA}* exhibited a lift of 2.46, indicating that such crashes were more than twice as likely to result in high-severity outcomes compared to the baseline. When improper turning behavior was introduced, *{Number of Vehicles = Multi, Contributing Factor = Improper Turn}*, the lift increased to 4.05 with a LIC of 1.65, indicating that the addition of turning errors to multi-vehicle crashes strengthened the association with KA injury outcomes. Rule KA2 further demonstrates that when commercial motor vehicle involvement was added, the lift rose sharply to 40.5 with a LIC of 10, suggesting that this third factor dramatically intensified the risk beyond the initial two-variable relationship. Even in the absence of improper turning, Rule KA3 shows that the combination of multi-vehicle crashes and commercial motor vehicles resulted in a lift of 17.4 (LIC = 7.07), reinforcing the substantial role of vehicle type and traffic complexity in severe U-turn crash outcomes. These patterns underscore the compounded danger presented by multiple interacting vehicles, particularly when large commercial vehicles are involved. This is supported by findings showing that multi-vehicle collisions not only occurred more frequently but also accounted for the majority of fatal crashes, reinforcing their critical role in high-severity outcomes (Hosseinpour et al., 2018; Milton and Mannering, 1998).

Posted speed limits between 65 and 70 MPH also appeared as a consistent severity factor, with the rule *{Posted Speed Limit = 65–70 MPH → Injury Severity = KA}* showing a lift of 2.38. This trend is further supported by findings that fatality rates increase with the rise in the posted speed limit, reinforcing the elevated risk associated with high-speed environments (Farmer, 2017). The addition of commercial motor vehicle presence, *{Posted Speed Limit = 65–70 MPH, Commercial Motor Vehicle = Yes}*, the lift increased to 5.07 with a LIC of 2.13. Pairing high-speed settings with improper turning behavior produced a lift of 4.77 (LIC = 2.00), and Rule KA6 shows that the addition of a non-standard sequence of events further raised the lift to 12.16 with a LIC of 2.55. Commercial motor vehicle involvement alone showed a moderate association (Lift = 1.94), but combinations with factors such as four-way intersections, female drivers, and interstate routes substantially amplified the severity. For instance, involvement at four-way intersections led to a lift of 5.63 (LIC = 2.91), while crashes involving commercial motor vehicles operated by female drivers or those occurring on interstate routes produced lifts of 4.96 and 15.20 with LIC values of 2.56 and 3.06, respectively. Lighting conditions further influenced crash outcomes. Crashes occurring on dark, unlighted roadways had a lift of 1.58, which increased to 5.07 (LIC = 3.20) when associated with four-way intersections. Rule KA13 highlights that the combination *{Lighting Condition = Dark - Roadway Not Lighted, Location = Four-Way Intersection, Crash Type = Angle}* resulted in a lift of 20.27 with a LIC of 4.00, emphasizing the significant amplification of risk under complex and low-visibility environments. Semi-tractors showed a moderate risk when considered individually (Lift = 1.40), but their involvement at intersections or during collisions involving moving vehicles considerably elevated the crash severity, reaching lifts of 11.06 and 6.49 and corresponding LIC values of 7.91 and 4.64, respectively.

### Crash Patterns Associated with BC-Level Injuries

This section outlines the association rules for BC injury outcomes in U-turn-related crashes. Table 3.4 summarizes 15 rules identifying conditions that contribute to moderate crash severity. Contributing factors include sideswipe collisions (BC1–BC3), posted speed limits of 45–60 MPH (BC4–BC7), improper turning (BC8–BC11), failure to yield (BC12–BC13), and the involvement of specific vehicle types, such as sport utility vehicles (BC14–BC15). These patterns reveal how combinations of roadway features, vehicle types, and behavioral conditions influence the probability of minor injury outcomes.

Table 3.4. Frequent Patterns Associated with BC Injuries in U-Turn Crashes.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **ID** | **Antecedent** | **S** | **C** | **L** | **LIC** |
| n/a | {CrType=Sideswipe} | 0.134 | 0.27 | 1.14 | NA |
| BC1 | {CrType=Sideswipe, VehTyp=Semi-Tractor} | 0.003 | 0.33 | 1.43 | 1.26 |
| BC2 | {CrType=Sideswipe, VehTyp=Semi-Tractor, PSL=30-40 MPH} | 0.001 | 1.00 | 4.29 | 3.00 |
| BC3 | {CrType=Sideswipe, VehTyp=Semi Tractor, Wthr\_Cond=Cloudy} | 0.001 | 0.50 | 2.15 | 1.5 |
| n/a | {PSL=45-60 MPH} | 0.072 | 0.27 | 1.14 | NA |
| BC4 | {PSL=45-60 MPH, Lighting\_Condition=Dark - Lighted Roadway} | 0.008 | 0.33 | 1.41 | 1.24 |
| BC5 | {PSL=45-60 MPH, Lighting\_Condition=Dark - Lighted Roadway, NumVeh=Multi} | 0.001 | 0.75 | 3.22 | 2.28 |
| BC6 | {PSL=45-60 MPH, Lighting\_Condition=Dark - Lighted Roadway, Location=T-Intersection} | 0.002 | 0.63 | 2.68 | 1.90 |
| BC7 | {PSL=45-60 MPH, Lighting\_Condition=Dark – Lighted Roadway, Contri\_Fac=Improper Lane Change} | 0.001 | 0.60 | 2.57 | 1.83 |
| n/a | {Contri\_Fac=Improper Turn} | 0.119 | 0.25 | 1.07 | NA |
| BC8 | {Contri\_Fac=Improper Turn, Location=T-Intersection} | 0.017 | 0.33 | 1.41 | 1.32 |
| BC9 | {Contri\_Fac=Improper Turn, Location=T-Intersection, Road\_Conition=Curve Level} | 0.001 | 1.00 | 4.29 | 3.04 |
| BC10 | {Contri\_Fac=Improper Turn, Location=T-Intersection, ThruLn=One} | 0.001 | 1.00 | 4.29 | 3.04 |
| BC11 | {Contri\_Fac=Improper Turn, Location=T-Intersection , Lighting\_Condition=Dawn/Dusk} | 0.001 | 0.57 | 2.45 | 1.74 |
| n/a | {Contri\_Fac=Failure To Yield} | 0.039 | 0.25 | 1.09 | NA |
| BC12 | {Contri\_Fac=Failure To Yield, DrGen=Male} | 0.024 | 0.28 | 1.18 | 1.09 |
| BC13 | {Contri\_Fac=Failure To Yield, DrGen=Male, Surface\_Cond=Snow} | 0.001 | 0.60 | 2.57 | 2.18 |
| n/a | {VehTyp=Sport Utility Vehicle} | 0.049 | 0.24 | 1.01 | NA |
| BC14 | {VehTyp=Sport Utility Vehicle, Lighting\_Condition=Dark - Lighted Roadway} | 0.011 | 0.32 | 1.39 | 1.37 |
| BC15 | {VehTyp=Sport Utility Vehicle, Lighting\_Condition=Dark - Lighted Roadway, Contri\_Fac=Improper Lane Change} | 0.001 | 0.67 | 2.86 | 2.07 |

*Note: S = Support, C = Confidence, L = Lift, LIC = Lift Increase Criterion*

The crash type "sideswipe" was found to be a key contributing factor for BC injuries during U-turn-related crashes. The rule *{Crash Type = Sideswipe → Injury Severity = BC}* has been identified as a 2-itemset rule (Lift = 1.137), suggesting that sideswipe crashes are slightly more likely to result in BC injuries compared to general crash conditions. The severity risk increased when sideswipe crashes involved semi-tractors, as shown in *{Crash Type = Sideswipe, Vehicle Type = Semi-Tractor}*, where the lift rose to 1.430 with a LIC of 1.26. Rule BC2 highlights that when semi-tractors were involved under posted speed limits of 30–40 MPH, the lift increased significantly to 4.291 (LIC = 3.00), indicating a strong compounding effect. This is consistent with previous findings showing that sideswipe collisions often result in more severe injuries than other same-direction crash types due to unexpected lateral impact and lane departure dynamics (Hua and Fan, 2023). Weather conditions also influenced severity outcomes, with Rule BC3 indicating that cloudy weather during such crashes raised the lift to 2.145 (LIC = 1.5).

Posted speed limits between 45 and 60 MPH were associated with an elevated risk of BC injury outcomes, with the rule *{Posted Speed Limit = 45–60 MPH → Injury Severity = BC}* identified as another 2-itemset rule (Lift = 1.137). When crashes under these speed limits occurred under dark but lighted roadway conditions, *{Posted Speed Limit = 45–60 MPH, Lighting Condition = Dark – Lighted Roadway}*, the lift increased to 1.410 (LIC = 1.24). Rule BC5 demonstrates that adding multi-vehicle involvement under these conditions further increased the lift to 3.218 (LIC = 2.28). Related combinations such as crashes at T-intersections and improper lane changes also showed elevated lifts between 2.5 and 2.7. Improper turns, when combined with T-intersections *{Contributing Factor = Improper Turn, Location = T-Intersection}*, produced a lift of 1.410 (LIC = 1.32), and Rule BC9 shows that further addition of curve-level roadway conditions raised the lift to 4.291 (LIC = 3.04). One through lane conditions resulted in a similar lift and LIC, while dawn or dusk lighting modestly amplified the risk. Failure to yield was another notable contributing factor to BC injuries. The 2-itemset *{Contributing Factor = Failure to Yield, Driver Gender = Male}* had a lift of 1.184 and a LIC of 1.09, indicating a modest increase in severity compared to the baseline. However, when snowy surface conditions were added, as in Rule BC13, the lift increased substantially to 2.574 with a LIC of 2.18. This demonstrated that adverse surface conditions, when combined with behavioral and demographic factors, significantly elevated the likelihood of BC-level outcomes. Sport utility vehicles also contributed to increased crash severity under specific environmental and behavioral contexts. The 2-itemset *{Vehicle Type = Sport Utility Vehicle, Lighting Condition = Dark – Lighted Roadway}* showed a lift of 1.386 and a LIC of 1.37. When improper lane changes were introduced to this combination, the lift rose to 2.860 with a LIC of 2.07, as reflected in Rule BC15. This pattern emphasized that maneuver-related errors involving certain vehicle types in reduced visibility conditions further amplified the risk of moderate injury crashes. This is consistent with prior research suggesting that sport utility vehicles due to their higher center of gravity, are more prone to rollovers, an outcome that increases the likelihood of severe occupant injuries during loss-of-control events (Khattak and Rocha, 2003).

### Crash Patterns Associated with O-Level Injuries

This section presents the association rules of O (no injury) crash outcomes identified from U-turn-related incidents. Table 3.5 displays 16 rules that describe the patterns leading to no-injury outcomes, focusing on combinations of environmental, behavioral, and roadway-related variables. The rules highlight several contributing factors, including collisions with parked vehicles (O1–O3), low posted speed limits (O4–O9), poor lighting conditions (O10–O12), and cloudy or adverse weather settings (O13–O16). These associations suggest specific roadway and visibility contexts, especially those involving single-vehicle crashes, wet or snowy surfaces, and reduced lighting—are more likely to result in crashes without reported injuries.

Table 3.5. Frequent Patterns Associated with O-Level U-Turn Crashes.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **ID** | **Antecedent** | **S** | **C** | **L** | **LIC** |
| n/a | {CrType=Parked Vehicle} | 0.027 | 0.92 | 1.24 | NA |
| O1 | {CrType=Parked Vehicle, Functional\_Class=Interstate Route} | 0.001 | 1.00 | 1.35 | 1.08 |
| O2 | {CrType=Parked Vehicle, Lighting\_Condition=Dawn/Dusk} | 0.001 | 1.00 | 1.35 | 1.08 |
| O3 | {CrType=Parked Vehicle, Surface\_Cond=Wet} | 0.003 | 1.00 | 1.35 | 1.08 |
| n/a | {PSL=25 MPH or less} | 0.251 | 0.80 | 1.08 | NA |
| O4 | {PSL=25 MPH or less, Contri\_Fac=Drove Off Road} | 0.016 | 0.86 | 1.16 | 1.08 |
| O5 | {PSL=25 MPH or less, Contri\_Fac=Drove Off Road, Lighting\_Condition=Dark - Roadway Not Lighted} | 0.004 | 1.00 | 1.35 | 1.16 |
| O6 | {PSL=25 MPH or less, Contri\_Fac=Drove Off Road, VehTyp=Semi-Tractor} | 0.001 | 1.00 | 1.35 | 1.16 |
| O7 | {PSL=25 MPH or less, NumVeh=Single} | 0.041 | 0.85 | 1.15 | 1.06 |
| O8 | {PSL=25 MPH or less, NumVeh=Single, Wthr\_Cond=Snow} | 0.001 | 1.00 | 1.35 | 1.17 |
| O9 | {PSL=25 MPH or less, NumVeh=Single, Functional\_Class=Interstate Route} | 0.001 | 1.00 | 1.35 | 1.17 |
| n/a | {Lighting\_Condition=Dark - Roadway Not Lighted} | 0.067 | 0.79 | 1.06 | NA |
| O10 | {Lighting\_Condition=Dark - Roadway Not Lighted, Surface\_Cond=Wet} | 0.019 | 0.87 | 1.17 | 1.1 |
| O11 | {Lighting\_Condition=Dark - Roadway Not Lighted, Surface\_Cond=Wet, DrImp=Yes} | 0.002 | 1.00 | 1.35 | 1.15 |
| O12 | {Lighting\_Condition=Dark - Roadway Not Lighted, Surface\_Cond=Wet, PSL=65-70 MPH} | 0.002 | 1.00 | 1.35 | 1.15 |
| n/a | {Wthr\_Cond=Cloudy} | 0.179 | 0.76 | 1.02 | NA |
| O13 | {Wthr\_Cond=Cloudy, PSL=25 MPH or less} | 0.058 | 0.83 | 1.12 | 1.1 |
| O14 | {Wthr\_Cond=Cloudy, PSL=25 MPH or less, Lighting\_Condition=Dark - Roadway Not Lighted} | 0.003 | 1.00 | 1.35 | 1.2 |
| O15 | {Wthr\_Cond=Cloudy, PSL=25 MPH or less, Object\_ Struck =Traffic Sign Post} | 0.001 | 1.00 | 1.35 | 1.2 |
| O16 | {Wthr\_Cond=Cloudy, PSL=25 MPH or less, Road\_Conition=Curve Grade} | 0.003 | 1.00 | 1.35 | 1.2 |

*Note: S = Support, C = Confidence, L = Lift, LIC = Lift Increase Criterion*

Collisions involving parked vehicles were found to be a key factor associated with O no injury outcomes during U-turn-related crashes. The rule *{Crash Type = Parked Vehicle → Injury Severity = O}* has been identified as a 2-itemset rule (Lift = 1.24), suggesting that crashes involving parked vehicles were slightly more likely to result in no injuries compared to other crash types. The severity likelihood slightly increased when additional roadway or environmental factors were considered. Crashes involving parked vehicles on interstate routes, during dawn or dusk lighting, or under wet surface conditions, all showed a lift of 1.35 with LIC values around 1.08, emphasizing that minor roadway and environmental conditions could incrementally enhance the no-injury likelihood. Similar findings have shown that the probability of possible or no injury increases when crashes occur off the main roadway, such as in parking lots or driveways (Kim et al., 2010).

Low-speed environments were also associated with higher probability of O-level outcomes. The rule *{Posted Speed Limit = 25 MPH or less → Injury Severity = O}* has been identified as another 2-itemset rule (Lift = 1.08). When driving off occurred under these low-speed zones, the lift increased to 1.16 (LIC = 1.08). Rule O5 highlights that the addition of driving off the roadway under dark, unlighted conditions raised the lift to 1.35 (LIC = 1.16), suggesting that reduced visibility compounded with driver error further promoted no-injury outcomes. Single-vehicle involvement at low speeds also produced a modest lift of 1.15 (LIC = 1.06), and when combined with snowy weather or interstate routes, the lift increased to 1.35 with LIC values around 1.17. Lighting condition was also found to be an influential factor in determining injury severity. The base rule *{Lighting Condition = Dark - Roadway Not Lighted → Injury Severity = O}* produced a lift of 1.06. When combined with wet surfaces, the lift increased to 1.17 with a LIC of 1.10, and further inclusion of driver impairment elevated the lift to 1.35 (LIC = 1.15), highlighting the compounding effect of visibility and behavioral risks. Cloudy weather conditions *{Weather Condition = Cloudy}* led to a baseline lift of 1.02, but Rule O14 demonstrates that when combined with low speeds and unlighted roadways, the lift again increased to 1.35 with a LIC of 1.20. Roadway design factors such as curve grades similarly maintained an elevated lift, reinforcing that roadway geometry and environmental risks influenced no-injury outcomes.

### Severity-Based Analysis of U-Turn Crash Patterns

This section focuses on identifying U-turn crash scenarios that result in KA injuries, using LIC as an indicator of elevated risk. Table 3.6 highlights how the interaction of vehicle involvement, roadway features, vehicle type, and demographic attributes influences injury severity. Multi-vehicle crashes appear as the mother rule, where the addition of commercial motor vehicle presence and improper turning behavior significantly increases the likelihood of severe outcomes. High-speed environments, dark roadways, and intersection complexity further compound these risks. Notably, the darkest red cells in the LIC column indicate the most critical combinations, such as multi-vehicle crashes involving both improper turns and commercial vehicles (LIC = 10.0), and semi-tractor crashes at four-way intersections (LIC = 7.91), underscoring scenarios where intervention is most urgently needed.

Table 3.6. Visualization of Factors Linked to KA Injuries.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **First Antecedent** | **Crash and Roadway Features** | **Vehicle Type** | **Demographic** | **LIC** |
| Multi-Vehicle Crash | Improper Turn |  |  | 1.65 |
| Improper Turn | Commercial Vehicle |  | 10.0 |
|  | Commercial Vehicle |  | 7.07 |
| Posted Speed Limit (65–70 MPH) |  | Commercial Vehicle |  | 2.13 |
| Improper Turn |  |  | 2.00 |
| Improper Turn, Other Event |  |  | 2.55 |
| Commercial Motor Vehicle | Four-Way Intersection |  |  | 2.91 |
|  |  | Driver Gender = Female | 2.56 |
| Interstate Route |  | Driver Gender = Female | 3.06 |
|  | Passenger Car |  | 2.53 |
| Interstate Route | Passenger Car |  | 2.76 |
| Lighting: Dark Roadway | Four-Way Intersection |  |  | 3.2 |
| Four-Way Intersection, Crash Type = Angle |  |  | 4.00 |
| Semi-Tractor Involvement | Four-Way Intersection |  |  | 7.91 |
| Motor Vehicle in Transport |  |  | 4.64 |

Table 3.7 highlights that sideswipe collisions, posted speed limits between 45–60 MPH, and improper turning behavior are key contributing factors to BC injury outcomes in U-turn crashes. Additional contributing conditions include dark-lighted roadway environments, T-intersections, and vehicle types such as semi-tractors and sport utility vehicles. Behavioral and demographic elements, including failure to yield by male drivers and improper lane changes during low-visibility conditions, are also associated with elevated BC injury risk.

Table 3.7. Visualization of Factors Linked to BC Injuries.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **First Antecedent** | **Crash and Roadway Features** | **Vehicle Type and Demographic** | **Environmental Factors** | **LIC** |
| Sideswipe Crash |  | Semi-Tractor |  | 1.26 |
| Posted Speed Limit = 30–40 MPH | Semi-Tractor |  | 3.00 |
|  | Semi-Tractor | Weather = Cloudy | 1.50 |
| Posted Speed Limit (45–60 MPH) |  |  | Lighting Condition = Dark – Lighted Roadway | 1.24 |
| Multi-Vehicle |  | Lighting Condition = Dark – Lighted Roadway | 2.28 |
| T-Intersection |  | Lighting Condition = Dark – Lighted Roadway | 1.90 |
| Improper Lane Change |  | Lighting Condition = Dark – Lighted Roadway | 1.83 |
| Improper Turn | T-Intersection |  |  | 1.32 |
| T-Intersection, Road Condition = Curve Level |  |  | 3.04 |
| T-Intersection, Thru Lane = One |  |  | 3.04 |
| T-Intersection |  | Lighting Condition = Dawn/Dusk | 1.74 |
| Failure to Yield |  | Driver Gender = Male |  | 1.09 |
|  | Driver Gender = Male | Surface Condition = Snow | 2.18 |
| Sport Utility Vehicle |  |  | Lighting Condition = Dark – Lighted Roadway | 1.37 |
| Improper Lane Change |  | Lighting Condition = Dark – Lighted Roadway | 2.07 |

Low-speed environments (≤25 MPH), parked vehicle collisions, and single-vehicle incidents are commonly associated with O (no injury) outcomes in U-turn crashes. As shown in Table 3.8, these crashes often occur under moderate-risk conditions, including wet surfaces, dark-unlighted roadways, or dawn/dusk lighting. Factors such as off-road deviations, roadway curvature, cloudy weather, and occasional driver impairment further characterize these scenarios. The presence of semi-tractors, lack of complex vehicle interactions, and simplified functional classes like interstate routes also contribute to outcomes where injuries are avoided.

Table 3.8. Visualization of Factors Linked to O No Injuries.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **First Antecedent** | **Crash and Roadway Features** | **Vehicle Type and Driver Condition** | **Environmental Factors** | **LIC** |
| Parked Vehicle Crash | Functional Class = Interstate Route |  |  | 1.08 |
|  |  | Lighting Condition = Dawn/Dusk | 1.08 |
|  |  | Surface Condition = Wet | 1.08 |
| Low Speed Zone (≤25 MPH) | Drove Off Road |  |  | 1.08 |
| Drove Off Road |  | Lighting Condition = Dark – Not Lighted | 1.16 |
| Drove Off Road | Semi-Tractor |  | 1.16 |
| Single Vehicle |  |  | 1.06 |
| Single Vehicle |  | Weather = Snow | 1.17 |
| Single Vehicle, Functional Class = Interstate Route |  |  | 1.17 |
| Dark, Unlighted Roadway |  |  | Surface Condition = Wet | 1.10 |
|  | Driver Impairment = Yes | Surface Condition = Wet | 1.15 |
| Speed Limit = 65–70 MPH |  | Surface Condition = Wet | 1.15 |
| Cloudy Weather | Speed Limit ≤ 25 MPH |  |  | 1.10 |
| Speed Limit ≤ 25 MPH |  | Lighting = Dark – Not Lighted | 1.20 |
| Speed Limit ≤ 25 MPH, Object Struck = Traffic Sign Post |  |  | 1.20 |
| Speed Limit ≤ 25 MPH, Road Condition = Curve Grade |  |  | 1.20 |

### Crash Narrative Review for Contextual Analysis

Narrative reports offer a valuable complement to rule-based analyses by providing contextual depth into how crash events unfold in real-world scenarios. This section synthesizes representative 20 crash narratives involving U-turn maneuvers, categorized by severity level: KA, BC and O. Each narrative was examined for roadway context, vehicle behavior, and fault patterns. Table 3.9 presents the structured summary of these crashes, identifying trends across multiple dimensions including location type, maneuver behavior, driver fault. To enrich the understanding of the patterns above, this study consider a few insights drawn from the qualitative review of crash narratives:

* Severity in lower-speed areas (KA narratives): Interestingly, several severe injury crashes in the narratives took place not on highways but on residential streets or rural local roads. In these instances, factors like limited visibility, steep grades, or unexpected maneuvers were key. For example, one narrative described a fatal crash where a driver was exiting a private driveway attempting a U-turn onto a rural road; due to a curve and trees obstructing the view, the driver pulled out and was struck by an oncoming vehicle at moderate speed, which tragically resulted in a fatal injury. This reinforces that even in lower speed zones, if sight lines are bad or drivers misjudge the situation, a severe outcome can occur.
* Moderate crashes and driver mistakes (BC narratives): The narratives frequently mentioned drivers attempting U-turns from the wrong lane (e.g., a vehicle in the rightmost lane of a multi-lane road trying to U-turn across other lanes) or making U-turns in places that caught other drivers off-guard. Many of these led to side-impact collisions that matched the ARM patterns for BC severity. For instance, a typical moderate crash narrative: “Driver A was southbound in the left lane and attempted to make a U-turn at an uncontrolled mid-block opening. Driver B, coming from behind in the adjacent lane, collided with Driver A’s vehicle in a sideswipe manner. Minor injuries reported.” Such real-world descriptions highlight that driver decision-making is a big factor and better road design, or control could reduce these incidents. Also, it underscores the need for public education on proper U-turn etiquette (for example, don’t try to U-turn from a through-lane when traffic is present; go to a safe location).
* No-injury mishaps (O narratives): The O-level narratives often read like odd anecdotes: a driver attempting a U-turn in a shopping plaza and hitting a light pole at 5 MPH, or a car doing a U-turn during a snowfall, spinning and ending up blocking the road without hitting anyone. These reinforce that low-speed, single-party incidents dominate the no-injury category. One insight is that some of these might be near-misses for something worse; for instance, had another car been nearby, the outcome might not have stayed property-only.

In summary, the narrative analysis corroborates the main themes discovered by ARM while adding context and confirming causal factors. They emphasize that human factors (like misjudgment and risk-taking) and environmental context (like hidden view or road layout) are behind the statistical associations. Recognizing these underlying causes is crucial for developing effective solutions.

Table 3.9. Narrative-Based Summary of U-Turn Crashes by Severity.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Severity Level** | **Road Context / Location** | **Fault Summary** | **U-Turn Behavior** | **Vehicle Interaction** | **Narrative Summary** |
| O | Intersection (rural road) | Failure to navigate | U-turn in intersection | No collision, off-road | Unit 1 performed a U-turn at an intersection, left the roadway, struck a ditch, and caused property damage. |
| O | Residential street | Loss of control on snow | Sudden U-turn | Rear-end by Unit 2 | Unit 1 spun out and did a U-turn in front of Unit 2; collision occurred due to lack of stopping time. |
| O | Highway median | Disoriented driving, prohibited area | U-turn in median | Single-vehicle crash | Unit 1 made a U-turn in a signed no U-turn zone and slid off into trees. |
| O | Intersection (urban) | Disputed maneuver | Unclear/suspected U-turn | Sweeper struck Unit 2 | Unit 1 (sweeper) possibly made a U-turn; unclear fault due to conflicting reports. |
| O | Signalized intersection | Failed pursuit | U-turn from red light | Struck by Unit 2 | Unit 1 attempted a U-turn to pursue violator and was hit by Unit 2. |
| O | Multilane road | Unsafe maneuver | U-turn across lanes | Sideswipe impact | Unit 2 began U-turn from turn lane and struck Unit 1. |
| O | Urban street | Improper U-turn | Mid-block U-turn | Side collision with Unit 2 | Unit 1 made a U-turn and was struck on the left by Unit 2. |
| BC | Urban two-lane road | Improper U-turn | U-turn into same lane | Struck by Unit 2 | Unit 1 attempted U-turn and was hit by Unit 2 in same travel lane. |
| BC | Mid-block urban road | Fleeing scene after U-turn | Mid-block U-turn | Side impact by Unit 2 | Unit 1 made a U-turn and was struck by Unit 2; fled scene after crash. |
| BC | Highway shoulder | Failure to yield | U-turn from roadside | Side collision | Unit 2 attempted U-turn from shoulder and was struck by Unit 1. |
| BC | Highway yard | Stuck after U-turn | U-turn across lanes | Trailer struck by Unit 2 | Unit 1 attempted U-turn, became stuck; Unit 2 struck trailer. |
| BC | Major road (Cincinnati Dayton Rd) | Failure to yield | U-turn in traffic | Hit by Unit 2 | Unit 1 made U-turn and was struck by Unit 2 in adjacent lane. |
| BC | Main road (Westwood Blvd) | Failure to yield | U-turn to opposite direction | Blinded driver impact | Unit 1 made U-turn and was struck by Unit 2; airbags affected driver visibility. |
| BC | Urban multilane road (University Ave) | Improper U-turn | U-turn from right lane | Unit 1 struck on left side by Unit 2 | Unit 1 attempted U-turn across lanes; struck by Unit 2 from left. |
| KA | Little York Rd | Loss of control | U-turn before ditch | Off-road crash | Unit 1 lost control during U-turn and ended up in ditch. |
| KA | Intersection on grade | Improper U-turn | Intersection U-turn on slope | T-bone crash | Unit 2 made U-turn on grade and was struck by Unit 1. |
| KA | Residential driveway | Failure to yield | Driveway U-turn | Hit by oncoming Unit 2 | Unit 1 exited driveway attempting U-turn and was struck by Unit 2. |
| KA | Private drive near highway | Unsafe reentry | Private driveway U-turn | Hit by Units 1 and 2 | Unit 3 made U-turn from private drive; struck by two vehicles. |
| KA | Highway berm | Failure to yield | Shoulder U-turn | Unit 1 swerved, off-road | Unit 2 made a U-turn; Unit 1 swerved and left roadway. |
| KA | Rural two-lane road | Unsafe pass and U-turn | Unexpected U-turn | Motorcyclist ejected | Unit 1 made U-turn while Unit 2 passed; ejected rider. |

### Major Findings

The study identifies critical factors contributing to U-turn-related crash severity, emphasizing how specific combinations of roadway, vehicle, environmental, and driver-related attributes influence injury outcomes. KA level injury is most associated with multi-vehicle crashes involving improper turning behavior, commercial motor vehicles, and high posted speed limits (65–70 MPH), particularly under dark and unlighted conditions at four-way intersections. Female drivers operating commercial vehicles and semi-tractor involvement at intersections also contribute to elevated risk. For BC level injury, sideswipe collisions in 45–60 MPH zones, especially involving semi-tractors or occurring at T-intersections, are key contributors. Additional risks arise from improper turns on curved or single-lane roads, as well as failure to yield by male drivers in poor weather. In contrast, O level (no-injury) crashes are largely linked to low-speed conditions (≤25 MPH), parked vehicle involvement, and single-vehicle scenarios under wet or low-visibility environments such as cloudy weather and dawn/dusk lighting. These findings underscore the importance of targeted interventions such as speed regulation, intersection redesign, and enhanced lighting to mitigate crash severity across varying roadway conditions.

## Conclusions

This study contributes to understanding U-turn-related crashes by applying ARM to uncover critical patterns in crash data from Ohio (2017–2021). The analysis identifies distinct crash scenarios, where high-risk conditions involve multi-vehicle interactions, improper turning maneuvers, high-speed environments, commercial motor vehicle involvement, and poor lighting at complex intersections, while lower-risk crashes are associated with low-speed, single-vehicle events under less complex roadway conditions. The methodological contribution lies in leveraging ARM to identify key multi-attribute relationships among categorical variables without relying on rigid statistical assumptions. By systematically uncovering hidden interactions within multidimensional crash datasets, the study provides a clear depiction of underlying crash patterns, enabling a deeper understanding of contributing factors often overlooked by traditional analyses. This approach bridges the gap between data complexity and practical roadway safety interventions, offering actionable knowledge for targeted engineering and policy strategies.

Key findings reveal that KA injuries are closely associated with multi-vehicle crashes involving improper turning behavior, particularly when combined with commercial motor vehicle involvement and high posted speed limits (65–70 MPH). Poor lighting conditions at complex intersections further exacerbate the severity of these crashes. BC injuries are frequently linked to sideswipe collisions occurring in moderate-speed zones (45–60 MPH), especially under dark-lighted conditions and at T-intersections with geometric constraints. Improper lane changes and failure to yield by male drivers also contribute to moderate injury outcomes. O (no injury) crashes are commonly associated with low-speed environments (≤25 MPH), involving single-vehicle incidents, collisions with parked vehicles, and adverse environmental conditions such as wet or snowy road surfaces. Environmental and roadway factors, such as poor lighting and curve-level roads, are also common contributors to non-injury events. Crash narrative analysis was conducted using a sample of police-reported descriptions from crash reports to validate some of the findings.

The results highlight the need for interventions designed for different roadway environments and crash scenarios. Strategies such as implementing dedicated U-turn lanes or bays, enhancing signage and pavement markings, improving lighting infrastructure at intersections, and applying dynamic speed management tools can significantly mitigate crash severity, particularly in high-risk corridors. In moderate-risk environments, addressing improper turning behaviors through roadway design improvements and public education campaigns is essential. In lower-speed areas, traffic calming measures, clearer markings, and designated U-turn spaces can enhance maneuverability and reduce conflicts. Strengthening roadside infrastructure through barriers or stabilized shoulders can also minimize the severity of single-vehicle departures.

While the study contributes valuable insights, several limitations should be acknowledged. The analysis is based on historical crash report data, which may not fully capture dynamic factors such as real-time driver behavior, temporary traffic conditions, or localized environmental influences. Additionally, critical variables such as driver distraction, fatigue, and near-miss incidents were not available in the dataset, potentially limiting the behavioral analysis. The study also focuses specifically on U-turn crash events, without examining broader traffic interactions along adjacent corridors or intersections. Moreover, although some crash events in the dataset may have occurred at alternative or innovative intersections such as RCUTs or MUTs, the dataset was not primarily composed of such intersection types. Furthermore, the categorical nature of the dataset constrained the analysis of continuous or socioeconomic variables that may also influence crash outcomes.

Future research should aim to integrate richer datasets, including real-time traffic, weather, and sensor-based telemetry data, to capture a more dynamic and comprehensive understanding of crash causation. Expanding the analytical scope to include intersection- and corridor-level crash patterns and adopting predictive modeling techniques could further enhance proactive safety strategies. The application of ARM in this study demonstrated its effectiveness in revealing complex multi-factor crash dynamics, offering a valuable framework for informing data-driven roadway safety improvements and targeted interventions to reduce U-turn-related crash risks.

# CLUSTER CORRESPONDENCE ANALYSIS

**IV.**

## Introduction

Crashes involving U-turn maneuvers pose significant safety risks, especially in high-traffic environments where drivers may misjudge the distance or speed of oncoming vehicles. U-turns, particularly in high-traffic or unsignalized areas, introduce complex traffic maneuvers that increase the likelihood of conflict with oncoming vehicles, leading to elevated crash risks (Schneider et al., 2019). According to data from the Federal Highway Administration (FHWA), U-turn and left-turn maneuvers at unsignalized median openings have a crash rate of approximately 0.41 crashes per opening per year in urban areas and 0.20 in rural areas, underscoring the relative frequency of these incidents (FHWA, 2023).

As urbanization and traffic volumes continue to grow, U-turns are becoming an increasingly common traffic maneuver, making their safety implications a critical area of research. In efforts to mitigate these risks, innovative intersection designs have proven beneficial. Studies suggest that replacing direct left turns with right-turn-plus-U-turn configurations can significantly reduce crash rates by as much as 17.8% and decrease injury and fatality rates by 27.3% on major arterials, demonstrating the safety benefits of intersection redesign (Lu et al., 2001). In previous studies, researchers used before-and-after crash data and statistical methods to evaluate the effectiveness of intersection design changes (Ott et al., 2012). By applying methods such as the Empirical Bayes approach, studies have isolated the impact of design modifications on safety outcomes (Edara et al., 2015). Additionally, traffic flow and capacity analyses across intersection types have demonstrated that managing U-turn movements can improve both traffic efficiency and safety (Fan et al., 2014; Liu et al., 2008b). Analytical models and simulation tools have shown promise in optimizing intersection flow and reducing conflict points, contributing to safer environments for U-turns. However, despite these findings, a substantial gap remains in understanding the broader set of factors influencing U-turn crashes. While much of the existing research focuses on roadway design and flow management, it often fails to account for the complex interactions between driver demographics, roadway characteristics, environmental conditions, and temporal factors in real-world crash scenarios.

To address these gaps, this study employs Correspondence Cluster Analysis (CCA), a novel method for analyzing categorical data in multidimensional datasets (Rahman et al., 2022). Through clustering, CCA identifies key factors associated with intersection types, roadway conditions, and driver behaviors, providing a multidimensional understanding of U-turn crash dynamics. U-turn crashes often involve complex interactions that heighten the risk of severe injuries and fatalities, particularly in high-speed or high-traffic environments where drivers struggle to accurately judge the speed and distance of oncoming vehicles. Challenges such as inadequate intersection design, poor visibility, and dense traffic further exacerbate these risks, frequently resulting in multi-vehicle collisions with severe consequences. Unlike traditional statistical approaches, CCA enables the exploration of intricate attribute relationships, revealing nuanced insights into the underlying conditions that contribute to U-turn crashes. By systematically clustering attributes, CCA not only uncovers latent patterns but also helps to identify critical risk factors that may otherwise go unnoticed in conventional analyses. This understanding is critical for developing evidence-based safety protocols, optimizing intersection layouts, and implementing targeted public safety measures. By applying CCA to analyze these dynamics, this study aims to inform data-driven policy interventions and guide improvements in intersection design, ultimately reducing crash risks and enhancing road safety for all users.

### U-Turn Safety Challenges

Conflicts and crash risks associated with U-turns at median openings have been a focal point in research aimed at improving safety and design practices. One study analyzed U-turns at uncontrolled median openings, highlighting the complexity of critical gap acceptance influenced by driver frustration, varied gap acceptance across vehicle types, and significant traffic volumes (Sharma et al., 2017). Data collected from six median openings were used to estimate critical gap requirements using traditional, Influence Area for Gap Acceptance (INAFOGA), and Modified Raff’s methods, comparing their effectiveness and reliability. Another study emphasized the importance of critical gap acceptance for U-turn safety at mid-block median openings, noting that tighter gaps led to unpredictable interactions and increased crash potential (Khan et al., 2021). The study determined minimum safe gaps for various vehicle types using methods such as Modified Raff, Ashworth, Occupancy Time, and Binary Logit models to inform safer design practices. J-turn safety was analyzed using a driving simulator, demonstrating that an acceleration–deceleration lane configuration reduced critical events by 66.3% compared to a deceleration-only setup (Sun et al., 2017). The study also noted that shorter U-turn spacing intensified lane changes, leading to a higher likelihood of conflicts and safety-critical events. Another study used vehicle trajectory data and binary logit models to estimate gap acceptance probabilities, considering factors like gap size, median width, and opening distance (Dung and Hoi, 2022). The findings indicated that wider medians could obstruct sight lines, while aggressive gap acceptance and minimal time-to-collision gaps significantly increased collision risk. Similarly, U-turn headway acceptance at unsignalized intersections was studied, showing that narrow medians and limited turning space raised crash likelihood due to larger gap requirements and the potential for vehicle encroachment (Liu et al., 2007).

Focusing on the impact of U-turns and modified intersection designs on traffic safety and congestion provides critical insights for improving road infrastructure. A cellular automaton (CA) model was used to analyze the impact of U-turn movements on congestion and vehicle interactions at intersections, finding that such movements increased average control delay and heightened the risk of rear-end collisions due to sudden braking (Fan et al., 2014). Furthermore, using VISSIM and SSAM, rural unsignalized restricted crossing U-turn (RCUT) intersections, where direct through and left-turn movements from the minor road are prohibited, requiring drivers to turn right and then make a U-turn at a designated median opening, were studied (Olarte et al., 2011). The analysis revealed that increased traffic volumes amplified merging and weaving conflicts, notably rear-end and lane-change collisions. The study identified critical conflict zones within RCUTs. Another study applied crash modification factors (CMFs) and a before-after empirical Bayes study for RCUT intersections, as well as a cross-sectional approach for MUT sites, finding that these designs effectively reduced severe crashes by relocating conflict points but increased single-vehicle and non-motorized crashes due to inadequate signalization and pedestrian crosswalks at MUT crossovers (Al-Omari et al., 2020). Critical gap acceptance at U-turn median openings in Hyderabad City, India, was analyzed, comparing the modified INAFOGA method with the probability equilibrium method. The findings suggested the modified INAFOGA method was better suited for mixed traffic conditions due to higher critical gap values (Pannela and Bhuyan, 2017). In a related study, the impact of substituting left turns with U-turns at roundabouts was analyzed, calculating delays and vehicle queues, and it was concluded that such substitutions increased delays on other approaches, reducing intersection capacity and potentially hindering community development (Lobază, 2022). RCUT intersections were compared to conventional stop-controlled intersections in Maryland through operational and crash analyses, and it was found that RCUTs led to a 28% to 44% reduction in crashes and lower crash severity using a 3-year before-after analysis, adjusted comparisons, and the empirical Bayes method Inman et al. (2013).

Analyzing U-turn safety and intersection configurations is essential for understanding and mitigating conflicts and the risks associated with vehicle interactions, congestion, and collision potential. The Surrogate Safety Assessment Model (SSAM), combined with VISSIM simulations, was used to evaluate safety at different U-turn offset lengths, finding that insufficient offsets increased lane-changing conflicts and collision risks (Xu et al., 2017). Similarly, a Cooperative Vehicle Infrastructure System (CVIS) was developed to simulate interactions between U-turning and oncoming vehicles, considering variables like waiting times and vehicle priority. The results revealed that conflicts often occurred when U-turning vehicles experienced long waits or lacked cooperation from oncoming traffic, especially at high arrival rates, leading to delays and risky maneuvers (Wu et al., 2020). Superstreet designs were examined, and it was noted that unconventional crossing paths, such as diagonal and midblock crossings, could confuse pedestrians and cyclists, increasing collision risks and posing challenges for those with limited mobility or visibility (Holzem et al., 2015). These issues raised the likelihood of side-swipe or rear-end collisions as cyclists merged with faster traffic after U-turns. In a different study, citation data from 2011 to 2016 for traversable medians and emergency crossovers were analyzed using a sequential Poisson regression model with LASSO and logistic regression. The findings identified that illegal U-turns on limited-access roads often led to rear-end, sideswipe, and head-on collisions, primarily due to drivers misjudging gaps, underestimating the speed of oncoming vehicles, or losing control during high-speed maneuvers (Al-Sahili et al., 2018).

Several studies have identified a wide range of factors contributing to the high crash risk associated with U-turn movements. Geometric and operational design deficiencies—such as narrow median openings, insufficient turning radii, short weaving distances, and lack of deceleration lanes—have been linked to increased crash frequencies (Carter et al., 2005; Liu et al., 2008a; Meel et al., 2016). Inadequate spacing between U-turns and driveways has also been found to elevate conflict potential, while well-designed offset distances can help reduce crash rates (Liu et al., 2008a). Driver behavior also plays a critical role, as aggressive driving, noncompliance with traffic rules, and poor gap acceptance are common, particularly in settings with weak enforcement (Ulak et al., 2020; Zubair and Shaikh, 2015). Sudden lane changes—often triggered by unclear signage or confusing layouts—further contribute to U-turn-related risks (Zubair and Shaikh, 2015), and the dangers are compounded by high approach speeds and limited driver awareness where infrastructure fails to guide movements appropriately (Shahdah and Azam, 2021). Environmental and contextual factors also influence crash outcomes; in low- and middle-income countries, the combination of substandard infrastructure and limited enforcement significantly worsens safety at U-turn facilities (Ulak et al., 2020), while high-speed, unsignalized roads pose elevated risks for angle and rear-end collisions (Mishra and Pulugurtha, 2022). Seasonal and weather-related factors also significantly influence crash risk and severity. Fatality rates tend to peak in October and drop in March (Sivak, 2009). Rain and snow are associated with increased fatal crash risk, though the first snowfall of the season may raise injury-only crashes due to driver adaptation (Eisenberg and Warner, 2005; Stevens et al., 2019). Extreme heat and rainy conditions have been linked to elevated crash likelihood, particularly in single-vehicle incidents (Jung et al., 2010; Nazif-Munoz et al., 2025). Additionally, crash frequencies increase in summer months due to higher exposure and recreational travel (Weast, 2018). Recent findings indicate that rainfall during the rainy season leads to smaller increases in crash risk compared to rainfall during the dry season, likely due to heightened driver caution (Hsu, 2024). Moreover, high temperatures combined with high humidity have been shown to further elevate crash risk, suggesting that weather stressors may amplify one another’s effects. In response, a variety of countermeasures have been introduced. Geometric strategies such as RCUTs, MUTs, and RTUTs simplify movements and eliminate direct conflict points, resulting in significant reductions in crash frequency and severity (Kay et al., 2022; Pirinccioglu et al., 2006; Sun et al., 2019a), and design features like extended weaving zones, deceleration lanes, and wider turning radii further mitigate crash risk (Carter et al., 2005; Meel et al., 2017). In tandem, behavioral and enforcement approaches—such as protected signal phases, clearer lane-change guidance, and active enforcement of speed and turning violations—have proven effective in encouraging safer U-turn behavior (Shafie and Rahman, 2016; Stamatiadis et al., 2004; Zubair and Shaikh, 2015). Emerging technologies provide further support through tools like IR sensors and ultrasonic alerts that improve driver awareness (Mullani et al., 2022; Sivaprakash and John, 2024), predictive analytics for identifying high-risk areas (Molan et al., 2022), and adaptive signal control systems to reduce pedestrian and vehicle conflicts (Abdel-Aty et al., 2020; Kittelson and Associates, 2021).

### CCA in Transportation Safety Research

CCA has emerged as a powerful analytical tool in transportation safety research, enabling the discovery of hidden structures among categorical crash data and supporting the design of targeted safety interventions. The application of correspondence-based methods in this field began with studies using Multiple Correspondence Analysis (MCA), which provided a framework for associating driver behavior, roadway conditions, and environmental factors in fatal crash patterns. One of the earliest examples examined fatal run-off-road crashes in Louisiana and revealed strong associations with driver age, road type, vehicle class, and impaired driving (Das and Sun, 2016). MCA was later applied to analyze wrong-way driving crashes, identifying sixteen significant clusters tied to lighting, roadway separation, signage, and local context (Das et al., 2018a). In another early contribution, pedestrian crash data from Louisiana were used to identify nontrivial clusters related to gender, vehicle occupancy, roadway design, and nighttime lighting conditions, further validating MCA’s strength in pattern recognition for categorical safety data (Das and Sun, 2015). Building on these early applications, researchers applied CCA to analyze single-vehicle roadway departure crashes on rural curved segments, generating interpretable clusters to guide safety improvements (Hossain et al., 2024). Similarly, CCA was employed to examine nighttime pedestrian fatalities in India, using scenario-based clustering to capture contextual crash dynamics (Rangam et al., 2024). In a global context, MCA was used alongside kernel density estimation to study pedestrian crashes in Malta, identifying spatiotemporal injury risks across different age groups and crash settings (Bajada and Attard, 2021).

Recent studies demonstrate CCA’s versatility in addressing a range of crash types, populations, and behavioral factors. Analysis of light delivery vehicle crashes in Louisiana yielded six clusters reflecting fatigue, alcohol impairment, youth involvement, and road type (Das et al., 2021a), while national HAZMAT crash data revealed fatality clusters tied to collision types, road geometry, and weather conditions (Sun and Zhou, 2023). Researchers also extended MCA to the study of AV perceptions using survey responses from non-motorists in Pittsburgh, uncovering stakeholder-based differences in safety views and technology adoption (Das et al., 2020a). More recently, a hybrid CCA and machine learning framework was applied to child bicyclist crashes in Texas, identifying six data-driven clusters shaped by lighting, driver behavior, intersection control, and rural road infrastructure (Chakraborty et al., 2025b). Barrier-related crash analysis using CCA exposed key risk conditions including dry weather, absence of traffic control, and driver distraction across over 63,000 Texas crashes (Chakraborty et al., 2025a). Additionally, a Utah-based study on motorcyclist crash severity integrated CCA clustering with hierarchical binary logit modeling, showing that temporal factors, road alignment, and rider age were significant predictors of injury outcomes (Dzinyela et al., 2025).

## Data

### Exploratory Data Analysis

The dataset utilized in this study comprises 2,716 U-turn-related crash observations recorded in Ohio, U.S., between 2017 and 2021, classified according to the KABCO severity scale. For analytical purposes, the five severity levels were consolidated into three broader categories: severe injuries (SI), minor injuries (MI), and no injuries (NI). Crash severity is closely linked to the fundamental physics of collisions, where kinetic energy (*½mv²*) plays a critical role, meaning severity increases exponentially with speed (*v²*) and linearly with mass. Additionally, the angle of collision (e.g., head-on vs. sideswipe) affects deceleration forces, with head-on collisions typically resulting in greater severity than sideswipes due to higher energy transfer. Gap acceptance is influenced by traffic volumes, which dictate the frequency and duration of available gaps for drivers to execute maneuvers safely. However, traffic volume data were not included as an independent variable in this investigation due to unavailability of comprehensive and location-specific traffic volume records for the analyzed sites. In the absence of reliable volume data, this study focused on other crash, vehicle, roadway and environment related data. Table 4.1 displays the percentage distribution of key attributes across these categories, with 67 incidents classified as SI, 633 as MI, and 2,016 as NI. Among the attributes, crash type significantly impacts severity, with angle crashes accounting for 37.3% of SI outcomes but only 26.7% of NI crashes. In contrast, sideswipe crashes are more common in NI incidents (48.7%) than in SI crashes (44.8%), indicating that crash type is a pivotal determinant of injury severity. The presence of commercial motor vehicles (p < 0.001) is disproportionately associated with severe crashes, contributing to 22.4% of SI cases compared to 12.5% in NI crashes. Lighting conditions also demonstrate a strong influence (p < 0.001). Dark, unlit roadways are involved in 13.4% of SI crashes, compared to 9.03% in NI crashes. Daylight conditions dominate all severity categories but are slightly less associated with severe crashes (67.2%) than with NI crashes (70.3%). Roadway type is another critical factor, with two-way roadways contributing to 64.2% of SI crashes, emphasizing their role in crash severity. Driver demographics further highlight disparities, with male drivers involved in 67.2% of SI crashes compared to 57% in NI crashes. Driver impairment, although infrequent, is more prominent in SI outcomes (4.48%) than in NI incidents (2.03%), underscoring its impact on severe injuries. Road surface conditions also play a role, with crashes on dry roads dominating across all severity levels. However, wet surfaces are more frequently associated with NI crashes (19.7%) than with SI crashes (2.99%), indicating the influence of surface conditions on crash outcomes. Speed limits significantly affect crash outcomes, with 45–60 mph limits contributing to 50.7% of SI crashes but only 25.1% of NI incidents. This highlights the elevated risk of severe injuries in high-speed environments. Additionally, crashes at four-way intersections are more prevalent in SI outcomes (19.4%) than in NI incidents (16%), indicating the complexity and risk associated with these locations.

The p-value column, derived from the chi-square test, indicates whether the distribution of each variable significantly differs across the three severity categories. A low p-value (p < 0.05) suggests that the variable is strongly associated with crash severity and warrants further attention in subsequent analyses. For instance, lighting conditions and commercial motor vehicles exhibit significant p-values, highlighting their importance in influencing crash outcomes. The p-value column, therefore, guides the identification of critical variables that should be prioritized for deeper exploration, modeling, and policy development. This approach ensures that the most relevant factors are used to inform targeted safety interventions.

Table 4.1. Distribution of Variable Categories by Severity Group.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable Category** | Severe Injury  N=67 | Minor Injury  N=633 | No Injury  N=2016 | p-val |
| **Crash Type (CrType)** |  |  |  | . |
| Angle | 25 (37.3%) | 194 (30.6%) | 539 (26.7%) |  |
| Fixed Object | 2 (2.99%) | 30 (4.74%) | 281 (13.9%) |  |
| Other | 10 (14.9%) | 38 (6.00%) | 141 (6.99%) |  |
| Parked Vehicle | 0 (0.00%) | 6 (0.95%) | 73 (3.62%) |  |
| Sideswipe | 30 (44.8%) | 365 (57.7%) | 982 (48.7%) |  |
| **Road facility type (Facility)** |  |  |  | 0.043 |
| One Way Roadway | 0 (0.00%) | 4 (0.63%) | 13 (0.64%) |  |
| Other | 24 (35.8%) | 350 (55.3%) | 1114 (55.3%) |  |
| Ramp | 0 (0.00%) | 5 (0.79%) | 22 (1.09%) |  |
| Two Way Roadway | 43 (64.2%) | 274 (43.3%) | 867 (43.0%) |  |
| **Commercial Motor Vehicle (Commercial\_Motor\_Vehicle )** |  |  |  | <0.001 |
| No | 52 (77.6%) | 586 (92.6%) | 1764 (87.5%) |  |
| Yes | 15 (22.4%) | 47 (7.42%) | 252 (12.5%) |  |
| **Lighting Condition (Lighting\_Condition)** |  |  |  | . |
| Dark - Lighted Roadway | 12 (17.9%) | 123 (19.4%) | 322 (16.0%) |  |
| Dark - Roadway Not Lighted | 9 (13.4%) | 40 (6.32%) | 182 (9.03%) |  |
| Dawn/Dusk | 1 (1.49%) | 25 (3.95%) | 82 (4.07%) |  |
| Daylight | 45 (67.2%) | 444 (70.1%) | 1418 (70.3%) |  |
| Other / Unknown | 0 (0.00%) | 1 (0.16%) | 12 (0.60%) |  |
| **Number of vehicles (NumVeh)** |  |  |  | . |
| Multi | 4 (5.97%) | 21 (3.32%) | 41 (2.03%) |  |
| Single | 8 (11.9%) | 39 (6.16%) | 370 (18.4%) |  |
| Two | 55 (82.1%) | 573 (90.5%) | 1605 (79.6%) |  |
| **Location (Location)** |  |  |  | . |
| Four-Way Intersection | 13 (19.4%) | 109 (17.2%) | 322 (16.0%) |  |
| Not An Intersection | 47 (70.1%) | 424 (67.0%) | 1397 (69.3%) |  |
| Other | 3 (4.48%) | 22 (3.48%) | 96 (4.76%) |  |
| T-Intersection | 4 (5.97%) | 78 (12.3%) | 201 (9.97%) |  |
| **Road Surface Condition (Surface\_Cond)** |  |  |  | . |
| Dry | 65 (97.0%) | 512 (80.9%) | 1569 (77.8%) |  |
| Other / Unknown | 0 (0.00%) | 3 (0.47%) | 13 (0.64%) |  |
| Snow | 0 (0.00%) | 9 (1.42%) | 37 (1.84%) |  |
| Wet | 2 (2.99%) | 109 (17.2%) | 397 (19.7%) |  |
| **Road Condition (Road\_Condition)** |  |  |  | . |
| Curve Grade | 3 (4.48%) | 17 (2.69%) | 63 (3.12%) |  |
| Curve Level | 1 (1.49%) | 19 (3.00%) | 45 (2.23%) |  |
| Other / Unknown | 0 (0.00%) | 0 (0.00%) | 3 (0.15%) |  |
| Straight Grade | 17 (25.4%) | 117 (18.5%) | 337 (16.7%) |  |
| Straight Level | 46 (68.7%) | 480 (75.8%) | 1568 (77.8%) |  |
| **Contributing Factors (Contri\_Fac)** |  |  |  | . |
| Drove Off Road | 0 (0.00%) | 12 (1.90%) | 104 (5.16%) |  |
| Failure To Yield | 13 (19.4%) | 106 (16.7%) | 300 (14.9%) |  |
| Improper Lane Change | 4 (5.97%) | 52 (8.21%) | 179 (8.88%) |  |
| Improper Turn | 33 (49.3%) | 322 (50.9%) | 939 (46.6%) |  |
| Other | 17 (25.4%) | 141 (22.3%) | 494 (24.5%) |  |
| **Driver Gender (DrGen)** |  |  |  | <0.001 |
| Female | 18 (26.9%) | 214 (33.8%) | 629 (31.2%) |  |
| Male | 45 (67.2%) | 393 (62.1%) | 1150 (57.0%) |  |
| Unknwon | 4 (5.97%) | 26 (4.11%) | 237 (11.8%) |  |
| **Driver impairment (DrImp)** |  |  |  | 0.221 |
| No | 64 (95.5%) | 617 (97.5%) | 1975 (98.0%) |  |
| Yes | 3 (4.48%) | 16 (2.53%) | 41 (2.03%) |  |
| **Number of Through Lanes (ThruLn)** |  |  |  | . |
| Multi | 12 (17.9%) | 197 (31.1%) | 465 (23.1%) |  |
| One | 2 (2.99%) | 19 (3.00%) | 68 (3.37%) |  |
| Two | 53 (79.1%) | 417 (65.9%) | 1483 (73.6%) |  |
| **Object struck (Object)** |  |  |  | . |
| Ditch | 1 (1.49%) | 5 (0.79%) | 80 (3.97%) |  |
| Nothing Struck | 60 (89.6%) | 581 (91.8%) | 1709 (84.8%) |  |
| Other | 6 (8.96%) | 34 (5.37%) | 162 (8.04%) |  |
| Traffic Sign Post | 0 (0.00%) | 3 (0.47%) | 42 (2.08%) |  |
| Utility Pole | 0 (0.00%) | 10 (1.58%) | 23 (1.14%) |  |
| **Posted speed limit (PSL)** |  |  |  | . |
| 25 MPH or less | 11 (16.4%) | 159 (25.1%) | 683 (33.9%) |  |
| 30-40 MPH | 17 (25.4%) | 260 (41.1%) | 765 (37.9%) |  |
| 45-60 MPH | 34 (50.7%) | 195 (30.8%) | 507 (25.1%) |  |
| 65-70 MPH | 5 (7.46%) | 19 (3.00%) | 61 (3.03%) |  |
| **Sequence of events (Seq\_Event)** |  |  |  | . |
| Cross Centerline OD of Travel | 7 (10.4%) | 24 (3.79%) | 70 (3.47%) |  |
| Motor Vehicle in Transport | 44 (65.7%) | 534 (84.4%) | 1462 (72.5%) |  |
| Other | 13 (19.4%) | 45 (7.11%) | 178 (8.83%) |  |
| Parked Motor Vehicle | 0 (0.00%) | 4 (0.63%) | 72 (3.57%) |  |
| Ran Off Road | 3 (4.48%) | 26 (4.11%) | 234 (11.6%) |  |
| **Vehicle type (VehTyp)** |  |  |  | . |
| Other | 22 (32.8%) | 82 (13.0%) | 247 (12.3%) |  |
| Passenger Car | 31 (46.3%) | 363 (57.3%) | 1036 (51.4%) |  |
| Pick Up | 4 (5.97%) | 46 (7.27%) | 180 (8.93%) |  |
| Semi-Tractor | 5 (7.46%) | 10 (1.58%) | 130 (6.45%) |  |
| Sport Utility Vehicle | 5 (7.46%) | 132 (20.9%) | 423 (21.0%) |  |
| **Weather condition (Wthr\_Cond)** |  |  |  | . |
| Clear | 55 (82.1%) | 414 (65.4%) | 1254 (62.2%) |  |
| Cloudy | 12 (17.9%) | 144 (22.7%) | 486 (24.1%) |  |
| Other | 0 (0.00%) | 2 (0.32%) | 20 (0.99%) |  |
| Rain | 0 (0.00%) | 59 (9.32%) | 210 (10.4%) |  |
| Snow | 0 (0.00%) | 14 (2.21%) | 46 (2.28%) |  |
| **Arterial Expressway (Arterial\_Expressway)** |  |  |  | 0.064 |
| No | 26 (38.8%) | 234 (37.0%) | 850 (42.2%) |  |
| Yes | 41 (61.2%) | 399 (63.0%) | 1166 (57.8%) |  |

### Spatial Distribution

Figure 4.1 depicts the spatial distribution and density of U-turn-related crashes across Ohio from 2017 to 2021, categorized by crash severity: SI, MI, and NI. It is found that SI crashes are concentrated in specific urban and suburban areas, particularly in the northeastern and southwestern regions of Ohio. These clusters highlight regions with higher traffic complexity and potentially inadequate safety measures. The MI panel reveals a broader distribution of crashes, with notable densities in mid-sized urban centers and surrounding areas, reflecting their occurrence in a variety of roadways and traffic environments. The NI panel demonstrates the most widespread distribution, with the densest clusters observed in major metropolitan areas such as Columbus, Cleveland, and Cincinnati. This pattern indicates that low-severity crashes are more prevalent in high-traffic urban regions, where minor collisions and property damage incidents are common. The density heatmap uses green gradients to represent crash density, with darker shades indicating areas of higher concentration.

A map of different regions

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Figure 4.1. Density Maps of U-turn Crashes in Ohio by Crash Severity Level.

This Cramér’s V heatmap in Figure 4.2 illustrates the strength of association between pairs of categorical variables in the U-turn crash dataset. Most variable pairs demonstrate low to moderate correlation (Cramér’s V < 0.3), indicating limited multicollinearity among predictors. However, a few pairs exhibit modest associations, for instance, weather condition and surface condition, vehicle type and commercial motor vehicle involvement, and sequence of events and crash type reflecting expected contextual overlaps.

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Figure 4.2. Cramer’s V Correlation Plot.

## Methodology

CCA is a well-established method for categorical data analysis. CCA investigates the connections between categorical variables (Sourial et al., 2010). This method is intended for the analysis of categorical data, and its primary objective is to identify meaningful clusters in the dataset by utilizing a predetermined set of observable factors. More specifically, CCA seeks to increase the variance across groups by determining cluster allocations and scaling values for categories of categorical variables. The CCA approach was initially presented by (van de Velden et al., 2017). This method is created by joining correspondence analysis and K-means cluster analysis. This obtains a cluster allocation as well as optimal scaling values (i.e., coordinates) for the categories of p categorical variables maximizing variation between the groups. The cluster allocation and category weights (i.e., the coordinates in reduced space) that simultaneously optimize the variances between clusters and across categories were determined by considering the cross-tabulation of cluster memberships by variable categories. The method produces simple visuals that make it possible to understand a standard biplot. The following discussion will delve into the mathematical algorithm used in CCA. Initially, a standard data matrix with observations and categorical variables is converted into a new matrix , known as the super indicator matrix. This matrix is achieved through one-hot encoding, converting each categorical variable into a binary matrix, represented as , where is an matrix of the encoded j-categorical variable with number of categories. The indicator matrix has the same number of rows and number of columns. One can define as a binary matrix indicating the memberships of each observation into the number of clusters. To examine the relationship between clusters and categorical variables, a cross-tabulation of the indicator and membership matrices is constructed as a matrix, i.e.,. By applying CA to contingency matrix , scaling values corresponding to clusters and categorizing that maximize the inter -group variances will be optimized. Under optimal conditions, the clusters will separate the observations to achieve the maximum variances from the distributions over categorical variables, while also obtaining the distributions of categories within each variable. The Cluster CA procedure begins by randomly assigning observations to clusters, creating an initial membership matrix and a contingency matrix . Next, correspondence analysis is performed on matrix to obtain the category quantifications matrix . Furthermore, the object coordinate matrix is calculated.  Finally, k-means clustering is applied to , continuously updating until it converges to a fixed value (van de Velden et al., 2017). The resulting provides , the optimal cluster centroid matrix, and the category quantification matrix . These matrices are used to create a biplot of clusters and categories. For better interpretation, the matrices are scaled by a constant . The new coordinate matrixes , and have the same average squared deviation from the origin that will be used for biplot presentations of analysis (van de Velden et al., 2017).

### Research Framework

The study design, as illustrated in Figure 4.3, provides a comprehensive framework for analyzing U-turn crashes using data collected from Ohio datasets spanning the years 2017 to 2021. The workflow begins with the extraction of raw crash data from the Ohio datasets, which undergoes an initial data cleaning process to ensure accuracy and consistency by removing duplicates, errors, and irrelevant records. Once cleaned, the data is preprocessed to standardize variables, format attributes, and prepare it for advanced analysis. This preprocessed dataset is then subjected to clustering using the K-means algorithm, which segments the data into meaningful groups based on shared characteristics of U-turn crashes. The clustering process identifies distinct patterns within the data, laying the groundwork for further analysis. Following the clustering phase, the CCA model is executed to explore relationships between crash attributes and identified clusters, enabling a deeper understanding of the contributing factors and dynamics of U-turn crashes. Insights derived from the clustering and CCA are then translated into actionable findings, informing policy implications aimed at improving road safety and mitigating U-turn crash risks.

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Figure 4.3. Research Framework for U-turn Crash Analysis.

## Results and Discussions

### Variable Importance Analysis

Variable importance analysis was conducted on the dataset to identify the most influential factors contributing to crash severity predictions. The results, presented in Figure 4.4 , rank the key variables in descending order of importance. The variables are listed along the y-axis, while their corresponding importance scores are represented on the x-axis. The analysis utilized a Gradient Boosting Machine (GBM) and random forest (RF) algorithm to determine the relative importance of variables. The dataset, consisting of 2,716 crash observations, was split into 70% for training and 30% for testing, ensuring adequate data for model evaluation. The GBM model was configured with key parameters, including a learning rate of 0.3, 100 iterations (trees), and a maximum tree depth of 5. The GBM model demonstrated superior performance, achieving a higher overall accuracy of 85%, compared to RF’s 82%, and a higher F1-score, indicating better balance between precision and recall. Given this, GBM model was selected for the final variable importance analysis to ensure the most reliable identification of influential factors. Variable importance was computed using the importance function, ranking features based on their contribution to reducing prediction error.

The analysis reveals that Contributing Factors (Contri\_Fac) have the highest importance score, approximately 0.11, signifying their critical role in predicting crash severity. This variable likely captures driver actions and road dynamics, such as lane configurations, traffic volumes, and sight distance, that directly influence crash outcomes. Following this, Vehicle Type (VehTyp) and Location rank second and third, with scores around 0.10 and 0.09, respectively, highlighting the significant impact of the type of vehicle and crash location on severity levels. Other notable variables include Driver Gender (DrGen) and Posted Speed Limit (PSL), both scoring above 0.08, highlighting the influence of driver-related characteristics and regulatory factors on crash severity. Environmental conditions, such as Weather Condition (Wthr\_Cond) and Road Condition (Road\_Condition), along with visibility-related variables like Lighting Condition (Lighting\_Condition), exhibit moderate importance, indicating their roles in influencing crash risks. Less impactful variables, including Object Struck (Object), Driver Impairment (DrImp), and Number of Vehicles (NumVeh), have lower importance scores but remain relevant in specific contexts. These factors contribute to the understanding of crash dynamics.

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Figure 4.4. Ranked Importance of Variables in Crash Severity.

Figure 4.5 illustrates the silhouette scores for varying numbers of clusters, with the highest score of 0.15 observed at six clusters. This indicates that the six-cluster solution provides the most coherent and well-separated grouping structure.

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Figure 4.5. Optimum Number of Clusters Utilizing Silhouette Score.

### CCA Results

Six meaningful clusters were derived using CCA, with Figure 4.6 presenting a scatter biplot that illustrates the relationships between crash attributes along two key dimensions (Dim 1 and Dim 2). These dimensions capture variation across several domains, including roadway features (e.g., speed limits, facility types, number of lanes), vehicle-related attributes (e.g., vehicle type, commercial involvement, number of vehicles), driver risk factors (e.g., impairment, contributing actions), and environmental conditions (e.g., weather, lighting, road surface). To enhance visual clarity, semi-transparent elliptical shapes enclose each cluster grouping. The top 20 residuals for each cluster, which highlight key contributing factors, are further illustrated in Figure 4.7 to Figure 4.12. These centroids in the biplot represent the average position of crash attributes within each cluster. The clusters form a dispersed pattern across the dimensions, indicating variations in crash characteristics within and between clusters. Cluster 6, positioned toward the lower-middle of the plot, is associated with driveway access and specific crash types that are less complex and isolated. Cluster 1, located at the top-left, captures broader crash scenarios such as single-vehicle crashes, off-road incidents, and fixed object collisions. Cluster 2, positioned below Cluster 1, represents crashes involving low-speed environments, single lanes, and multi-vehicle interactions. Cluster 3, found in the upper-middle section, is associated with high-speed crashes, improper turns, and severe outcomes. Cluster 5, situated at the top-right, highlights crashes involving semi-tractors, fixed object collisions, and adverse roadway conditions, such as dark unlit roads. Cluster 4, located toward the center-right of the plot, emphasizes crashes involving driver impairment and environmental factors, such as roadside hazards or wet road conditions. Terms farther from the centroids, such as parked motor vehicle and running off road, represent specific scenarios or rare events. These attributes highlight unique conditions, such as environmental challenges or vehicle-specific factors, that deviate from more generalized crash patterns found closer to the centroids. Clusters positioned nearer to the center reflect common crash patterns, such as those involving passenger cars, clear weather, and typical roadway conditions.

CCA simultaneously analyzes the relationships between multiple categorical variables by projecting them into a low-dimensional space (typically two or three dimensions) where the proximity of points reflects their association strength. The threshold for assigning points to a cluster is based on their proximity to a cluster centroid, which represents the average position of points in that group. Cluster boundaries are not hard separations but probabilistic regions where data points share stronger associations with their assigned centroid than with others. Regarding the apparent closeness of centroids for clusters 1, 2, and 3, it is important to emphasize that a closer centroid does not imply that clusters are identical or lack distinction. Instead, it indicates greater similarity in the patterns of variable relationships captured by CCA. This similarity is natural in complex crash data. Importantly, even small centroid separations in a reduced-dimensional space can correspond to meaningful differences in the original high-dimensional space due to projection effects inherent to dimension reduction techniques. CCA, like other multivariate methods (e.g., PCA, MCA), compresses multi-variable relationships into fewer dimensions for interpretability, which can visually compress distances but retain the underlying relational structure. Thus, proximity in the map should be interpreted as a reflection of relative similarity, not identity. In this study, CCA method was employed to examine pattern recognition and risk analysis in U-turn crashes using the top 20 variables and pedestrian injury severity outcomes. The analysis was conducted using the “clustrd” package in the R software (van de Velden et al., 2017).

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Figure 4.6. Clusters Developed from U-turn Crash Data.

Table 4.2 presents dimensions, sizes, and compactness measures for six clusters derived from the analysis of U-turn crash data. The dataset includes a total of 2,716 observations, with Cluster 1 accounting for the largest portion, representing 43.5% of the dataset (1,182 observations). Cluster 2 contributes 27.5% (747 observations), and Cluster 3 accounts for 10.6% (287 observations). Collectively, these three clusters represent 81.6% of the total dataset, while the remaining three clusters (Clusters 4, 5, and 6) account for the remaining 18.4% of the dataset, with Cluster 6 being the smallest, comprising only 3.1% (83 observations). The dimensions (Dim1 and Dim2) indicate the coordinates of the cluster centroids, representing the central point for each cluster within the data space. For example, Cluster 1 has centroid coordinates of -0.0094 and 0.0050 along Dim1 and Dim2, respectively, while Cluster 6 has centroid coordinates of -0.0004 and -0.0651. These centroids reflect the average characteristics of crashes within each cluster. The table also provides the within-cluster sum of squares, which measures the compactness of each cluster. A lower value indicates that observations within the cluster are closer to the centroid, reflecting greater similarity. Cluster 3 exhibits the highest compactness, with a sum of squares of 0.0099, while Cluster 6 shows the least compactness, with a sum of squares of 0.0176, suggesting greater variability within the cluster.

Table 4.2. Centroids and Size of the Clusters.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Cluster** | **U-turn crashes** | | | |
| **Dim 1** | **Dim 2** | **Within cluster sum of squares** | **Size** |
| Cluster 1 | -0.0094 | 0.0050 | 0.0128 | 1182 |
| Cluster 2 | -0.0076 | -0.0029 | 0.0123 | 747 |
| Cluster 3 | 0.0022 | 0.0032 | 0.0099 | 287 |
| Cluster 4 | 0.0314 | 0.0010 | 0.0156 | 223 |
| Cluster 5 | 0.0474 | 0.0030 | 0.0110 | 194 |
| Cluster 6 | -0.0004 | -0.0651 | 0.0176 | 83 |

The findings from Figure 4.7 to Figure 4.12 provide a clear understanding of the factors associated with U-turn crashes across six distinct clusters, highlighting the specific conditions and variables that influence crash risks. Table 4.3 represents a summarized profile of each cluster based on positively contributing variables and their contextual interpretation. Detailed discussions of the results are presented in the subsequent subsections, offering insights into crash dynamics, contributing factors, and implications for safety interventions.

Table 4.3. Summary of Cluster Characteristics Based on Positively Influencing Variables.

|  |  |  |
| --- | --- | --- |
| **Cluster** | **Right side variables** | **Detailed Cluster Interpretation** |
| C1 | 7 | U-turn crashes in this cluster mostly occur on moderate-speed roads (30–40 MPH), featuring multiple through lanes and arterial expressways with active vehicle movement. |
| C2 | 6 | Crashes in this cluster typically take place in simple, low-speed (≤25 MPH) roadway settings with single lanes and absence of arterial features. |
| C3 | 11 | This cluster is marked by U-turn crashes in high-speed (45–70 MPH) zones under dark and unlit conditions, often involving multiple vehicles and severe outcomes. |
| C4 | 13 | This Cluster reflects crashes involving single vehicles that lose control and collide with fixed or undefined roadside objects, commonly influenced by driver impairment and road departure behaviors. |
| C5 | 14 | Crashes here are driven by commercial motor vehicles running off the road and striking roadside hazards such as ditches and signs, with environmental factors like dark, unlit roads and limited traffic playing a role. |
| C6 | 12 | This cluster involves low-speed crashes often caused by failed U-turn maneuvers near parked vehicles in constrained environments with single lanes. |

### Cluster C1: Moderate Speed Multi- Lane Roadways

In Figure 4.7, C1 accounts for 43.5% of the crash data associated with U-turn crashes. Among the 20 variables analyzed, 7 exhibit a positive correlation, with frequencies above the average. Strong positive associations are observed for moderate speed limits of 30-40 mph, multiple through lanes, arterial expressways, and motor vehicles in transport. Conversely, 13 variables demonstrate negative correlations, including low speed limits of 25 mph or less, single-vehicle crashes, failure to yield, and drivers running off the road.

The results indicate that U-turn crashes in Cluster C1 predominantly occur in moderate-speed, multi-lane environments with high vehicular activity. These findings align with previous studies suggesting that higher traffic volumes and increased vehicle interactions at unsignalized intersections can contribute to increased opportunities for crash conflicts, particularly through lane changes and rear-end collisions (Olarte et al., 2011). The combination of structured traffic flow and intentional driver actions in this environment may increase opportunities for conflicts during U-turn maneuvers. Key interventions to mitigate risks in C1 include designing and implementing dedicated U-turn lanes or bays on arterial expressways to reduce conflicts with through traffic. Enhancing signage and pavement markings at unsignalized intersections can help guide drivers and reduce confusion. Additionally, traffic signal improvements, such as dedicated U-turn signals, and speed management strategies like dynamic speed display signs or lane narrowing can moderate vehicular speeds and lower crash risks in these areas (Sheykhfard et al., 2023).

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Figure 4.7. Top 20 Residual Representations in Cluster C1.

### Cluster C2: Low-Speed Non-Arterial Roadways

Cluster C2 represents 27.5% of U-turn crashes, as shown in Figure 4.8. These crashes predominantly occur in low-speed environments and are strongly associated with posted speed limits of 25 mph or less, motor vehicles in transport, and roads other than arterial expressways, typically featuring single through lanes. Negative correlations were observed for variables such as posted speed limits of 45–60 mph, fixed object crashes, running off the road, dark not lighted roadways, and crashes involving semi-tractors.

The characteristics of Cluster C2 suggest that U-turn crashes in this cluster often occur in straightforward traffic environments where drivers encounter lower speeds, limited complexity, and minimal arterial expressway involvement. The presence of posted speed limits of 25 mph or less and single through lanes highlights the importance of ensuring appropriate design and signage to guide drivers in these environments. Traffic engineering countermeasures such as dedicated U-turn bays, clear signage, and, where feasible, traffic calming strategies like speed humps or raised medians can help manage vehicle speeds and reduce potential conflicts in these low-speed, non-arterial settings.

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Figure 4.8. Top 20 Residual Representations in Cluster C2.

### Cluster C3: High-Speed Locations with No Lighting at Dark

Cluster C3, shown in Figure 4.9, represents 10.6% of U-turn crashes and is strongly associated with high-speed environments. Positive correlations include posted speed limits of 65–70 mph and 45–60 mph, multiple vehicle involvement, fatal or severe crash outcomes, dark not lighted roadways, driver impairment, and crashes involving crossing the centerline or running off the road. These attributes suggest that crashes in this cluster typically occur in high-speed zones with elevated vehicle densities and complex maneuvering. Negative correlations are observed for posted speed limits of 25 mph or less, single-vehicle crashes, fixed object crashes, motor vehicles in transport, two-way roadways, and drivers running off the road. The variable for female drivers appears on the left-hand side, indicating that female drivers in this cluster are associated with a lower residual contribution compared to the reference group (male).

The characteristics of Cluster C3 highlight that U-turn crashes at high speeds often involve complex traffic dynamics, compounded by reduced visibility and higher vehicle densities. These findings align with previous literature suggesting that high-speed maneuvers, such as U-turns in high-traffic areas, can result in increased crash severity due to drivers misjudging gaps or underestimating the speed of oncoming vehicles (Al-Sahili et al., 2018). The presence of multiple vehicle involvement, dark, unlit roadways, and high rates of driver impairment further contribute to the potential for severe crashes. The observed patterns of crossing the centerline and running off the road reflect the challenges of maintaining vehicle control under these conditions. Interventions to address these risks include redesigning intersections to incorporate dedicated U-turn lanes, installing advanced lighting systems to improve visibility on dark, unlit roadways, and implementing speed management measures such as variable speed limit signage and dynamic speed warning systems (Edara et al., 2016; Hu et al., 2022). Deploying collision avoidance technologies can assist drivers in making safer decisions during high-speed maneuvers. Given the significant role of driver impairment, enhanced enforcement of impaired driving laws and targeted public awareness campaigns are also recommended to reduce crash risks and severity in high-speed, multi-vehicle scenarios.

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Figure 4.9. Top 20 Residual Representations in Cluster C3.

### Cluster C4: Single-Vehicle Fixed Object Collisions and Driver Impairment

Cluster C4, as shown in Figure 4.10, represents 8.2% of U-turn crashes and is strongly associated with single-vehicle incidents and collisions involving fixed objects. Positive correlations include single-vehicle crashes, fixed object crashes, vehicles running off the road, and collisions with undefined objects. Driver impairment also shows a strong positive correlation, highlighting the significant role of driver-related factors in these crashes. Negative correlations are observed for two-vehicle crashes, sideswipes, motor vehicles in transport, and failure-to-yield incidents. Improper turns and other driver-related errors exhibit weaker associations in this cluster.

The characteristics of Cluster C4 indicate that U-turn crashes in this group frequently involve vehicles losing control and striking stationary objects, such as utility poles, ditches, or other roadside features. This pattern suggests that driver-related factors, including intoxication or physical impairment, may be key contributors to crash occurrence and severity in this cluster. These findings are consistent with previous research showing that driver misjudgment and high-speed maneuvers in U-turn situations can lead to loss of control and collisions with fixed objects, resulting in severe outcomes (Al-Sahili et al., 2018). To address these risks, key strategies include installing roadside barriers or crash cushions near fixed objects to reduce crash severity, improving road lighting for better visibility, and designing forgiving roadways with wider shoulders to minimize vehicle runoff. Enforcement and public awareness campaigns targeting impaired driving should also be prioritized. Additionally, integrating advanced driver-assistance systems (ADAS), such as lane departure warnings, can help drivers maintain better control and avoid collisions with stationary objects.

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Figure 4.10. Top 20 Residual Representations in Cluster C4.

### Cluster C5: Commercial Motor Vehicle Run-off-Road Crashes

Cluster C5, depicted in Figure 4.11, accounts for 7.1% of U-turn crashes and is distinct in its association with single-vehicle incidents that result in off-road collisions. Positive correlations include single-vehicle crashes, fixed object crashes, vehicles leaving the roadway, collisions with roadside hazards such as ditches and traffic signposts, driver impairment, and the involvement of commercial motor vehicles. Environmental challenges in this cluster include crashes on dark, unlit roads and roads frequented by semi-tractors. Negative correlations are observed for multi-vehicle crashes, sideswipes, motor vehicles in transport, and improper turns, indicating that these crashes primarily involve isolated single-vehicle incidents rather than dynamic traffic interactions.

The characteristics of Cluster C5 highlight that U-turn crashes involving commercial motor vehicles often occur in off-road scenarios, where drivers lose control and strike roadside hazards such as ditches and traffic signposts. These crashes are influenced by driver impairment, vehicle dynamics, and environmental factors like dark, unlit roads. The presence of larger vehicles in these crashes emphasizes the importance of considering vehicle size and maneuverability in crash prevention strategies. Key actions to address these concerns include improving roadway design by installing barriers and energy-absorbing crash cushions near roadside hazards, enhancing lighting infrastructure to improve nighttime visibility, and implementing lane widening and shoulder stabilization to safely accommodate larger vehicles. Targeted enforcement and public education campaigns addressing impaired driving and driver errors can also play a critical role in reducing the risks associated with these high-risk environments.

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Figure 4.11. Top 20 Residual Representations in Cluster C5.

### Cluster C6: Parked Vehicles and Low-Speed Conditions

Cluster C6, illustrated in Figure 4.12, comprises 3.1% of U-turn crashes and is characterized by incidents involving parked vehicles. Positive correlations are observed for sequential events involving parked motor vehicles and parked vehicle crashes, indicating that stationary vehicles are a primary element in this cluster. Additional correlations with posted speed limits of 25 mph or less suggest that these crashes occur in low-speed environments, likely in urban or suburban areas. Other contributing attributes include single traffic lanes and the limited presence of multi-vehicle involvement, indicating that U-turn crashes in this cluster often occur in constrained roadway conditions. Negative correlations are observed for higher speed limits (30–40 mph and 45–60 mph), sideswipe crashes, and arterial expressways, reinforcing the localized, low-complexity nature of this cluster.

The characteristics of Cluster C6 suggest that U-turn crashes in low-speed, single-lane urban or suburban areas often involve collisions with parked vehicles. These findings highlight the challenges drivers face when maneuvering around stationary vehicles in confined roadway layouts. The limited involvement of multi-vehicle crashes further indicates that these incidents are typically isolated, rather than resulting from complex traffic interactions. To improve safety in these environments, interventions should focus on enhancing road markings and signage to clearly define parking zones and U-turn areas, thereby reducing the likelihood of conflicts. Enforcing U-turn restrictions in constrained single-lane roadway conditions can also minimize maneuvering difficulties and improve safety. Additionally, designing dedicated U-turn bays to separate turning vehicles from parked cars can further reduce the risk of collisions in these low-complexity settings. Although previous research in Louisiana (Rahman et al., 2022) identified rainy weather as a defining factor in some crash clusters, our analysis of Ohio crash data did not reveal rain as a dominant condition influencing U-turn crash severity. This may be due to geographic and climatic differences between the two states, or due to differences in crash types analyzed.

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Figure 4.12. Top 20 Residual Representations in Cluster C6.

### Policy Implications

The comprehensive analysis of U-turn crashes reveals several interrelated factors that significantly contribute to crash risk and severity. A primary concern is the roadway speed environment, as U-turn crashes frequently occur in both moderate-speed (30–40 mph) multi-lane settings and high-speed arterial roads (45–70 mph), where inadequate turning infrastructure, such as missing or poorly designed U-turn bays, can increase conflict points. These environments often involve heavy traffic flows, making it difficult for drivers to find safe gaps to turn, thus elevating the likelihood of angle and rear-end collisions. Lane configuration and intersection design further exacerbate these risks; both constrained single-lane low-speed roads and wide multi-lane roads without clear turning guidance contribute to maneuver errors. In addition, vehicle type plays a critical role, as larger vehicles like commercial motor trucks are more prone to loss-of-control events, particularly in environments lacking wide shoulders or stable turn radii, while smaller vehicles are involved in low-speed crashes near parked cars in residential zones. Behavioral factors, such as impaired driving, failure to yield, and improper turning, are consistently associated with more severe outcomes, reinforcing the necessity of strict enforcement policies, driver awareness initiatives, and the integration of advanced driver-assistance systems (ADAS) (Ortega et al., 2023) to support safer maneuvering. Environmental conditions, particularly wet surfaces and poorly lit roadways, further contribute to crash risks, especially during nighttime or inclement weather.

These findings emphasize the need for a tiered application of countermeasures. The Safe System Roadway Design Hierarchy (Hopwood et al., 2024) provides a structured framework of four escalating tiers removing severe conflicts, reducing vehicle speeds, managing conflicts in time, and increasing attentiveness and awareness to systematically minimize crash risks and injury severity. First, to remove severe conflicts (Tier 1), dedicated U-turn bays (USDOT, 2014) should be implemented to physically separate turning vehicles from through traffic, thereby minimizing high-risk vehicle interactions. Second, to reduce vehicle speeds (Tier 2), lane narrowing (Hale et al., 2021), dynamic speed displays (Hallmark et al., 2015), and high-friction surface treatments (Kline et al., 2018) should be applied in areas where speeding exacerbates crash risks, particularly in high-speed zones with limited lighting. Third, to manage conflicts in time (Tier 3), traffic signal modifications such as dedicated U-turn phases (USDOT, 2014) and better signal coordination at intersections can help regulate movements and prevent misjudged gaps during maneuvers. Fourth, to increase attentiveness and awareness (Tier 4), enhanced signage (Katz et al., 2022), pavement markings (Hopwood et al., 2024), and roadway lighting can improve visibility and alert drivers to turning rules and potential hazards, especially in low-speed, single-lane, or residential environments. Finally, across all tiers, targeted enforcement and driver education campaigns are essential to address behavioral risks such as impairment, misjudgment, and unsafe vehicle maneuvers.

## Conclusions

U-turn-related crashes present a persistent safety concern in both urban and suburban traffic environments, often resulting from the complex maneuvering required to execute such turns, particularly in high-speed or unsignalized roadway settings. These crashes frequently involve misjudgments in gap acceptance, poor visibility, inadequate roadway design, and interactions with oncoming traffic, leading to heightened risk of severe outcomes. Despite various studies exploring infrastructure solutions and operational designs to reduce U-turn conflicts, there has been a limited understanding of how diverse factors such as roadway conditions, vehicle type, driver behavior, environmental context, and crash sequence interact to influence crash patterns and injury severity. This gap in understanding calls for a more holistic and data-driven approach to uncover the underlying associations among these categorical factors in real-world U-turn crash events.

To address this issue, U-turn crash data from Ohio (2017–2021), comprising 2,716 observations, were analyzed using CCA, a multivariate method suited for identifying associations among categorical variables. This method allowed the data to be grouped based on shared characteristics across crashes, revealing multidimensional patterns not readily captured by conventional statistical techniques. The findings indicate that U-turn crash risks are shaped by a combination of roadway environment (e.g., number of lanes, lighting, and speed limits), driver behavior (e.g., impairment or improper turning), vehicle type (e.g., commercial versus private vehicles), and situational context (e.g., weather, intersection involvement, or object struck). Crashes occurring under high-speed and low-light conditions were often associated with severe injuries and involved multiple vehicles or impaired drivers. In contrast, less severe crashes tend to occur in low-speed, constrained environments, frequently involving stationary objects or parked vehicles. The analysis also revealed that male drivers were more commonly associated with high-severity crashes compared to female drivers, particularly in complex or impaired driving scenarios. Additionally, improper turning maneuvers and failure-to-yield behaviors were among the most frequent contributing factors across crash types, regardless of speed or road type.

This study provides important insights into U-turn-related crashes, yet several limitations must be acknowledged. The analysis relies on aggregated crash data, which may overlook temporal and spatial issues such as time-of-day variations or localized conditions that could refine the understanding of crash contexts. While CCA is effective for uncovering latent relationships among categorical variables, it does not quantify these relationships or handle continuous data comprehensively, indicating potential benefits of combining CCA with predictive modeling. CCA illustrates the associations among the factors and outcomes but does not imply causality. The study's scope is further constrained by the absence of critical, often underreported variables like driver distraction, fatigue, or near-miss events, which could be better captured through in-vehicle telemetry or sensor-based data. Broader sociocultural and policy influences, including regional driving norms or differences in enforcement, were not fully considered, which may affect observed crash patterns. Notably, traffic volume data, an important factor influencing gap acceptance, were excluded due to the unavailability of comprehensive and site-specific volume records for the analyzed locations. The absence of this variable limits the model's capacity to fully capture the interaction between traffic flow and crash dynamics. Additionally, the dataset does not consistently differentiate between intersection-related and midblock median U-turn crashes, and intersection control types (e.g. stopped control/signalized intersections) which may obscure differences in crash patterns and contributing factors between these two contexts. Furthermore, the data collection period overlaps with the COVID-19 pandemic, during which driver behavior, traffic volumes, and speeds were atypical. These changes may influence crash patterns and model interpretations. Future research should incorporate granular traffic data, integrate real-time environmental conditions, and apply advanced analytical methods to deepen understanding of U-turn crash risks and enhance prevention strategies.

# CONCLUSIONS

**V.**

## Summary of Findings

This study examined U-turn crash safety by integrating advanced analytical methodologies to address critical research gaps identified in the existing literature. The analysis was structured around two main approaches: ARM-LIC and CCA. These methods were applied to a comprehensive dataset of U-turn crashes, focusing on identifying key factors influencing crash occurrence and severity, with particular emphasis on maneuver-specific risk patterns and multifactorial relationships.

The first analytical framework employed ARM-LIC to systematically extract significant association rules from the U-turn crash dataset. This approach effectively identified combinations of contributing factors (e.g., road geometry, traffic control type, environmental conditions, and driver actions) that were frequently associated with severe crash outcomes. Notably, ARM-LIC revealed that variables related to driver behavior and roadway configuration often interact in complex ways to influence crash severity. For example, the presence of high-speed road segments combined with inadequate signage and driver misjudgment was frequently linked to elevated crash risks. The LIC provided a robust measure of association strength, allowing the study to highlight priority areas for targeted safety interventions.

The second analytical approach utilized CCA to classify crash records into distinct clusters based on shared characteristics and severity outcomes. This method enabled the identification of homogeneous crash subgroups that exhibited similar patterns of contributing factors, facilitating a deeper understanding of the underlying risk profiles associated with different U-turn scenarios. The CCA revealed that certain clusters were characterized by a predominance of environmental factors—such as poor lighting conditions and adverse weather—while others were more strongly associated with driver-related behaviors, such as improper lane-changing and inadequate gap acceptance. These clusters provided critical insights into the heterogeneity of U-turn crash severity, emphasizing the need for context-specific countermeasures.

## Practical Implications

The findings from this research have several important implications for transportation engineers, planners, and policymakers seeking to enhance the safety of U-turn facilities and improve overall intersection design. By applying advanced analytical techniques, specifically ARM-LIC and CCA, this study revealed complex patterns and interactions among factors contributing to U-turn crash severity. These insights can inform both engineering design practices and policy decisions aimed at reducing crash risks.

First, the identification of high-risk factor combinations through ARM-LIC underscores the need for policymakers to consider multifactorial influences on U-turn crash severity in their decision-making processes. For example, the study highlights that areas with high approach speeds, limited visibility, and inadequate signage are particularly susceptible to severe crashes. Policymakers can prioritize funding allocations and regulatory measures—such as implementing speed management policies, requiring uniform signage standards, and enforcing stricter design guidelines at high-risk U-turn locations—to systematically reduce crash risks.

Second, the classification of crash patterns using CCA emphasizes the heterogeneity of U-turn crash risks across different contexts, supporting the case for context-sensitive policy frameworks. Policymakers can develop targeted interventions, including region-specific safety programs, to address the unique factors influencing crash severity in different environments. For example, clusters characterized by driver behavior factors may necessitate educational campaigns, enhanced enforcement measures, and integration of behavioral insights into policy guidelines, while clusters influenced by environmental conditions may require infrastructure funding for lighting, drainage, and visibility improvements.

Third, the application of these advanced analytical tools demonstrates the value of data-driven policymaking. Transportation agencies and regulatory bodies can consider adopting similar methodologies to analyze local crash data and inform policy development. Integrating ARM-LIC and CCA findings into transportation planning processes can enable policymakers to prioritize interventions based on empirical evidence rather than generalized assumptions, ensuring that resources are allocated efficiently and effectively.

Furthermore, the study’s findings highlight the importance of collaborative policy development involving multiple stakeholders, including engineers, enforcement agencies, and community representatives. By engaging stakeholders in the interpretation of crash data and the design of countermeasures, policymakers can ensure that interventions are contextually relevant, socially acceptable, and technically feasible.

## Limitations

While this research offers valuable insights into U-turn crash safety and contributes to a deeper understanding of maneuver-specific crash patterns, several limitations must be acknowledged. First, the study is based on a single-state dataset, which may limit the generalizability of the findings to other regions with different traffic conditions, driver behaviors, and enforcement practices. Although the selected dataset provides substantial detail and relevance, regional differences in roadway design standards, cultural driving norms, and enforcement levels could influence crash patterns in ways not captured by this analysis.

Second, the reliance on historical crash data constrains the study’s ability to capture dynamic factors such as real-time driver behavior, momentary decision-making, and variable environmental conditions at the time of each crash. Elements like driver distraction, vehicle condition, and precise traffic flow conditions were not consistently available, which may influence the interpretation of contributing factors.

Third, while the use of ARM-LIC and CCA represents a methodological advancement, these approaches are inherently data-driven and exploratory. Although they effectively identify associations and clusters of contributing factors, they do not establish causality between variables and crash severity outcomes. As a result, the findings should be interpreted as indicative rather than definitive in terms of cause-and-effect relationships.

Fourth, although the dataset included a wide range of U-turn crashes across different intersection configurations—including conventional intersections and alternative intersection designs such as MUTs and RCUTs—the study did not explicitly distinguish between these configurations in the analysis. This limits the ability to assess the unique operational characteristics and safety performance of alternative intersection designs in detail. Future studies could benefit from a comparative analysis of U-turn crashes at alternative and conventional intersections to better understand their relative risks and mitigation strategies.

Finally, the integration of technological factors—such as driver warning systems and adaptive signal controls—was discussed conceptually in the literature review but was not directly incorporated into the analytical models due to data availability constraints. As technological solutions continue to evolve, future studies could explore the real-world impact of these interventions on U-turn crash severity.

## Recommendations for Future Research

Building upon the insights gained from this study, several avenues for future research are recommended to further enhance the understanding of U-turn crash safety and to develop more effective countermeasures. First, future studies could extend the current analysis by incorporating data from multiple states or regions to examine the influence of diverse roadway conditions, traffic regulations, and driver behaviors on U-turn crash patterns. Such studies would enhance the generalizability of findings and support the development of regionally tailored safety strategies.

Second, integrating real-time driver behavior data and environmental conditions into the analytical framework would provide a more dynamic and comprehensive understanding of crash risk. The inclusion of factors such as driver distraction, vehicle speeds, and instantaneous decision-making could yield valuable insights into the immediate precursors of U-turn crashes, supporting the design of targeted interventions.

Third, while ARM-LIC and CCA effectively identified multifactorial crash patterns, future research could employ complementary modeling techniques—such as structural equation modeling or agent-based simulation—to explore causal relationships and simulate driver interactions in complex traffic scenarios. Such models could enhance the predictive power of the analysis and guide the evaluation of proposed safety countermeasures.

Fourth, expanding the analysis to include a comparative assessment of U-turn crashes at alternative versus conventional intersection configurations would provide a clearer understanding of the specific safety challenges posed by different designs. This would inform the selection and implementation of intersection treatments that best balance operational efficiency and safety.

Fifth, as technological innovations continue to evolve, research could focus on evaluating the effectiveness of driver assistance systems, adaptive signal controls, and real-time warning devices in mitigating U-turn crash risks. Field studies and pilot deployments could assess the feasibility and performance of these technologies under real-world conditions, informing future design and policy decisions.

Lastly, collaboration with transportation agencies and policymakers is recommended to facilitate the translation of research findings into practice. Engaging stakeholders in the interpretation of analytical results and the co-development of countermeasures would enhance the acceptance and effectiveness of safety interventions.

# REFERENCES

Abbaszadeh Lima, M.R., Hossain, M.M., Zhou, H., Song, Y., 2024. Data Mining Approach to Explore the Contributing Factors to Fatal Wrong-Way Crashes by Local and Non-Local Drivers. Future Transportation 4, 985–999. https://doi.org/10.3390/futuretransp4030047

Abdel-Aty, M.A., Lee, J., Yuan, J., Yue, L., Al-Omari, M., Abdelrahman, A., 2020. Evaluation of Innovative Alternative Intersection Designs in the Development of Safety Performance Functions and Crash Modification Factors.

Abdelrahman, A., 2012. Safety Evaluation of Innovative Intersection Designs: Diverging Diamond Interchanges and Displaced Left-turn Intersections. Cairo University.

Abou-Senna, H., Radwan, E., Tabares, S., Wu, J., Chalise, S., 2015. Evaluating transportation systems management & operations (TSM&O) benefits to alternative intersection treatments. (No. BDV24-977– 09).

Agrawal, R., Imieliński, T., Swami, A., 1993. Mining association rules between sets of items in large databases. SIGMOD Rec. 22, 207–216. https://doi.org/10.1145/170036.170072

Agrawal, R., Srikant, R., 1994. Fast Algorithms for Mining Association Rules in Large Databases, in: Proceedings of the 20th International Conference on Very Large Data Bases, VLDB ’94. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp. 487–499.

Al-Omari, M.M.A., Abdel-Aty, M., Lee, J., Yue, L., Abdelrahman, A., 2020. Safety Evaluation of Median U-Turn Crossover-Based Intersections. Transportation Research Record 2674, 206–218. https://doi.org/10.1177/0361198120921158

Al-Sahili, O., Al-Deek, H., Sandt, A., Mantzaris, A.V., Rogers, J.H., Faruk, M.O., 2018. Investigating and Modeling the Illegal U-Turn Violations at Medians of Limited Access Facilities. Transportation Research Record: Journal of the Transportation Research Board 2672, pp-73-84. https://doi.org/10.1177/0361198118778941

Azizi, L., Sheikholeslami, A., 2013. Safety Effect of U-Turn Conversions in Tehran: Empirical Bayes Observational Before-and-After Study and Crash Prediction Models. J. Transp. Eng. 139, 101–108. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000469

Bajada, T., Attard, M., 2021. A typological and spatial analysis of pedestrian fatalities and injuries in Malta. Research in Transportation Economics, Active Travel Policies 86, 101023. https://doi.org/10.1016/j.retrec.2020.101023

Bared, J., 2009. Restricted Crossing U-Turn Intersection. Federal Highway Administration.

Brin, M.F., 1997. Botulinum toxin: Chemistry, pharmacology, toxicity, and immunology. Muscle & Nerve 20, 146–168. https://doi.org/10.1002/(SICI)1097-4598(1997)6+<146::AID-MUS10>3.0.CO;2-4

Carter, D., Hummer, J.E., Foyle, R.S., Phillips, S., 2005. Operational and Safety Effects of U-Turns at Signalized Intersections. Transportation Research Record.

Chakraborty, R., Das, S., Mimi, M.S., Kutela, B., 2025a. Investigating Factor Associations in Barrier Crashes through Cluster Correspondence Analysis. Transportation Research Record 2679, 860–879. https://doi.org/10.1177/03611981241297976

Chakraborty, R., Mills, D., Das, S., 2025b. Children on wheels: Identifying crash determinants using cluster correspondence analysis. Accident Analysis & Prevention 216, 108025. https://doi.org/10.1016/j.aap.2025.108025

Claros, B.R., Edara, P., Sun, C., Brown, H., 2015. Safety Evaluation of Diverging Diamond Interchanges in Missouri. Transportation Research Record 2486, 1–10. https://doi.org/10.3141/2486-01

Cunningham, C.M., Chase, R.T., Yang, G., Callister, L., 2023. Groundwork for the Second Edition of the Alternative Intersection and Interchange Informational Report.

Das, S., Avelar, R., Dixon, K., Sun, X., 2018a. Investigation on the wrong way driving crash patterns using multiple correspondence analysis. Accident Analysis & Prevention 111, 43–55. https://doi.org/10.1016/j.aap.2017.11.016

Das, S., Dutta, A., Jalayer, M., Bibeka, A., Wu, L., 2018b. Factors influencing the patterns of wrong-way driving crashes on freeway exit ramps and median crossovers: Exploration using ‘Eclat’ association rules to promote safety. International Journal of Transportation Science and Technology 7, 114–123. https://doi.org/10.1016/j.ijtst.2018.02.001

Das, S., Dutta, A., Rahman, M., 2021a. Pattern recognition from light delivery vehicle crash characteristics. Journal of Transportation Safety & Security 14. https://doi.org/10.1080/19439962.2021.1995800

Das, S., Dutta ,Anandi, and Fitzpatrick, K., 2020a. Technological perception on autonomous vehicles: perspectives of the non-motorists. Technology Analysis & Strategic Management 32, 1335–1352. https://doi.org/10.1080/09537325.2020.1768235

Das, S., Dutta ,Anandi, and Sun, X., 2020b. Patterns of rainy weather crashes: Applying rules mining. Journal of Transportation Safety & Security 12, 1083–1105. https://doi.org/10.1080/19439962.2019.1572681

Das, S., Dutta ,Anandi, Avelar ,Raul, Dixon ,Karen, Sun ,Xiaoduan, and Jalayer, M., 2019. Supervised association rules mining on pedestrian crashes in urban areas: identifying patterns for appropriate countermeasures. International Journal of Urban Sciences 23, 30–48. https://doi.org/10.1080/12265934.2018.1431146

Das, S., Kong ,Xiaoqiang, and Tsapakis, I., 2021b. Hit and run crash analysis using association rules mining. Journal of Transportation Safety & Security 13, 123–142. https://doi.org/10.1080/19439962.2019.1611682

Das, S., Sun, X., 2016. Association knowledge for fatal run-off-road crashes by Multiple Correspondence Analysis. IATSS Research 39, 146–155. https://doi.org/10.1016/j.iatssr.2015.07.001

Das, S., Sun, X., 2015. Factor Association with Multiple Correspondence Analysis in Vehicle–Pedestrian Crashes. Transportation Research Record 2519, 95–103. https://doi.org/10.3141/2519-11

Das, S., Tamakloe, R., Zubaidi, H., Obaid, I., Alnedawi, A., 2021c. Fatal pedestrian crashes at intersections: Trend mining using association rules. Accident Analysis & Prevention 160, 106306. https://doi.org/10.1016/j.aap.2021.106306

Dissanayake, S., Lu, J.J., Castillo, N., 2002. Should Direct Left Turns from Driveways Be Avoided? A Safety Perspective. ITE JOURNAL.

Dixon, K.K., Avelar, R.E., Dastgiri, M.S., Dadashova, B., 2018. Safety Evaluation for Turnarounds at Diamond Interchanges: Assessing the Texas U-Turn. Transportation Research Record: Journal of the Transportation Research Board 2672, 61–71. https://doi.org/10.1177/0361198118797186

Dung, C.T., Hoi, T.D., 2022. Gap Acceptance at U-turn Median Openings – A Case Study in Hanoi, VietNam. Journal of the Eastern Asia Society for Transportation Studies 14, 1814–1823. https://doi.org/10.11175/easts.14.1814

Dzinyela, R., Dadashova, B., Westfall, G., Das, S., Silvestri-Dobrovolny, C., Adanu, E.K., Lord, D., 2025. Analysis of motorcyclists crash severity using cluster correspondence and hierarchical binary logit models. Multimodal Transportation 4, 100197. https://doi.org/10.1016/j.multra.2025.100197

Edara, P., 2024. Safety Evaluation of J-turn Intersections in Missouri.

Edara, P., Breslow, S., Sun, C., Claros, B.R., 2015. Empirical Evaluation of J-Turn Intersection Performance: Analysis of Conflict Measures and Crashes. Transportation Research Record 2486, 11–18. https://doi.org/10.3141/2486-02

Edara, P., Qing, Z., Brown, H., Sun, C., Baek, H.J., 2024. Safety Evaluation of J-turn Intersections in Missouri (No. cmr 24-011).

Edara, P., Sun, C., Breslow, S., 2013. Evaluation of J-turn Intersection Design Performance in Missouri (Digital/other).

Edara, P., Sun, C., Brown, H., Claros, B.R., Zhu, Z., University of Missouri--Columbia. Dept. of Civil and Environmental Engineering, 2016. System-Wide Safety Treatments and Design Guidance for J-Turns : Final Report (No. cmr 16-013).

Eisenberg, D., Warner, K.E., 2005. Effects of Snowfalls on Motor Vehicle Collisions, Injuries, and Fatalities. Am J Public Health 95, 120–124. https://doi.org/10.2105/AJPH.2004.048926

El-Urfali, A., 2019. Development of Safety Performance Functions for Restricted Crossing U-Turn (RCUT) Intersections (BDV30-977-19). Florida Department of Transportation Research.

Fan, H., Jia, B., Tian, J., Yun, L., 2014. Characteristics of traffic flow at a non-signalized intersection in the framework of game theory. Physica A: Statistical Mechanics and its Applications 415, 172–180. https://doi.org/10.1016/j.physa.2014.07.031

Fan, H.-Q., Jia, B., Li, X.-G., Tian, J.-F., Yan, X.-D., 2013. Characteristics of Traffic Flow at Nonsignalized T-Shaped Intersection with U-Turn Movements. The Scientific World Journal 2013, 856416. https://doi.org/10.1155/2013/856416

Farmer, C.M., 2017. Relationship of traffic fatality rates to maximum state speed limits. Traffic Injury Prevention 18, 375–380. https://doi.org/10.1080/15389588.2016.1213821

FHWA, 2023. Safety of U-Turns at Unsignalized Median Openings on Urban and Suburban Arterials.

FHWA, 2017. Safety Evaluation of Restricted Crossing U-Turn Intersection (No. FHWA-HRT-17-083).

Gu, C., Xu, J., Gao, C., Mu, M., E, G., Ma, Y., 2022. Multivariate analysis of roadway multi-fatality crashes using association rules mining and rules graph structures: A case study in China. PLOS ONE 17, e0276817. https://doi.org/10.1371/journal.pone.0276817

Gutiérrez-Rodríguez, R., Rojí, E., Cuadrado, J., 2025. Identifying relevant patterns between injury crashes and road safety inspection deficiencies. Journal of Safety Research 93, 99–134. https://doi.org/10.1016/j.jsr.2025.02.014

Hale, D., Kondyli, A., Argote, J., Zhang, X., Schroeder, B., Button, L., Atkinson, J., Stock, D., Cheema, A., Sajjadi, S., Aycin, M., Brackstone, M., Canayon, G., Casas, J., Lenorzer, A., Jia, A., Chetan, J., James, R.M., Leidos, Inc., University of Kansas, University of Virginia, Kittelson & Associates, I., Aimsun Inc., PTV Group, 2021. Narrowing Freeway Lanes and Shoulders to Create Additional Travel Lanes (No. FHWA-HRT-21-005).

Hallmark, S., Hawkins, N., Smadi, O., Iowa State University. Center for Transportation Research and Education, 2015. Evaluation of Dynamic Speed Feedback Signs on Curves: A National Demonstration Project (No. FHWA-HRT-14-020;IHRB Project TR-579;InTrans Project 08-320).

Hochstein, J.L., Maze, T.H., Welch, T.M., Preston, H., Storm, R., 2009. J-Turn Intersection: Design Guidance and Safety Experience. Presented at the Transportation Research Board 88th Annual MeetingTransportation Research Board.

Holzem, A.M., Hummer, J.E., Cunningham, C.M., O’Brien, S.W., Schroeder, B.J., Salamati, K., 2015. Pedestrian and Bicyclist Accommodations and Crossings on Superstreets. Transportation Research Record 2486, 37–44. https://doi.org/10.3141/2486-05

Hopwood, C., Little, K., Gaines, D., Cambridge Systematics, Inc., Burgess and Niple, Inc., 2024. Safe System Roadway Design Hierarchy: Engineering and Infrastructure-related Countermeasures to Effectively Reduce Roadway Fatalities and Serious Injuries (No. FHWA-SA-22-069).

Hossain, A., Sun, X., Islam, S., Rahman, A., Das, S., 2024. Single-vehicle roadway departure crashes at rural two-lane highway curved segments: A diagnosis using pattern recognition. International Journal of Transportation Science and Technology 15, 298–318. https://doi.org/10.1016/j.ijtst.2023.10.005

Hosseinpour, M., Sahebi, S., Zamzuri, Z.H., Yahaya, A.S., Ismail, N., 2018. Predicting crash frequency for multi-vehicle collision types using multivariate Poisson-lognormal spatial model: A comparative analysis. Accident Analysis & Prevention 118, 277–288. https://doi.org/10.1016/j.aap.2018.05.003

Howard, J., Molan, A.M., Xu, S., Sajjadi, S., Pande, A., 2023. Modeling the performance of restricted crossing U-turn intersections including the effects of connected and autonomous vehicles: a case study in California. Can. J. Civ. Eng. 50, 560–570. https://doi.org/10.1139/cjce-2022-0098

Hsu, C.-K., 2024. Reconsidering Seasonality, Weather, and Road Safety in Non-temperate Areas: the Case of Kaohsiung, Taiwan. Travel Behaviour and Society 34, 100710. https://doi.org/10.1016/j.tbs.2023.100710

Hu, S., Jia, Z., Yang, A., Xue, K., He, G., 2022. Evaluating the Sustainable Traffic Flow Operational Features of U-turn Design with Advance Left Turn. Sustainability 14, 6931. https://doi.org/10.3390/su14116931

Hua, C., Fan, W. (David), 2023. Injury severity analysis of time-of-day fluctuations and temporal volatility in reverse sideswipe collisions: A random parameter model with heterogeneous means and heteroscedastic variances. Journal of Safety Research 84, 74–85. https://doi.org/10.1016/j.jsr.2022.10.009

Hughes, W., Jagannathan, R., Sengupta, D., Hummer, J., others, 2010. Alternative Intersections/Interchanges: Informational Report (AIIR). United States. Federal Highway Administration. Office of Research ….

Hummer, J., Ray, B., Daleiden, A., Jenior, P., Knudsen, J., Kittelson & Associates, 2014. Restricted crossing u-turn : informational guide. (No. FHWA-SA-14-070).

Hummer, J., Reid, J., 2000. Unconventional left-turn alternatives for urban and suburban arterials: an update. Transportation research circular.

Hummer, J.E., Haley, R.L., Ott, S.E., Foyle, R.S., Cunningham, C.M., 2010. Superstreet Benefits and Capacities.

Hummer, J.E., Rao, S., 2017. Safety Evaluation of Signalized Restricted Crossing U-Turn Intersections (No. FHWA-HRT-17-082). Federal Highway Administration.

Inman, V.W., Haas, R.P., 2012. Field Evaluation of a Restricted Crossing U-Turn Intersection.

Inman, V.W., Haas, R.P., Yang, C.Y.D., 2013. Evaluation of Restricted Crossing U-Turn Intersection as a Safety Treatment on Four-Lane Highways. ITE Journal 83, pp-29-35.

Jagannathan, R., Gimbel, M., Bared, J.G., Hughes, W.E., Persaud, B.N., Lyon, C., 2006. Safety Comparison of New Jersey Jug Handle Intersections and Conventional Intersections. Transportation Research Record: Journal of the Transportation Research Board.

Javed, S.A., Tusti, A.G., Pandey, B., Das, S., 2025. From Maneuver to Mishap: A Systematic Literature Review on U-Turn Safety Risks. https://doi.org/10.48550/arXiv.2502.12556

Johnson, N., Ancy Jenifer, J., Khan, A., Jyothi, A., 2023. Smart Roads: U-Turn Accident Prevention System, in: 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC). Presented at the 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 17–21. https://doi.org/10.1109/ICESC57686.2023.10193649

Jung, S., Qin, X., Noyce, D.A., 2010. Rainfall effect on single-vehicle crash severities using polychotomous response models. Accident Analysis & Prevention 42, 213–224. https://doi.org/10.1016/j.aap.2009.07.020

Katz, B., Kissner, E., Hallmark, S., United States. Department of Transportation. Federal Highway Administration. Office of Research, D., and Technology, 2022. Enhancing Conspicuity for Standard Signs and Retroreflectivity Strips on Posts [tech brief] (No. FHWA-HRT-22-066).

Kay, J., Gates, T.J., Savolainen, P.T., Shakir Mahmud, M., 2022. Safety Performance of Unsignalized Median U-Turn Intersections. Transportation Research Record: Journal of the Transportation Research Board 2676.

Khan, T., Vivek, A.K., Mohapatra, S.S., 2021. Comparative Appraisal of Critical Gap Estimation Techniques in the Context of U-turning Vehicles. Transportation Research Record: Journal of the Transportation Research Board 2675, pp-1408-1421. https://doi.org/10.1177/03611981211035761

Khattak, A.J., Rocha, M., 2003. Are SUVs “Supremely Unsafe Vehicles”?: Analysis of Rollovers and Injuries with Sport Utility Vehicles - Asad J. Khattak, Marta Rocha, 2003. Transportation Research Record: Journal of the Transportation Research Board. https://doi.org/10.3141/1840-19

Khavarian, K., Sahebi, S., 2025. Robust crash modification factor estimation with case-control method. Traffic Injury Prevention 0, 1–12. https://doi.org/10.1080/15389588.2025.2484654

Kim, J.-K., Ulfarsson, G.F., Shankar, V.N., Mannering, F.L., 2010. A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. Accident Analysis & Prevention 42, 1751–1758. https://doi.org/10.1016/j.aap.2010.04.016

Kim, T., Edara, P., Bared, J., 2006. Traffic Efficiency of Two Non-Traditional Intersections, in: Super Street and Through-About. Presented at the Presented at 7th Conference on Access Management, Park City, UT.

Kittelson, Associates, 2021. Guide for Pedestrian and Bicyclist Safety at Alternative and Other Intersections and Interchanges. Transportation Research Board, Washington, D.C.

Kline, C.F., Mullins, M., Linsenmayer, M., CTC & Associates LLC, 2018. High Friction Surface Treatments, Transportation Research Synthesis (No. TRS 1802).

Kong, X., Das, S., Jha, K., Zhang, Y., 2020. Understanding speeding behavior from naturalistic driving data: Applying classification based association rule mining. Accident Analysis & Prevention 144, 105620. https://doi.org/10.1016/j.aap.2020.105620

Kronprasert, N., Kuwiboon, P., Wichitphongsa, W., 2021. Safety and Operational Analysis for Median U-Turn Intersections in Thailand. GEOMATE Journal 18, 156–163.

Levinson, H.S., Potts, I.B., Harwood, D.W., Gluck, J., Torbic, D.J., 2005. Safety of U-Turns at Unsignalized Median Openings: Some Research Findings. Transportation Research Record: Journal of the Transportation Research Board 1912, 72–81. https://doi.org/10.1177/0361198105191200109

Liu, J.J., Pirinccioglu, F., Pernia, J.C., 2005. Safety Evaluation of Right Turns Followed by U-Turns (4 Lane Arterials) as an Alternative Direct Left Turns - Conflict Analysis. Florida Department of Transportation.

Liu, P., Lu, J.J., Chen, H., 2008a. Safety effects of the separation distances between driveway exits and downstream U-turn locations. Accid Anal Prev 40, 760–767. https://doi.org/10.1016/j.aap.2007.09.011

Liu, P., Pan, T., Lu, J.J., Cao, B., 2008b. Estimating Capacity of U-Turns at Unsignalized Intersections: Conflicting Traffic Volume, Impedance Effects, and Left-Turn Lane Capacity. Transportation Research Record 2071, 44–51. https://doi.org/10.3141/2071-06

Liu, P., Wang, X., Lu, J., Sokolow, G., 2007. Headway Acceptance Characteristics of U-Turning Vehicles at Unsignalized Intersections. Transportation Research Record: Journal of the Transportation Research Board pp-52-57. https://doi.org/10.3141/2027-07

Lobază, M.G., 2022. Roundabout with a strong U-Turn traffic. Romanian Journal of Transport Infrastructure 11, 1–14. https://doi.org/10.2478/rjti-2022-0003

Lu, J., Dissanayake, S., Castillo, N., Williams, K., 2001. Safety Evaluation of Right Turns Followed by U-Turns as an Alternative to Direct Left Turns - Conflict Analysis.

Lu, J.J., Dissanayake, S., 2002. Safety Evaluation of Direct Left Turns Vs Right Turns Followed by U-Turns Using Traffic Conflict Technique, in: Traffic And Transportation Studies (2002). Presented at the International Conference on Traffic and Transportation Studies (ICTTS) 2002, American Society of Civil Engineers, Guilin, China, pp. 1039–1046. https://doi.org/10.1061/40630(255)144

Lu, J.J., Liu, P., Pirinccioglu, F., 2005. Determination of the Offset Distance between Driveway Exits and Downsstream U-turn Locations for Vehicles making Right Turns Followed by U-turns. Florida Department of Transportation.

Meel, I.P., Satirasetthavee, D., Kanitpong, K., Taneerananon, P., 2016. Using Czech TCT to Access Safety Impact of Deceleration Lane at Thai U-Turns. EJ 20, 121–135. https://doi.org/10.4186/ej.2016.20.1.121

Meel, I.P., Vesper, A., Borsos, A., Koren, C., 2017. Evaluation of the effects of auxiliary lanes on road traffic safety at downstream of U-turns. Transportation Research Procedia 25, 1931–1945. https://doi.org/10.1016/j.trpro.2017.05.186

Milton, J., Mannering, F., 1998. The relationship among highway geometrics, traffic-related elements and motor-vehicle accident frequencies. Transportation 25, 395–413. https://doi.org/10.1023/A:1005095725001

Mimi, M.S., Chakraborty, R., Liu, J., Barua, S., Das, S., 2025. Exploring patterns in older pedestrian involved crashes during nighttime. Accident Analysis & Prevention 209, 107815. https://doi.org/10.1016/j.aap.2024.107815

Mishra, R., Pulugurtha, S.S., 2022. Safety evaluation of unsignalized and signalized restricted crossing U-turn (RCUT) intersections in rural and suburban areas based on prior control type. IATSS Research 46, 247–257. https://doi.org/10.1016/j.iatssr.2021.12.007

Mishra, R., Pulugurtha, S.S., 2021. Evaluating the Safety Effectiveness Of restricted Crossing U-turn (rcut) Intersections. p. 17p.

Molan, A.M., Howard, J., Islam, M., Pande, A., 2022. A Framework for Estimating Future Traffic Operation and Safety Performance of Restricted Crossing U-Turn (RCUT) Intersections. TOTJ 16, e187444782111151. https://doi.org/10.2174/18744478-v16-e2111151

Montella, A., Mauriello, F., Pernetti, M., Rella Riccardi, M., 2021. Rule discovery to identify patterns contributing to overrepresentation and severity of run-off-the-road crashes. Accident Analysis & Prevention 155, 106119. https://doi.org/10.1016/j.aap.2021.106119

Moreland, M., Leuer, D., Saari, I., Minnesota. Department of Transportation. Office of Traffic Engineering, 2024. Traffic Safety Evaluation at J-turns in Minnesota (No. 2024– 05).

Mullani, M.B., Nadaf, S., Patel, I., Shinde, K., Shinde, R., 2022. U turn Accident Prevention System. IRJMETS.

Nadimi, N., Zare, A., Khalifeh, V., Naseralavi, S., 2025. Identifying safety issues of vulnerable road users in urban streets and optimizing countermeasures through the integration of association rule mining and mathematical programming methods. Journal of Transportation Research. https://doi.org/10.22034/tri.2025.485094.3293

Nazif-Munoz, J.I., Gilani, V.N.M., Rana, J., Choma, E., Spengler, J.D., Cedeno-Laurent, J.G., 2025. The influence of heatwaves on traffic safety in five cities across Québec with different thermal landscapes. Injury Epidemiology 12, 12. https://doi.org/10.1186/s40621-025-00564-2

NCHRP, 2004. Safety of U-Turns at Unsignalized Median Openings (Report 524). Transportation Research Board.

Nemmang, M.S., Rahman, R., Rohani, M.M., Mashros, N., Diah, J.M., 2017. Analysis of Speeding Behaviour During Approaching the U-Turn Facility Road Segment Based On Driving Simulation Test. MATEC Web Conf. 103, 08008. https://doi.org/10.1051/matecconf/201710308008

NHTSA, 2015. Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey (No. DOT HS 812 115). National Highway Traffic Safety Administration, Washington, DC.

Nye, T.S., Cunningham, C.M., Byrom, E., 2019. National-Level Safety Evaluation of Diverging Diamond Interchanges. Transportation Research Record 2673, 696–708. https://doi.org/10.1177/0361198119849589

Olarte, R., Bared, J.G., Sutherland, L.F., Asokan, A., 2011. Density Models and Safety Analysis for Rural Unsignalised Restricted Crossing U-turn Intersections. Procedia - Social and Behavioral Sciences 16, 718–728. https://doi.org/10.1016/j.sbspro.2011.04.491

Ortega, Josue, Lengyel, H., Ortega, Jairo, 2023. Design and Analysis of the Trajectory of an Overtaking Maneuver Performed by Autonomous Vehicles Operating with Advanced Driver-Assistance Systems (ADAS) and Driving on a Highway. Electronics 12, 51. https://doi.org/10.3390/electronics12010051

Ott, S.E., Haley, R.L., Hummer, J.E., Foyle, R.S., Cunningham, C.M., 2012. Safety effects of unsignalized superstreets in North Carolina. Accident Analysis & Prevention 45, 572–579. https://doi.org/10.1016/j.aap.2011.09.010

Pannela, S.K., Bhuyan, P.K., 2017. Modified INAFOGA method for critical gap estimation at u-turn median openings. International Journal of Civil Engineering 15, pp-967-977. https://doi.org/10.1007/s40999-017-0179-6

Phillips, S.L., Carter, D.L., Hummer, J.E., Foyle, R.S., 2004. Effects of Increased U-Turns at Intersections on Divided Facilities and Median Divided Versus Five-Lane Undivided Benefits. North Carolina Department of Transportation.

Pirinccioglu, F., Lu, J.J., Liu, P., Sokolow, G., 2006. Right Turn from Driveways Followed by U-Turn on Four-Lane Arterials: Is It Safer Than Direct Left Turn? Transportation Research Record: Journal of the Transportation Research Board 1953, 172–179. https://doi.org/10.1177/0361198106195300120

Rahman, M.A., Chakraborty ,Rohit, Das ,Subasish, Mohammed, Nurul-Haq, Hossain ,Md. Mahmud, and Junaed, S., 2025. Identifying attribute associations in fatal speeding crashes using latent class clustering and association rule mining. Journal of Transportation Safety & Security 17, 510–549. https://doi.org/10.1080/19439962.2024.2429095

Rahman, M.A., Das, S., Sun, X., 2022. Using Cluster Correspondence Analysis to Explore Rainy Weather Crashes in Louisiana. Transportation Research Record 2676, 159–173. https://doi.org/10.1177/03611981221082582

Rangam, H., Sivasankaran ,Sathish Kumar, and Balasubramanian, V., 2024. Generation of nighttime pedestrian fatal precrash scenarios at junctions in Tamil Nadu, India, using cluster correspondence analysis. Traffic Injury Prevention 25, 870–878. https://doi.org/10.1080/15389588.2024.2350695

Reid, J., Sutherland, L., Ray, B., Daleiden, A., Jenior, P., Knudsen, J., Kittelson & Associates, 2014. Median u-turn intersection : informational guide. (No. FHWA-SA-14-069).

Sando, T., Chimba, D., Kwigizile, V., Walker, H., 2010. Safety Characteristics of Unconventional Continuous Green Through Lane Intersections. Presented at the Transportation Research Board 89th Annual MeetingTransportation Research Board.

Schneider, H., Barnes, S., Pfetzer, E., Hutchinson, C., Louisiana State University. Highway Safety Research Group, 2019. Economic Effect of Restricted Crossing U-Turn Intersections in Louisiana (No. FHWA/LA.17/617).

Schroeder, B., Cunningham, C., Ray, B., Daleiden, A., Jenior, P., Knudsen, J., Kittelson & Associates, 2014. Diverging diamond interchange : informational guide. (No. FHWA-SA-14-067).

Schroeder, B., Warchol, S., Semensky, S., Osman, O.A., Ray, B., Leidos, Inc., 2024. Synthesis of Alternative Intersection Forms (No. FHWA-HRT-24-090).

Shafie, N., Rahman, R., 2016. An Overview of Vehicles Lane Changing Model Development in Approaching at U-Turn Facility Road Segment. Jurnal Teknologi 78. https://doi.org/10.11113/jt.v78.9482

Shahdah, U.E., Azam, A., 2021. Safety and mobility effects of installing speed-humps within unconventional median U-turn intersections. Ain Shams Engineering Journal 12, 1451–1462. https://doi.org/10.1016/j.asej.2020.08.033

Sharma, V.K., Mondal, S., Gupta, A., 2017. A Comparison of Critical Gap of U Turning Vehicles at Uncontrolled Median Opening Based on Different Methods. Journal of the Eastern Asia Society for Transportation Studies 12, pp-1728-1739. https://doi.org/10.11175/easts.12.1728

Sheykhfard, A., Haghighi, F., Kavianpour, S., Shaaban, K., Nadimi, N., 2023. Evaluating Driver Response to an Advanced Speed Display near Uncontrolled Median Openings. Sustainability 15, 502. https://doi.org/10.3390/su15010502

Shi, M., Tian, X., Li, X., Pan, B., 2023. The Impact of Parallel U-Turns on Urban Intersection: Evidence from Chinese Cities. Sustainability 15, 14356. https://doi.org/10.3390/su151914356

Siregar, M., Agah, H.R., Hidayatullah, F., 2018. Near-miss accident analysis for traffic safety improvement at a ‘channelized’ junction with U-turn. Int. J. SAFE 8, 31–38. https://doi.org/10.2495/SAFE-V8-N1-31-38

Sivak, M., 2009. During which month is it riskiest to drive in the United States? Traffic Inj Prev 10, 348–349. https://doi.org/10.1080/15389580902975820

Sivaprakash, S., John, P.M., 2024. Iot Based U-Turn Vehicle Accident Prevention System (Blindends). International Advanced Research Journal in Science, Engineering and Technology 11. https://doi.org/10.17148/IARJSET.2024.11525

Smith, D., 2013. Development of a New Jughandle Design for Facilitating High-Volume Left Turns and U-Turns [WWW Document]. URL https://d-scholarship.pitt.edu/18187/ (accessed 2.7.25).

Sourial, N., Wolfson, C., Zhu, B., Quail, J., Fletcher, J., Karunananthan, S., Bandeen-Roche, K., Béland, F., Bergman, H., 2010. Correspondence analysis is a useful tool to uncover the relationships among categorical variables. Journal of Clinical Epidemiology 63, 638–646. https://doi.org/10.1016/j.jclinepi.2009.08.008

Stamatiadis, N., Kala, T., Clayton, A., Agent, K., 2004. U-Turns at Signalized Intersections.

Stevens, S.E., Schreck, C.J., Saha, S., Bell, J.E., Kunkel, K.E., 2019. Precipitation and Fatal Motor Vehicle Crashes: Continental Analysis with High-Resolution Radar Data. https://doi.org/10.1175/BAMS-D-18-0001.1

Sun, C., Qing, Z., Edara, P., Balakrishnan, B., Hopfenblatt, J., 2017. Driving Simulator Study of J-Turn Acceleration–Deceleration Lane and U-Turn Spacing Configurations. Transportation Research Record: Journal of the Transportation Research Board pp-26-34. https://doi.org/10.3141/2638-04

Sun, M., Zhou, R., 2023. Investigation on Hazardous Material Truck Involved Fatal Crashes Using Cluster Correspondence Analysis. Sustainability 15, 9369. https://doi.org/10.3390/su15129369

Sun, X., Rahman, M.A., Sun, M., 2019a. Safety Analysis of RCUT Intersection, in: 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). Presented at the 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), IEEE, Cracow, Poland, pp. 1–6. https://doi.org/10.1109/MTITS.2019.8883332

Sun, X., Rahman, M.A., University of Louisiana at Lafayette. Dept. of Civil Engineering, Louisiana Transportation Research Center, 2019b. Investigating Safety Impact of Center Line Rumble Strips, Lane Conversion, Roundabout, and J-Turn Features on Louisiana Highways (No. FHWA/LA.18/597).

Ulak, M.B., Ozguven, E.E., Karabag, H.H., Ghorbanzadeh, M., Moses, R., Dulebenets, M., 2020. Development of Safety Performance Functions for Restricted Crossing U-Turn Intersections. J. Transp. Eng., Part A: Systems 146, 04020038. https://doi.org/10.1061/JTEPBS.0000346

USDOT, 2014. Median U-Turn Intersection - Michigan Avenue and South Harrison Road, East Lansing, MI (No. FHWA-SA-14-050).

van de Velden, M., D’Enza, A.I., Palumbo, F., 2017. Cluster Correspondence Analysis. Psychometrika 82, 158–185. https://doi.org/10.1007/s11336-016-9514-0

VDOT, 2023. Thru-cut - Intersection | Virginia Department of Transportation [WWW Document]. URL https://www.vdot.virginia.gov/about/our-system/highways/innovative-intersections/thru-cut/ (accessed 2.11.25).

Walls, J., Rab, M., Qi, Y., Fries, R., 2018. Safety Evaluation of Diverging Diamond Interchanges Design for Intersections in Minnesota.

Weast, R., 2018. Temporal factors in motor-vehicle crash deaths: Ten years later. J Safety Res 65, 125–131. https://doi.org/10.1016/j.jsr.2018.02.011

Wei, F., Zhou, Y., Yongqing, G., Guo, Y., Xu, P., 2024. Analysis the Severity of Motorcycle Single-Vehicle Crashes on Rural Roads Under Diverse Lighting Conditions. https://doi.org/10.2139/ssrn.4887629

Wood, J., Donnell, E.T., 2016. Safety evaluation of continuous green T intersections: A propensity scores-genetic matching-potential outcomes approach. Accident Analysis & Prevention 93, 1–13. https://doi.org/10.1016/j.aap.2016.04.015

Wu, W., Sun, R., Li, Y., Chen, R., 2020. Cooperative U-Turn Merging Behaviors and Their Impacts on Road Traffic in CVIS Environment. Journal of Advanced Transportation 2020, 14p. https://doi.org/10.1155/2020/4158569

Xu, L., Yang, X., Chang, G.-L., 2017. Computing the Minimal U-Turn Offset for an Unsignalized Superstreet. Transportation Research Record: Journal of the Transportation Research Board pp-48-57. https://doi.org/10.3141/2618-05

Zhang, H., Guo, B., Chen, Y., 2024. Research on Optimization of Speed Limit Setting of Deceleration Zone at U-Shaped Left-Turn Three-Road Intersection. Presented at the 2024 International Conference on Rail Transit and Transportation (ICRTT 2024), Atlantis Press, pp. 222–230. https://doi.org/10.2991/978-94-6463-610-9\_25

Zhao, Q., Bhowmick, S., 2003. Association Rule Mining: A Survey.

Zhou, H., Lin, P.-S., Shen, J., 2008. An Unconventional Design for Bus U-Turns at Signalized Intersections. JPT 11, 89–103. https://doi.org/10.5038/2375-0901.11.4.5

Zlatkovic, M., 2019. Development of Performance Matrices for Evaluating Innovative Intersections and Interchanges [MPC-19-391] (No. MPC-19-391).

Zubair, S., Shaikh, M.A., 2015. U-Turns and road safety — perspective from Karachi. J Pak Med Assoc.