A MULTIDIMENSIONAL FRAMEWORK FOR TRANSPORTATION SAFETY: LINKING PERCEPTIONS, POLICIES, AND ENVIRONMENTAL CONTEXTS

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DEDICATION

To

All those who walk, drive, and dream toward a world

where safety and compassion share the same road.

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ABSTRACT

Road safety remains a complex and evolving challenge shaped by behavioral, institutional, and environmental systems. This dissertation integrates multiple analytical perspectives to advance a holistic understanding of how enforcement technologies, workforce readiness, and environmental context collectively influence transportation safety. Through a combination of crash analysis, behavioral research, organizational assessment, and spatial modeling, this dissertation connects technical effectiveness with human and ecological dimensions of safety. The research begins with an evaluation of red-light camera (RLC) enforcement in Phoenix, combining crash data analysis with professional perspectives to assess the program's operational and safety impacts. Using a before-during-after design with Empirical Bayes estimation, the findings reveal substantial reductions in angle crashes and severe injury during operation. These safety gains remained largely stable even after the program's termination indicating lasting behavioral adaptation and long-term benefits of enforcement visibility. Building on this evidence, the next phase transitions from professional assessments and data analysis to public perceptions, examining how fairness, transparency, and safety beliefs shape acceptance of RLCs in Arizona and New York. Structural equation modeling demonstrates that fairness and clarity mediate the relationship between safety beliefs and support, underscoring the central role of legitimacy and communication in sustaining automated enforcement programs. The analysis then shifts toward technological transitions and organizational readiness through an examination of electric vehicle (EV) adoption among Minnesota's public agencies. Surveys and interviews highlight that while environmental commitment and policy alignment foster optimism, persistent concerns about charging reliability, maintenance, and cold-weather performance continue to constrain large-scale implementation. Extending this focus on sustainability and safety, the final investigation emphasizes that transportation safety is not limited to human protection alone. Applying a grid-based spatial model of wildlife-vehicle collisions in Tucson, Arizona, the investigation reveals that roadway density, travel speed, and population exposure are the strongest predictors of crash likelihood, demonstrating how human infrastructure shapes risks for both people and wildlife. Together, these studies form an integrated framework linking behavioral legitimacy, institutional capacity, and ecological context. The findings contribute empirical and methodological insights that advance the design of transportation systems that are safer, more adaptive, and sustainable for all users.

Chapter 1: Introduction

Transportation safety and sustainability are shaped by the dynamic interplay of human behavior, technological adoption, environmental context, and institutional readiness. While roadway systems are designed to promote the safe and efficient movement of people and goods, they remain the setting for persistent risks such as crashes leading to injuries and fatalities, risky driver behaviors, and broader environmental impacts and consequences (IIHS-HLDI, 2025; NHTSA, 2024). These challenges are compounded by societal demands for transportation systems that are not only safe but also equitable and environmentally responsible (USDOT, 2024). As agencies and policymakers strive to balance objectives such as safety, equity, sustainability, and efficiency, transportation research must move beyond narrowly assessing individual interventions and instead adopt an integrated approach that considers behavioural, organizational, technological, and environmental perspectives.

One prominent example of this complexity can be seen in the adoption of automated enforcement technologies, particularly red-light cameras (RLCs). RLCs have been adopted in many jurisdictions to deter red-light running and reduce the frequency of severe intersection crashes (F. Llau et al., 2015; Mahmassani et al., 2017; Retting et al., 1999). Despite their safety benefits, RLCs have remained highly controversial, with debates centering on fairness, transparency, privacy, and the equitable distribution of enforcement burdens (McCartt and Eichelberger, 2012; Sutton and Tilahun, 2022). Public perception plays a decisive role in the long-term viability of such programs: even when empirical evidence supports their effectiveness, opposition rooted in concerns over fairness and legitimacy has led to program bans in several states (Cohn et al., 2020; Higgins et al., 2011; Maisel, 2013). Understanding how the public perceives automated enforcement technologies is therefore critical for evaluating not just their technical effectiveness but also their social sustainability.

Parallel to safety-focused enforcement, transportation agencies are navigating another profound transition: the electrification of vehicle fleets. Driven by climate imperatives and the pursuit of sustainability goals (USDOT Climate Change Center, 2024), fleet electrification promises reductions in emissions and long-term operational savings (Electrification Coalition, 2024; Wood et al., 2024). Yet, successful adoption is contingent upon far more than the availability of charging infrastructure or vehicle costs. Institutional readiness, workforce acceptance, and operational constraints play equally critical roles (Abdul Qadir et al., 2024; Khatua et al., 2023; Roemer and Henseler, 2022; Zaino et al., 2024). For instance, concerns about cold-weather performance, charging reliability, maintenance, and safety can undermine enthusiasm for electric vehicle (EV) integration (Esparza et al., 2025; Izquierdo-Monge et al., 2025). The electrification of agency fleets therefore serves as a case study of how technological shifts require alignment with organizational culture, workforce preparedness, and context-specific planning in order to achieve policy goals.

In addition to engineering and policy analyses, this dissertation is informed by insights from human–computer interaction (HCI) and sociotechnical systems research, which emphasize that technologies deployed in public spaces such as automated enforcement cameras and electric vehicle systems must be understood within the social, institutional, and cultural contexts in which they operate. HCI scholarship critiques hardware-first approaches and argues that public trust, transparency, and perceived legitimacy are central to the effectiveness of data-driven technologies (Bannon, 2011; Baxter and Sommerville, 2011). Early HCI work on privacy and ubiquitous computing demonstrates that data collection in public environments shapes community attitudes toward fairness, surveillance, and accountability (Bellotti and Sellen, 1993; Dourish and Anderson, 2006). Recent contributions reinforce this perspective by showing how privacy expectations, data-handling practices, and user-informed design influence how communities interpret and engage with automated systems (Kim and Bratt, 2024). Related scholarship on data labor and governance highlights that the individuals and institutions responsible for generating, interpreting, and operationalizing data significantly shape public acceptance and technological legitimacy (Bratt et al., 2024). Integrating these HCI perspectives strengthens the framing of this dissertation by illustrating that the success of red-light camera programs, perceptions of fairness and transparency, and workforce acceptance of electric vehicle fleets depend not only on technical performance but also on how communities understand the purpose, equity implications, and data practices underlying these transportation technologies.

At the same time, roadway safety cannot be understood solely through the lens of technology or human behavior; it is also deeply intertwined with environmental systems. Wildlife-vehicle conflicts present a pressing example of this interdependence. These collisions not only endanger drivers and passengers (FHWA, 2008; Villamagna and Laflamme, 2024) but also threaten wildlife populations, disrupt ecological systems, and impose substantial economic costs (Balčiauskas et al., 2025). The likelihood and severity of wildlife-vehicle crashes are shaped by land use, roadway design, population distribution, and proximity to natural features such as parks and water resources (Pagany, 2020; Valerio et al., 2021). Addressing these risks requires spatially informed analysis that bridges transportation safety with ecological and land-use planning, underscoring the need for interdisciplinary approaches (Corazza, 2024; Hlatshwayo et al., 2024).

Taken together, these issues illustrate the multidimensional nature of transportation safety and sustainability. Programs and interventions cannot be evaluated solely on technical or operational grounds; they must also account for human attitudes, institutional capacity, and environmental context (CITE broad transportation safety/equity frameworks). This dissertation responds to this challenge by examining four interrelated case studies: (1) public perceptions of RLCs, (2) agency workforce attitudes and organizational readiness for EV fleet adoption, (3) the safety effectiveness of RLCs across crash types, and (4) the spatial dynamics of wildlife-vehicle conflicts. By bringing these domains together, this research contributes a holistic framework for understanding how public perception, institutional readiness, technological effectiveness, and environmental context jointly shape transportation outcomes, particularly at the local and regional levels.

1.1 Problem Statement

Transportation systems continue to face persistent safety and sustainability challenges, despite advances in engineering design, policy interventions, and technological innovation. Crashes remain a leading cause of injuries and fatalities, while broader societal pressures call for transitions that reduce environmental impacts and support long-term resilience. These outcomes are shaped not only by roadway design and individual behavior but also by institutional priorities, public attitudes, and interactions between human activity and the natural environment.

Conventional approaches to transportation safety often address these issues in isolation, focusing narrowly on technical effectiveness while overlooking the behavioral, organizational, and ecological contexts that determine long-term success. As a result, programs and policies that may show measurable benefits in controlled evaluations can encounter resistance, fail to achieve intended outcomes, or generate unintended consequences when implemented in practice. Similarly, sustainability initiatives can be slowed or undermined when workforce readiness, operational feasibility, or environmental considerations are not fully incorporated into planning and evaluation.

This research responds to these limitations by adopting a multidimensional perspective that integrates behavioral, institutional, technological, and environmental factors in the study of transportation systems. Through this broader lens, the dissertation aims to provide a more comprehensive understanding of the forces that shape safety and sustainability outcomes, offering insights to guide policies and practices that are evidence-based, context-sensitive, and durable.

1.2 Research Hypotheses

This dissertation is proposed to delve into several issues surrounding across safety, sustainability, and public trust. This involves assessing both the effectiveness and acceptance of interventions, while also considering organizational readiness and ecological influences. To guide this investigation, four hypotheses are proposed.

Research Hypothesis 1:

RLCs reduce the severity of crashes and result in different types of collisions at intersections. Following program termination, overall crash frequencies and severities exhibit shifts that reflect both behavioural adaptation and enforcement gaps.

Research Hypothesis 2:

Public perception of RLCs is influenced by an individual's understanding of safety benefits, fairness in enforcement, and clarity in policies, which together shape support or opposition to their use.

Research Hypothesis 3:

Adoption of electric vehicles in public agency fleets is influenced by workforce attitudes, organizational readiness, and perceptions of operational challenges such as charging *accessibility, cold-weather performance, and safety, which together shape the pace and success of fleet electrification and progress toward sustainability goals.*

Research Hypothesis 4:

Wildlife-vehicle collision (WVC) patterns can be effectively quantified through an integrated spatial framework that leverages locally available data, allowing for the assessment of how built-environment and ecological conditions jointly shape spatial patterns of crash likelihood.

1.3 Research Scope

The scope of this dissertation is to investigate transportation safety and sustainability through an integrated lens that connects behavioural, institutional, technological, and environmental dimensions. Specifically, it considers how human attitudes and perceptions influence the acceptance of safety measures, how organizational and policy contexts shape the adoption of emerging technologies, and how roadway systems interact with broader environmental and societal factors. By combining quantitative and qualitative approaches including surveys, crash data analyses, interviews, and spatial modeling, this research provides a multidimensional understanding of transportation challenges. By linking these domains, the research emphasizes that transportation interventions must be evaluated not only on measurable outcomes such as crash reductions or emission targets, but also on their broader social and environmental implications. In doing so, the dissertation contributes a holistic perspective that advances understanding of roadway safety while offering practical guidance for developing policies and programs that are adaptive, context-sensitive, and sustainable.

1.4 Dissertation Organization

The dissertation is organized as follows: Chapter 1 introduces the research by presenting the background, problem statement, hypotheses, and scope of the dissertation, establishing the foundation for examining transportation safety and sustainability through multiple perspectives. Chapter 2 provides a comprehensive literature review, synthesizing prior research on automated enforcement, crash outcomes, electric vehicle adoption, and environmental influences on roadway safety. This review identifies gaps, informs the methodological approach, and situates the dissertation within broader academic and policy discussions. Chapter 3 evaluates the safety effectiveness of RLCs on intersection outcomes, integrating crash data analysis with professional perspectives to capture both the benefits and limitations of these programs. Chapter 4 investigates public perceptions of RLCs through surveys conducted in Arizona and New York, highlighting the role of attitudes, fairness, and acceptance in shaping the viability of automated enforcement programs. Chapter 5 examines the transition to electric vehicle fleets within public agencies, drawing on survey responses and interviews with Minnesota agency personnel to assess organizational readiness, workforce concerns, and the broader sustainability implications of fleet electrification. Chapter 6 broadens the lens to consider environmental and spatial influences on roadway safety, analysing wildlife-vehicle conflicts using crash records, roadway characteristics, environmental features and census data to reveal patterns of human-environment interaction. Finally, Chapter 7 concludes the dissertation by synthesizing the findings, highlighting the contributions across behavioural, institutional, technological, and environmental dimensions, and discussing implications for future research and policy in advancing safe and sustainable transportation systems.

Chapter 2: Literature Review

Transportation safety and sustainability are increasingly recognized as socio-technical challenges that extend beyond roadway design. While engineering and enforcement strategies remain central, their effectiveness is often shaped by governance structures, public perception, institutional capacity, and environmental context. A growing body of research highlights that legitimacy, equity, and stakeholder acceptance are as critical to long-term outcomes as technical performance. Automated enforcement, for example, can deter risky behaviors but remains controversial when perceived as unfair or revenue-driven. Similarly, electric vehicle adoption promises environmental gains but is constrained by psychological barriers, organizational readiness, and infrastructure availability. Evaluations of RLCs demonstrate measurable safety benefits yet reveal mixed outcomes when programs lack stability or stakeholder trust. Wildlife-vehicle collisions further illustrate how transportation safety intersects with ecological systems, requiring interdisciplinary approaches that link human behavior, roadway networks, and habitat connectivity.

This chapter reviews prior research across four domains that provide the foundation for this dissertation: Section 2.1 evaluates the safety effectiveness of RLCs, Section 2.2 examines public perceptions of automated enforcement, Section 2.3 addresses the adoption of electric vehicles by consumers and agencies, and Section 2.4 considers wildlife-vehicle collisions as an ecological dimension of roadway safety. The review synthesizes key findings while also identifying persistent gaps, emphasizing how governance, legitimacy, and methodological approaches shape transportation outcomes. Section 2.5 provides a synthesis of the reviewed literature with a discussion of research gaps that inform the empirical analyses presented in subsequent chapters.

2.1 Effectiveness of Red-Light Cameras

RLCs have been implemented as an enforcement tool aimed at reducing RLR violations and improving intersection safety. Over the years, numerous studies have examined the effectiveness of RLCs using different methodologies, data sources, and analytical techniques. This section provides literature review which synthesizes key studies on RLC effectiveness, summarizing the methodological approaches, findings, and limitations of previous research. Additionally, it addresses gaps in the literature that this research seeks to fill, particularly in evaluating the long-term effects of RLC deactivation and the integration of professional perspectives.

2.1.1 Safety Outcomes and Methodological Approaches

A predominant approach in the literature involves before-and-after studies, which compare crash data from the periods prior to and following the installation of RLCs. These studies provide direct comparisons of crash frequencies and severities, but they are often subject to regression to the mean (RTM), where natural fluctuations in crash data may distort the true impact of RLC interventions. To mitigate this issue, Empirical Bayesian (EB) methods have become a standard technique, offering a more robust and reliable estimation of RLC effectiveness (Hadayeghi et al., 2007; Lee et al., 2016; Miller et al., 2006). For example, Hallmark et al. (2010) conducted a two-year before-and-after study evaluating RLCs at 16 intersections in Iowa. They employed Bayesian statistical analysis to assess the cameras' impact, revealing their effectiveness in reducing both total and RLR crashes. Moreover, the study found no increase in rear-end crashes associated with RLR at intersections with camera enforcement (Hallmark et al., 2010).

RLCs were recognized for their effectiveness in reducing red light violations, they were also noted for their efficacy in decreasing and increasing specific types of collisions (Ahmed and Abdel-Aty, 2015; F. Llau et al., 2015; Ko et al., 2017; Mahmassani et al., 2017; Wong, 2014). This is why angle collisions, left-turn collision, and rear-end collision are frequently considered when assessing the effectiveness of RLCs. A study by Walden (2008) conducted an intersection crash study to assess the impact of RLCs at 56 intersections. The study gathered data for 12 months before the installation of cameras and 12 months after. The research team observed a 30% reduction in overall crashes and a significant decrease of 43% in right-angle crashes. However, there was a slight increase of 5% in rear-end crashes. Despite these findings, the statistical significance of these results was limited due to the relatively small amount of data available for analysis (Walden, 2008).

Washington and Shin (2005) examined 14 intersections in Scottsdale, Arizona, and an additional 11 intersections in Phoenix, Arizona. The study revealed a reduction of 14% in right-angle crashes at the Scottsdale intersections and a decrease of 11% in right-angle crashes at the Phoenix intersections (Washington and Shin, 2005). Persaud et al. (2005) investigated the efficacy of RLC systems in reducing crashes at monitored intersections and on a jurisdiction-wide scale. Their findings aligned with many previous studies, showing a decrease in right-angle crashes and an increase in rear-end crashes. However, the magnitudes of these effects were somewhat lower compared to other sources (Persaud et al., 2005).Additionally, Persaud et al. (2005) aimed to identify all factors favoring the installation of RLC systems by using the aggregate economic benefit as the outcome variable. While they found weak indications of a spillover effect, further research, possibly in the form of a more definitive and prospective study, is required to fully understand this aspect (Persaud et al., 2005). Ahmed & Abdel-Aty (2015) employed empirical Bayesian analysis on 25 RLC-equipped intersections in Orange County, FL, assessing three levels: target RLC-equipped approaches, all RLC intersections, and non-RLC intersections on the same corridors. The study found reduced angle/left-turn crashes on target approaches, offset by increased rear-end crashes. Similar trends were observed across all intersections, with moderate spillover effects extending to neighboring non-RLC intersections, leading to shifts in crash patterns towards the county boundary (Ahmed and Abdel-Aty, 2015).

2.1.2 Factors Influencing RLC Camera Effectiveness

Pulugurtha and Otturu (2014) assessed the 32 signalized intersections and compared them for "before the installation," "after the installation," and "after the termination" periods in Charlotte, NC. They conducted a study involving descriptive analysis and paired *t*-tests to examine various types of crashes, including rear-end, sideswipe, left-turn, angle, and right-turn crashes, as well as the total number of crashes (Pulugurtha and Otturu, 2014). Sayed & de Leur (2007) assessed Edmonton's Intersection Safety Camera Program, summarizing the literature on RLC impact. Four studies comparing camera-equipped intersections to those without found more substantial violation reductions at camera sites (40-78%) than at non-camera sites (27-67%). Notably, one study reported a 50% decrease at non-camera sites and a 40% decrease at camera-equipped sites (Sayed and Leur, 2007).

Another study utilized structural equation modeling (SEM) to analyze factors impacting red-light-running crash severity. Three unobserved variables were introduced: precrash speed, the bullet vehicle's kinetic energy transfer to the subject vehicles, and crash severity. Findings highlighted the significant influence of kinetic energy on crash severity, alongside factors like pavement skid resistance, alcohol involvement, traffic conditions, and lighting (Shaaban et al., 2021). Another study also examined the severity of red-light running violations at signalized intersections and identified factors influencing their frequency. It was found that intersection delay and split failure increase the frequency of violations, while a longer yellow interval, cycle length, and number of lanes reduce less severe violations but increase more severe violations (Jalali Khalilabadi et al., 2023). Li et al. (2023) presented a novel approach and developed a model to analyze RLR frequency and implemented a multi-objective optimization technique Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimize signal timing while balancing RLR and traffic delay. Simulation tests on a 6-intersection road demonstrated effectiveness (Li et al., 2023).

The current literature revealed two main trends related to RLCs: a reduction in right-angle crashes at camera-equipped intersections and an increase in rear-end crashes due to sudden braking to avoid red lights. Additionally, some studies attempted to quantify the spillover effect of RLCs in other locations. Several factors have been identified as influencing RLR behavior. These include gender, e-bike use, location, traffic flow, intersection delay, number of approach lanes, split failure, and speed limit. Intersection delay, split failure, yellow interval, cycle length, and number of lanes influence the frequency and severity of violations. Multiple studies showed the effectiveness of RLCs in reducing crashes using different models and data. However, new findings and approaches are continuously emerging, which have proposed novel traffic signal control approaches to reduce RLR frequency. To gain a comprehensive understanding of this issue, it is essential to consider factors such as the spillover effect, the impact of traffic volume and density, the types and severity of crashes, and estimated crash costs. By examining these aspects, the study can offer a more comprehensive understanding of the overall effectiveness and implications of RLC enforcement.

While much of the existing literature focuses on quantitative crash data, fewer studies address professional perspectives regarding the successful implementation and effectiveness of RLCs. A survey comparing attitudes toward RLCs in 14 cities with established programs and Houston, Texas where cameras were removed revealed notable differences. In the 14 cities, two-thirds of drivers supported RLCs, with 42% strongly in favor, whereas in Houston, support was 45%, but strong opposition was higher (28% compared to 18%). Awareness of RLC programs was widespread, with nearly 90% of respondents in the 14 cities familiar with them, and 59% believed the cameras improved intersection safety. Similarly, a study in Oxnard found that nearly 80% of residents supported RLCs shortly after their implementation as a supplement to police enforcement efforts (Retting et al., 1999). While the more persuasive policy argument emphasizes preventing the dangerous behavior of red-light running to enhance safety, the effectiveness of RLC programs hinges on how transparently and persuasively these policies are communicated (Lehman, 2001). One study found that while drivers acknowledged the dangers of red light running (RLR), many, especially younger drivers, still engaged in the behavior. A key factor was the low perception of enforcement, with most drivers believing police would catch fewer than 20% of violators. Additionally, fewer than 6% had received a ticket for RLR, indicating minimal legal repercussions (Porter and Berry, 2001).

Prior studies emphasize the role of driver characteristics and behavioral tendencies in shaping RLR violations. Sahu et al. (2025) found that age, driving experience, education, and trip frequency significantly predict the likelihood of violations, with younger drivers and frequent commuters often overrepresented among offenders (Sahu et al., 2025). This study highlights that under certain conditions, gender differences in aberrant driving behaviors diminish, suggesting the importance of considering interactions among demographic variables rather than treating them as isolated predictors. These findings align with global studies showing younger drivers and two-wheeled vehicle riders to be among the most frequent violators, reflecting both risk-taking tendencies and contextual pressures such as congestion and trip purpose (Mohd Radzi et al., 2025). These findings highlight the importance of tailoring interventions to the distinct behaviors of diverse user groups.

This lack of legal consequences may reinforce the persistence of this habit. Despite these findings found in current literature, the underlying motivations for RLC deployment significantly shape public opinion (Higgins et al., 2011; Kennedy et al., 2025). The implementation of RLCs as a traffic enforcement measure has sparked significant debate across various regions due to a combination of technical, financial, and public perception factors. While RLCs have proven effective in reducing traffic violations and crashes in some areas, their adoption and continued use often depend on the priorities and challenges faced by key stakeholders, including policymakers, law enforcement agencies, and the public. These stakeholder’s perspectives play a crucial role in shaping the overall success and acceptance of RLC programs. Variations in regional barriers, such as budget constraints, technological feasibility, and political opposition, can significantly influence the extent to which RLCs are integrated into traffic enforcement systems. Furthermore, financial considerations, such as the costs associated with installing and maintaining RLC systems, can create additional challenges, particularly in economically strained municipalities.

The literature offers insights into the challenges and potential solutions related to red-light running, as well as the mixed outcomes from studies on the effectiveness of RLCs in reducing crashes. Various studies have developed and evaluated different models to understand and predict RLR behavior and assess the effectiveness of RLCs before and during their implementation. However, these studies often fall short of providing a comprehensive understanding of the cameras' effectiveness, often due to limited data or other constraints.

2.2 Public Perception of Red Light Cameras

Debate over automated enforcement at signalized intersections has persisted for decades, with two recurring narratives: advocates emphasize safety gains and deterrence of red-light running, while critics question fairness, accuracy, and the motives behind deployment (Decina et al., 2007; Herbel et al., 2013; Smith et al., 2000). Early program reviews already treated community acceptance as a core performance metric alongside violations and crash outcomes, noting that acceptance is shaped by design choices and communication practices (Decina et al., 2007; Smith et al., 2000). Subsequent evaluations and policy syntheses similarly conclude that legitimacy how fair, transparent, and safety-oriented a program is perceived to be is as consequential as measured effectiveness for long-term viability (Herbel et al., 2013; Porter et al., 2013).

2.2.1 Sources of Support and Opposition

Survey evidence consistently shows substantial baseline support in jurisdictions with active programs, especially when residents believe cameras improve safety. In a study of 14 cities, about two-thirds of drivers favoured camera enforcement, with many strongly in favor; opposition centered on perceptions that cameras make mistakes and are installed primarily for revenue rather than safety (McCartt and Eichelberger, 2012). In Washington, D.C., where automated enforcement was part of a broader safety strategy, support for RLCs reached roughly 87%, with respondents linking approval to perceived pedestrian and intersection safety benefits (Cicchino et al., 2014). These findings align with broader reviews that associate acceptance with clear, credible safety impacts and visible reductions in risky behaviors (Alobaidallah et al., 2025; Cohn et al., 2020; Decina et al., 2007; Herbel et al., 2013).

At the same time, opposition concentrates around fairness, revenue, and privacy. Stated-preference work shows preferences are sensitive to attributes that signal procedural justice e.g., how imagery is handled, whether thresholds feel reasonable, how revenue is used, and whether safety is the primary stated goal (Higgins et al., 2011). Program and legal reviews repeatedly raise several concerns: perceptions of 'gotcha' enforcement linked to yellow-light timing and threshold settings, skepticism about vendor payment and revenue-sharing models, risks of error or misidentification, and broader privacy and surveillance issues (Adams and Vandrasek, 2009; Aldossari et al., 2023; Farmer, 2017; Herbel et al., 2013; Shaheen et al., 2007). Evidence-based program design and clear communication such as the use of conspicuous signage, transparent site-selection criteria based on crash and violation risk, engineering-led signal timing, reasonable right-turn and threshold policies, publicly available performance dashboards, and reinvestment of fine revenues into safety initiatives are consistently identified as levers that mitigate skepticism and strengthen public acceptance (Adams and Vandrasek, 2009; Herbel et al., 2013; Li and Tian, 2009).

Context and exposure shape attitudes. Communities with longer histories of automated enforcement and consistent safety messaging tend to report higher acceptance; highly publicized controversies or abrupt rollbacks can erode trust (McCartt and Eichelberger, 2012; Porter et al., 2013). Analyses of behavior following program expiration show that removing cameras can change violation dynamics, underscoring how policy stability and communication affect perceived legitimacy (Porter et al., 2013). Broader literature on enforcement emphasizes that compliance and acceptance are strengthened when sanctions are visible, predictable, and perceived as certain (Farmer, 2017; Shaheen et al., 2007).

2.2.2 Governance, Equity, and Policy Design

Equity and distributional concerns have become increasingly prominent. Spatial and demographic analyses examine who is most exposed to automated enforcement and whether ticketing patterns align with risk-based placement (Eger et al., 2015; Factor and Sher, 2023). Legal policy critiques warns that automated monetary sanctions can impose disproportionate burdens on marginalized communities if not coupled with safeguards, transparent governance, and reinvestment mechanisms (Conner, 2017; Rankin et al., 2024). These strands reinforce that acceptance is not only about perceived safety gains; it is also about who bears costs, how decisions are made, and whether implementation aligns with procedural-justice principles. Program reviews respond by recommending explicit, published site-selection rubrics (e.g., crash/violation history, engineering review, periodic re-evaluation) and routine equity audits to sustain legitimacy (Adams and Vandrasek, 2009; Herbel et al., 2013).

Complementing these perception patterns, the literature also specifies how programs are designed and studied. Surveys and citywide questionnaires use structured Likert items to relate beliefs, exposure, and demographics to support, demonstrating that perceived legitimacy not just observed crash change drives acceptance (Cicchino et al., 2014; McCartt and Eichelberger, 2012). Stated-preference experiments quantify trade-offs over program attributes privacy safeguards, thresholds, signage/communication, and revenue use identifying concrete design levers that increase acceptability (Egbendewe-Mondzozo et al., 2010; Higgins et al., 2011). Quasi-experimental evaluations (before and after, interrupted time series; Poisson/negative-binomial models) provide context on safety outcomes by crash type and exposure, while post-expiration analyses show deterrence decay when programs are removed (Decina et al., 2007; Maccubbin et al., 2001; Porter et al., 2013; Smith et al., 2000). Systematic/critical reviews synthesize these heterogeneous designs and call for clearer reporting of thresholds, yellow/all-red intervals, right-turn policies, and communication practices to improve comparability (Alobaidallah et al., 2025; Cohn et al., 2020; Decina et al., 2007).

Viewing automated enforcement through a governance lens links program design to perceived legitimacy. Practices such as transparent, risk-based site selection, conspicuous warning signage, engineering-based signal timing, and reinvestment of revenues are consistently associated with greater public acceptance and reduced perceptions of “revenue primacy” (Adams and Vandrasek, 2009; Farmer, 2017; Herbel et al., 2013; Li and Tian, 2009). At the same time, legal and policy analyses warn that, without procedural safeguards and accessible adjudication, automated monetary sanctions can impose disproportionate burdens, reinforcing the need for equity audits and published siting rubrics (Conner, 2017; Herbel et al., 2013).

Despite this progress, gaps remain. Comparative evidence across distinct state policy environments is limited relative to single-city studies and national polls, making it difficult to isolate how legal design (civil vs. moving-violation treatment, fine magnitudes and points, owner liability, notice/signage practices) shapes attitudes (Cohn et al., 2020; Decina et al., 2007; Herbel et al., 2013). Moreover, fairness/legitimacy and equity are often discussed qualitatively but are not jointly operationalized with safety beliefs in the same empirical models (Factor and Sher, 2023; Higgins et al., 2011). This study addresses these gaps by implementing a two-state survey in jurisdictions with distinct legal/administrative frameworks and modeling acceptance as a function of Safety Beliefs, Fairness/Legitimacy, Transparency/Communication, and Equity/Placement, controlling for exposure and demographics, and testing for policy moderation of these associations (Adams and Vandrasek, 2009; Higgins et al., 2011).

2.3 Adoption of Electric Vehicles

This section provides the literature review presented on the various psychological and physical advantages and disadvantages associated with EV adoption, both as a public consumer, and from the perspective of public agencies.

2.3.1 Consumer Trends and Attitudes

Several studies have focused on the adoption of electric vehicles by consumers and fleets, specifically examining plug-in electric vehicles (PEVs), battery electric vehicles (BEVs), and EVs in general. The jump from standard gasoline vehicles to PHEVs or EVs as a whole has been met with both enthusiasm and apprehension. Generally, the primary reason individuals do not consistently use technology is a lack of trust in it (Zmud and Sener, 2017). Thus, a significant barrier to the adoption of electric vehicles is a lack of trust in their safety and reliability, driven by cognitive biases (Mahdavian et al., 2021). Some studies also suggest gender plays a role in adoption and attitudes, where men are more inclined than women to acquire electric vehicles. This gender-specific trend is presented in men's adoption of vehicles and greater willingness to invest in new technologies (Kyriakidis et al., 2015; Schoettle and Sivak, 2014).

Previous research has also found that individuals with better technological familiarity are more likely to adopt electric vehicles easily (Mahdavian et al., 2021). Specifically, one of the largest considerations when purchasing an electric vehicle is the all-electric range (AER), otherwise known as the distance that the vehicle can go using solely the battery (Farhar et al., 2016). To preserve or maintain a charge on an electric vehicle, it must be charged at a charging station for an extended period of time, depending on the level of charger (i.e., 4-36 hours for Power Level 1 charging; 1-6 hours for Power Level 2 charging) (Saraswathi and Ramachandran, 2024). This is a significant amount of time compared to filling a vehicle with gasoline, which may be less than ten minutes at a gas station. This phenomenon has caused anxiety among consumers, out of fear of running out of battery, a concept which has been deemed "range anxiety" (Berkeley et al., 2017; Rainieri et al., 2023).

Range anxiety stems from the consumer concern of charging management. Comparatively speaking, currently, public EV charging stations are much scarcer than gas stations for standard gasoline cars. A field study conducted at the University of Colorado at Boulder studied human adaptation over time with PEVs, and the human factors that impact electric range management. The study concluded that 90% of participants expressed a generally positive attitude towards driving the vehicle, that they either loved or liked their EV. Specifically, with a charging station at home, consumers found electric vehicles to be practical and environmentally friendly (Farhar et al., 2016). Additionally, an online survey conducted with fleet managers via a five-month research project in Italy collected empirical data on the factors influencing the adoption of electric vehicles in corporate fleets. The study highlighted a lack of awareness regarding the technical characteristics of these vehicles, with 59% of managers scoring low to medium in the area (Di Foggia, 2021).

One way to move towards increased EV adoption that has been explored is the use of incentives to influence consumer behavior. A common example of this is new electric vehicle purchasers receiving a monetary tax incentive. Another example is workplace promotion. Specifically, one company conducted a workplace study which observed the impact of company incentives on employee purchase behavior. The incentive from the workplace greatly increased the number of electric vehicle purchases (Decrinis et al., 2023). With both financial and workforce incentives, EV apprehension is eased compared to no incentives. Thus, understanding the role of incentives in public agency fleet adoption may be critical.

2.4 Wildlife Vehicle Crashes

Wildlife-vehicle collisions (WVCs) represent a persistent challenge at the intersection of transportation safety, ecological conservation, and economic cost. In the United States alone, millions of large-animal collisions are estimated each year, leading to significant damage to vehicles, human injuries, and fatalities, as well as the loss of wildlife populations and genetic connectivity (Huijser et al., 2008; Wilkins et al., 2019). Globally, research highlights that WVCs impose substantial financial burdens on transportation agencies and insurance systems, while also threatening biodiversity and ecological resilience (Ament et al., 2021; Balčiauskas et al., 2025). The frequency and severity of these incidents are not distributed randomly; rather, they cluster in predictable hotspots where roadway infrastructure interacts with environmental and human systems (Morelle et al., 2013; Shilling and Waetjen, 2015). Additional evidence from South America and Africa further reinforces this pattern. For example, Oddone Aquino and Nkomo (2021) documented how expanding road networks and settlement growth in African contexts create new conflict points, while Ascensão et al. (2021) demonstrated that roadkill hotspots in Brazil are strongly tied to agricultural frontiers and land-use change (Ascensão et al., 2021; Oddone Aquino and Nkomo, 2021).

2.4.1 Predictors of Wildlife Vehicle Crash Risk

The drivers of WVC risk are complex and multi-scalar. At one level, roadway characteristics such as design speed, curvature, lane width, and traffic volume create opportunities for collisions. At another level, environmental features such as land cover, forest edges, water bodies, and habitat connectivity shape wildlife movement across landscapes. Human population distribution, urbanization gradients, and land-use changes further alter both exposure and ecological availability. These dimensions are deeply intertwined: road networks not only fragment habitats but also redistribute human activity, influencing both wildlife behavior and reporting of crashes. Consequently, the scientific literature on WVCs has increasingly emphasized interdisciplinary approaches that integrate transportation safety analysis with ecological and spatial modeling (Gunson et al., 2011; Rytwinski et al., 2016).

A large body of work has investigated the determinants of WVCs, employing diverse spatial and statistical methods to disentangle the influences of road networks, environmental features, and human population dynamics. While the specific predictors vary across regions, consistent themes emerge that are directly relevant to modeling crash risk. Roadway configuration has long been identified as a central determinant of WVCs. Higher traffic volumes generally increase collision probability, yet the relationship is not strictly linear. Several studies find that beyond certain thresholds, very high traffic volumes may reduce WVC risk by creating effective "barriers" that animals avoid crossing (Gunson et al., 2011; Laflamme et al., 2024). Speed limits also show consistent effects: intermediate speeds (45–60 mph) often yield the highest crash likelihood, as they combine sufficient traffic volume with limited driver response time (Laflamme et al., 2024). Road curvature and visibility influence collision severity and frequency; segments with sharper curves or obstructed sightlines show elevated risk (Koju et al., 2025).

Functional road classification is equally important: interstates, while carrying heavy traffic, often report lower per-mile WVC frequencies due to access controls and fencing, whereas secondary roads near natural habitats report disproportionate crash counts (Laflamme et al., 2024). Supporting this, Roy and Ksaibati (2022) analyzed Wyoming crash records and found that secondary rural highways exhibited the highest WVC frequencies, largely due to their adjacency to open habitat and lack of mitigation features (Roy and Ksaibati, 2022). Young et al. (2007) further showed that roadway reconstruction in Wyoming unintentionally increased wildlife collisions by raising design speeds, even while reducing non-WVC crash rates (Young et al., 2007).

Road density at the landscape scale is another strong predictor. Denser road networks fragment habitats more extensively, increasing the likelihood of wildlife-road interactions. In Belgium, Morelle et al. (2013) found that WVC rates rose in tandem with ungulate populations and expanding road density (Morelle et al., 2013). Graph-based analyses similarly show that highly connected road segments overlapping ecological corridors emerge as hotspots (Llagostera et al., 2022). Bil et al. (2019) confirmed that accounting for clustering and road density substantially improved model predictions of moose collisions, illustrating that ignoring spatial correlation can underestimate roadway impacts (Bíl et al., 2019). Distance to road, often operationalized at the grid-cell scale, reflects immediate exposure and has been shown to negatively correlate with crash risk: areas closer to major roads have higher collision counts (Ha and Shilling, 2018). Together, these findings demonstrate that both local proximity and regional density of roads are necessary components in predicting WVC risk.

Environmental features strongly mediate where animals attempt to cross roads. Forest edges, natural parks, and protected areas often serve as sources of wildlife movement, with several studies reporting increased WVCs near these landscapes (Gunson et al., 2011; Malo et al., 2004). Agricultural mosaics adjacent to forest patches can exacerbate risks by concentrating foraging opportunities near roads (Malo et al., 2004). Similarly, proximity to wetlands, rivers, and riparian corridors consistently emerges as a critical predictor. Amphibian and reptile mortality is particularly high where roads intersect wetlands, while ungulate collisions cluster near riparian zones that provide forage and movement routes (Gunson et al., 2011; Ha and Shilling, 2018). Glista et al. (2009) reviewed multiple mitigation cases and emphasized that amphibians crossing between wetlands are especially vulnerable in fragmented networks, reinforcing the importance of riparian proximity (Glista et al., 2009). Koju et al. (2025) demonstrated that water proximity and road curvature were among the strongest predictors of crashes along park boundaries (Koju et al., 2025).

Connectivity has been highlighted in other studies as well. Ament et al. (2008) framed WVCs within the broader problem of habitat fragmentation, arguing that poorly sited road infrastructure creates barriers that undermine both safety and ecological continuity (Ament et al., 2008). More recently, Ament et al. (2021) reinforced this point in a U.S. Forest Service report, recommending a systematic nationwide network of crossings to restore connectivity while reducing crashes (Ament et al., 2021). Habitat connectivity is equally critical. Roadkill hotspots often coincide with ecological corridors where natural movement paths intersect roads. Network-based approaches reveal that structurally important links, such as those near rivers or forest corridors, disproportionately contribute to conflict risk (Llagostera et al., 2022). The literature underscores that environmental predictors should not only be treated as static variables but also as dynamic factors interacting with species' seasonal behaviors.

Population density introduces complexity into WVC modeling. On one hand, denser urban areas tend to suppress wildlife presence, leading to lower collision risk. On the other hand, exurban and peri-urban areas, where human density is moderate and habitats remain relatively intact, often report the highest WVC frequencies (Ha and Shilling, 2018; Laflamme et al., 2024). Nonlinear relationships are common, with risk rising at intermediate densities before declining in fully urbanized contexts. Studies in the U.S. have shown that rural, sparsely populated counties record higher per-capita WVC rates due to extensive road networks relative to population (Wilkins et al., 2019). Cherry et al. (2019) added that collisions in U.S. national parks clustered near developed visitor centers, showing that human presence interacts with animal movement even in protected areas. Similarly, Llagostera et al. (2022) showed that roads serving as central connectors between settlements and wildland edges carry heightened risks, illustrating how settlement distribution interacts with network structure.

Temporal and seasonal dimensions add further nuance. Collisions spike during dawn and dusk, coinciding with peak wildlife activity (Cherry et al., 2019; Morelle et al., 2013). Seasonal peaks align with breeding, migration, or dispersal periods: autumn surges are reported in both European ungulate studies and U.S. national park analyses (Cherry et al., 2019; Koju et al., 2025). These findings underscore the need to incorporate temporal dynamics into spatial models to avoid confounding effects. Creech et al. (2019) extended this work by separating livestock from wildlife collisions in Montana, finding distinct seasonal cycles: livestock-related crashes peaked in summer, while wildlife collisions peaked in autumn (Creech et al., 2019). This demonstrates the importance of distinguishing species groups when analyzing temporal trends.

Beyond the core predictors, studies have explored additional factors that refine WVC risk modeling. Land cover diversity has been identified as significant, with mixed landscapes (forest–open mosaics) associated with higher collision rates (Gunson et al., 2011). Animal abundance and population growth directly influence long-term trends, as illustrated in Belgium where rising ungulate populations explained much of the increase in collisions (Morelle et al., 2013).

Infrastructure features such as bridges, culverts, and fencing also shape spatial patterns: unfenced bridges in riparian zones often emerge as hotspots, while mitigation measures like fencing combined with crossings dramatically reduce collisions (Rytwinski et al., 2016). These findings emphasize that WVC risk is not solely a function of road and environmental context but is also mediated by species abundance and infrastructure interventions.

2.4.2 Methodological Approaches in Wildlife Vehicle Crash Research

Methodologically, the field has evolved from simple descriptive analyses to sophisticated spatial models. Count-based models dominate, with Poisson regressions often replaced by Negative Binomial (NB) models to handle over-dispersion (Gunson et al., 2011; Lao et al., 2011). Zero-inflated and hurdle variants further address the prevalence of zero counts in sparse networks (Murphy and Xia, 2016). Generalized Additive Models (GAMs) allow nonlinear effects, as demonstrated in severity analyses by Laflamme et al. (2024). Recent applications of association rule mining and machine learning have also added to this toolkit: Rahman et al. (2023) identified co-occurrence patterns between roadway features and crash types, while Zawad et al. (2025) applied gradient boosting to improve predictive accuracy across species (Rahman et al., 2023; Zawad et al., 2025). Sugiarto (2022) further explored hybrid approaches combining spatial regression with machine learning to balance interpretability and predictive performance (Sugiarto, 2023).

Spatial autocorrelation has increasingly been addressed through Bayesian hierarchical models, Conditional Autoregression (CAR), or network-based graph approaches (Llagostera et al., 2022; Murphy and Xia, 2016). Hotspot analyses using Kernel Density Estimation (KDE), Getis-Ord Gi*, and Local Moran's I remain widely applied for identifying priority mitigation sites (Morelle et al., 2013; Shilling and Waetjen, 2015). Machine learning methods, including MaxEnt and random forests, are emerging as alternatives for presence-only or highly imbalanced datasets (Ha and Shilling, 2018). Litvaitis and Tash (2008) also emphasized that different spatial scales segment, buffer, or grid can yield different predictor effects, illustrating the modifiable areal unit problem (MAUP) (Litvaitis and Tash, 2008). This concern is echoed in Gunson et al. (2011), who stress the importance of sensitivity testing for spatial units. Across these methods, the consistent use of exposure terms Average Annual Daily Traffic (AADT), road length, or population offsets is critical to ensure robust estimates.

Mitigation studies provide evidence that fencing combined with wildlife crossing structures reduces large-mammal roadkill by more than 80%, while fencing alone achieves approximately

50% in reductions (Rytwinski et al., 2016). By contrast, low-cost measures such as wildlife warning signs or reflectors show negligible impacts. Cost–benefit studies indicate that targeted hotspot interventions (e.g., fencing at high-density crash segments) yield faster payback periods compared to blanket measures across networks (Ament et al., 2021; Ascensão et al., 2021). Huijser et al. (2008) and Ament et al. (2021) further stressed that institutional coordination is essential for success, while Shilling & Waetjen (2015) showed that citizen-science reporting systems broadened spatial, taxonomic, and contextual insights into wildlife-vehicle collisions, capturing patterns and locations that agency data alone missed. When used together, these data sources improved the ability to identify WVC hotspots and prioritize mitigation strategies for both biodiversity conservation and driver safety. These findings highlight the importance of aligning modeling efforts with practical mitigation strategies.

The reviewed literature demonstrates strong consensus that WVC risk is structured by roadway, environmental, and human factors. Yet several research gaps remain. Most studies concentrate on temperate regions of North America and Europe, leaving arid and semi-arid systems underrepresented (Koju et al., 2025; Oddone Aquino and Nkomo, 2021). City-scale modeling is rare, with most work focused on rural highways or national scales (Roy and Ksaibati, 2022; Wilkins et al., 2019). Integration of roadway, environmental, and population predictors into a single framework is uncommon, as many studies emphasize one domain over others (Ha and Shilling, 2018; Lao et al., 2011). Spatial autocorrelation is often inadequately addressed (Bíl et al., 2019; Litvaitis and Tash, 2008). Finally, few studies link predictions to cost-effective thresholds for mitigation (Ament et al., 2021; Rytwinski et al., 2016).

2.5 Summary of Literature

The literature reviewed across automated enforcement, electric vehicle adoption, red-light cameras, and wildlife-vehicle collisions demonstrates that transportation safety challenges are shaped by more than physical infrastructure or technological tools. A consistent pattern is that outcomes depend on how policies are designed, communicated, and sustained within their institutional and social contexts. Questions of legitimacy, fairness, and trust frequently determine whether interventions are embraced or resisted, while technical effectiveness alone rarely guarantees durable results. Methodologically, there has been a steady progression from descriptive evaluations to more sophisticated statistical and spatial approaches, yet limitations in design and scope remain evident.

Despite the breadth of existing work, several gaps are apparent. Automated enforcement studies often rely on single-jurisdiction analyses, offering limited insight into how legal frameworks or administrative structures shape perceptions and compliance. In the area of electric vehicles, much of the research emphasizes consumer adoption, leaving fewer studies that connect organizational readiness, workforce skills, and long-term fleet management in agency settings. Red-light camera evaluations have demonstrated safety impacts but tend to concentrate on short-term outcomes, with relatively few analyses of post-termination effects or integration of professional viewpoints. Research on wildlife–vehicle collisions, while rich in temperate regions, underrepresents arid and urban–rural landscapes, and often treats predictors in isolation rather than within integrated multi-domain frameworks that reflect the complexity of real-world systems.

These observations point to opportunities for advancing knowledge. The chapters that follow address these gaps by explicitly linking public sentiment with safety beliefs and equity concerns, assessing enforcement outcomes within distinct policy environments, examining organizational barriers and opportunities in EV fleet transitions, and modeling WVC risk in a desert urban fringe where ecological and safety dimensions converge. Through these efforts, the dissertation aims to move beyond isolated evaluations and contribute evidence that connects technical effectiveness with governance, perception, and ecological context.

Chapter 3: Evaluating the Effectiveness of Red-Light Running Cameras on Intersection Crash Outcomes and Professional Perspectives

This chapter examines the effectiveness of red-light camera enforcement in improving intersection safety, positioning the analysis within broader debates on automated enforcement and roadway risk management. The chapter analyses crash data from periods before, during, and after camera operation to evaluate how enforcement influences both the number and severity of collisions. Particular attention is given to crash types closely linked to signal violations, including angle, left turn, and rear-end crashes, with outcomes compared across levels of injury severity, ranging from property damage to fatal incidents. Statistical models are applied to provide robust evidence on these patterns and to distinguish meaningful safety improvements from potential trade-offs, such as increases in rear-end crashes.

To complement the quantitative analysis, the chapter incorporates perspectives from transportation professionals involved in the design, implementation, and evaluation of enforcement programs. These insights highlight practical considerations such as administrative challenges, operational costs, and community responses that shape the long-term viability of red-light camera initiatives. By combining empirical crash evidence with professional experience, this chapter offers a comprehensive and policy-relevant assessment of automated enforcement. The findings contribute to understanding not only the measurable safety outcomes of RLCs but also the institutional and social dynamics that determine whether such programs can be maintained and supported over time.

3.1 Introduction

At signalized intersections, red-light running stands out as a highly risky behavior, increasingly emerging as a leading contributor to crashes involving intersections. The National Highway Traffic Safety Administration (NHTSA) reports an annual occurrence of approximately 2.3 million crashes at traffic intersections in the United States (NHTSA, 2012). The majority of reported crashes at signalized intersections were associated with red-light running, resulting in severe fatalities, property damage, and uncertainty (IIHS-HLDI, 2025; Jahangiri et al., 2016). Understanding and mitigating RLR violations and associated crashes necessitates a comprehensive grasp of RLR crash types, contributing factors, and potential severity levels. The drivers' behavior in RLR crashes is intricate, encompassing deliberate red-light evasion, "stop-go" psychological biases in response to flashing yellow signals, and instances where signal visibility is impaired or distracted driving occurs (Xiang et al., 2016). Studying this now is crucial due to the increasing incidence of RLR-related crashes and the evolving nature of driver behavior and traffic patterns. As urban areas continue to grow and traffic density increases, the need for effective interventions to reduce these dangerous behaviors at signalized intersections becomes more urgent. Red light camera (RLC) technology, along with public awareness efforts, offers a potential intervention to modify driving behavior and reduce red-light violations and intersection crashes.

Deliberate red-light runners with poor driving records seem undeterred by the small chance of getting caught (8). Since the launch of RLCs, numerous studies have examined the efficacy of RLC enforcement in reducing crashes at signalized intersections across different states in the US and other countries. However, in the United States, several states opted to discontinue and dismantle these programs after a specific period due to various concerns. These concerns encompassed unclear policies, apprehensions regarding privacy infringements, public speculation over revenue generation motives, and other related matters (Eger et al., 2015; Haroon et al., 2024; Letizia, 2009; Yang et al., 2013). Engineering measures like signal modifications and enforcement measures can help reduce red-light violations by modifying the infrastructure to enhance safety and guide drivers, while also addressing unsafe driver behavior. However, limited enforcement resources and logistical difficulties hinder conventional red-light enforcement, leading to persistent violations.

Overall, while many studies have explored the effectiveness of RLCs in reducing RLR-related crashes, the results remain mixed. Some studies report significant reductions in collisions, particularly right-angle crashes, while others note an increase in rear-end crashes due to driver’s sudden braking (Ahmed and Abdel-Aty, 2015; Hallmark et al., 2010; Ko et al., 2017; Persaud et al., 2005; Retting and Kyrychenko, 2002). Despite the varying outcomes, there is a clear need for further research to evaluate the long-term effectiveness of RLCs, particularly in regions where programs have been implemented and subsequently deactivated. This chapter aims to evaluate the effectiveness of RLCs in the City of Phoenix by analyzing crash data before, during, and after the deactivation of RLC operations. Additionally, professional opinions from engineers and law enforcement officers are integrated to provide a comprehensive understanding of the program's success and challenges. By examining both quantitative crash data and qualitative professional insights, this research seeks to provide valuable recommendations for optimizing RLC programs to improve intersection safety and reduce RLR-related incidents.

3.2 Methodology

3.2.1 Data Collection

This section details the methodology for collecting and processing data, essential for evaluating the impact of RLCs on intersection safety. The City of Phoenix was selected as the application area because it has a long history of discussions and initiatives surrounding red-light running photo enforcement. Over the years, the city has implemented, suspended, and reconsidered its program due to various technical, legal, and equity-related concerns. The RLCs were most recently deactivated in 2019 (City of Phoenix, n.d.). With recent council discussions in 2023 focused on restarting the program using data-driven and equity-based approaches, Phoenix presents a timely and contextually rich setting for analyzing automated enforcement practices and their potential role in enhancing traffic safety. Phoenix's RLR photo enforcement program has evolved over the last two decades through various discussions, primarily focused on reducing red-light violations and improving road safety. The data in this study encompasses crash records from the Arizona Crash Information System (ACIS), including details on crash types, locations, and contributing factors and traffic volume data from Arizona Department of Transportation (ADOT) and other platforms. It also includes information on intersection characteristics and RLC installation histories, ensuring a comprehensive analysis of both treatment and reference sites.

Study Sites

RLCs were installed at various intersections in Phoenix, Arizona in 2006, 2010, and 2015. RLC were initially deployed in 2006 at 12 intersections in Phoenix. Subsequently, in 2010, new intersections were selected for camera placement, with the exception of one intersection, where the camera remained operational but was relocated from the westbound approach to the northbound approach. Again, in 2015, camera locations were altered, although some intersections retained their cameras from 2010 to 2015. Notably, the camera locations changed each installation year, with a few exceptions. Furthermore, only the intersections with recent camera installation year of 2015 were considered in this study and there were 14 intersections equipped with RLC in Phoenix. All intersections equipped with RLCs are clearly indicated by advance warning signs, designed to alert drivers that photo enforcement is in operation. The COP, along with Redflex, their vendor and a primary supplier of RLC systems in the U.S., provided information about the intersection locations equipped with RLCs (ALTurki, n.d.; Washington and Shin, 2005). Table 3.1 offers detailed information on the installation periods, intersections, and the specific approach or target roads where the cameras were placed each year.

Table 3.1 RLC Intersections and Installation Year

Installation Year	2006	2010	2015
RLC Intersection	7th St & Bell Rd (W/B)	35th Ave & Dunlap Ave (N/B)	16th St & Jefferson St (S/B)
	35th Ave & McDowell Rd (N/B)	40th St & Pecos Rd (now the Loop 202 freeway) (W/B)	67th Ave & McDowell Rd (S/B)
	48th St & Ray Rd (E/B)	16th St & Jefferson St (S/B)	53rd Ave & Indian School Rd (E/B)
	40th St & Bell Rd (W/B)	51st Ave & Van Buren St (W/B)	7th St & Bell Rd (E/B)
	40th St & Cactus Rd (E/B)	67th Ave & McDowell Rd (N/B)	12th St & Camelback Rd (E/B)
	32nd St & McDowell Rd (W/B)	15th Ave & Missouri Rd (S/B)	21st Ave & Glendale (E/B)
	12th St & Indian School Rd (E/B)	53rd Ave & Indian School Rd (E/B)	24th St & Thomas Rd (N/B)
	7th Ave & Greenway Parkway (W/B)	12th St & Camelback Rd (E/B)	35th Ave & Cactus Rd (E/B)

	19th Ave & Thunderbird Rd (W/B)	7th St & McDowell Rd (S/B)	35th Ave & Glendale Ave (Alternative)
	19th Ave & Northern Ave (W/B)	Cave Creek Rd & Bell Rd	35th Ave & McDowell Rd (S/B)
	35th Ave & Dunlap Ave (W/B)	40th St & Broadway (W/B)	50th St & Ray Rd (E/B)
	51st Ave & Indian School Rd (W/B)	7th St & Union Hills (W/B)	Central Ave & McDowell Rd (S/B)
	NA	NA	Tatum Blvd & Thunderbird Rd (N/B)
	NA	NA	32nd St & Greenway (Alternative) (S/B)

Reference Sites

A total of 41 intersections were included as reference/comparison groups to account for the presence of potentially confounding factors such as changes in state traffic laws, weather conditions, and general economic conditions that could affect red light violations at the treatment sites over time. These 41 reference intersections were found to have similar characteristics to the treatment intersections, which is why they were chosen initially to ensure a robust comparison and sufficient sample size for statistical analysis. Factors such as comparable traffic volume, roadway geometry, and traffic control features were considered. Furthermore, various other factors in the vicinity, such as the presence of light rail tracks and nearby establishments, were taken into account when selecting non-RLC sites, as these factors could potentially influence crashes (Claros et al., 2017). Reference sites were selected at a minimum distance of 0.75 miles from the RLC sites to ensure spatial independence and minimize the potential influence of RLC enforcement on the reference site's traffic behavior (Claros et al., 2017; Geedipally and Consulting, 2014; Kitali et al., 2021; Ko et al., 2017; Mahmassani et al., 2017).

Crash Data

Crash data were gathered from ACIS for the periods of January 2012 to December 2018 and January 2021 to December 2023 for both RLC and non-RLC intersections, serving as treatment and comparison/reference groups, respectively. The intersections with the camera installation year of 2015 were only considered for the analysis. Crash data spanning at least three years before and during RLC operation periods, as well as three years post-ban on cameras in 2019, were included. This ensured a representative sample for each group of data. The reason for excluding the year 2019 is that the cameras were deactivated, and the year 2020 was excluded due to the impact of COVID-19 on traffic patterns. The crash data categorized as follows:

- Before period (2012–2014): Three years of crash data before the RLC activation year of 2015.
- During period (2016–2018): The years in which the RLC was operational.
- After period (2021–2023): The years following RLC deactivation in 2019, excluding 2020 to minimize potential COVID-19 impacts.

Only crashes occurring within 150 feet from the center of the intersection were included, focusing solely on intersection-related incidents for the analysis which is often used and suggested by traffic safety studies and guidelines to define “intersection-related crashes” (Miller et al., 2010; Sun et al., 2020). The processing of crashes occurring within 150 ft of the intersection was performed in ArcGIS using the spatial join feature. Furthermore, crashes due to driving under the influence of alcohol or drugs, illness, and sleep deprivation/fatigue, and distraction by texting, adverse weather were removed from the crash dataset to examine only the effect of the presence of an RLC (Ahmed and Abdel-Aty, 2015; Kitali et al., 2021; Ko et al., 2017). Table 3.2 provides a detailed summary of the crash data at treatment intersections with RLCs and nontreatment intersections without RLCs.

Traffic Volume

Traffic volume data were collected for the same period as the crash data; however, due to data availability, only the volume data from 2012 to 2017 were able to be obtained from ADOT. In instances where there was missing volume data for a certain year, neighboring intersection volumes were considered. Neighboring intersections refer to those located adjacent to the intersection where the traffic volume data is missing or where there's a gap in the Annual Average Daily Traffic (AADT) data for one of the road segments. These adjacent intersections' traffic volume data may be used as a proxy or substitute to see how much the volume is changing in the area when data is unavailable for the specific intersection under consideration if they have similar road characteristics and road type. Additionally, data interpolation was also conducted for specific years to address missing volume data gaps (Ahmed and Abdel-Aty, 2015; Kitali et al., 2021; Lord et al., 2021). In the case of intersections, when the AADT for one leg was unavailable, we extrapolated from the AADT of the opposite leg, extending through the intersection. Additionally, volume estimation was done based on the percentage change in volume from the previous year. A reasonable amount of volume data existed for the intersections where the cameras were installed in 2015. Moreover, to account for volume data beyond 2017, the Traffic Volume Trends report for all states by FHWA and the US Department of Transportation was utilized annually to project the volume for the years 2021 to 2023 (FHWA, 2024) .

Table 3.2 Descriptive Statistics for Treatment (RLC) and Non-treatment (Non-RLC) Intersections

Variable	Year	Treatment Intersections (RLC)				Nontreatment Intersections (Non-RLC)			
		Min	Max	Mean	Sd	Min	Max	Mean	Sd
Total Crashes (Crashes/ year/ Intersection)	2012	5	36	20.88	10.15	6	43	18.55	8.93
	2013	4	35	20.44	9.26	6	49	20.47	10.24
	2014	6	31	20	8.64	6	57	23.02	11.05
	2016	12	43	22.88	10.15	6	66	25.37	12.52
	2017	6	36	22.33	10.86	8	57	23.6	9.7
	2018	8	43	22.44	11.51	7	62	23.82	11.15
	2021	6	51	20.88	13.95	5	61	23.95	13.10

	2022	3	48	19.11	13.90	7	43	22.7	9.27
	2023	4	36	19.44	8.77	6	41	21.05	9.15
PDO Crashes	2012	5	28	13.88	7.01	2	29	12.42	6.55
(Crashes/	2013	2	21	10.44	5.57	3	31	12.95	6.97
year/	2014	6	19	13.33	5.09	1	37	14.65	7.67
intersection)	2016	9	31	16.33	7.51	5	42	16.87	8.18
	2017	5	28	15.55	8.47	3	40	15.6	7.34
	2018	7	31	16	7.98	4	47	16.9	8.63
	2021	3	34	14.88	9.79	3	44	17.65	9.72
	2022	3	35	13.22	9.97	5	30	16.57	7.19
	2023	4	28	14	6.72	4	29	14.97	6.24
FI Crashes	2012	1	15	7.87	3.94	2	17	6.12	3.45
(Crashes/	2013	2	16	10	4.92	1	18	7.52	4.18
year/	2014	4	13	7.5	3.77	1	20	8.37	4.51
intersection)	2016	2	12	6.55	3.6	1	24	8.5	5.24
	2017	1	13	6.77	3.45	2	17	8	3.51
	2018	1	14	6.44	4.61	3	17	7.10	3.53
	2021	3	17	6.75	4.39	1	19	6.46	4.52
	2022	1	13	6.62	3.85	1	15	6.44	2.99
	2023	3	8	6.12	1.8	1	15	6.23	3.71
Angle Crashes	2012	1	9	3.88	2.57	1	8	3.61	1.88
(Crashes/	2013	1	9	5.12	2.53	1	10	3.7	2.09
year/	2014	2	8	4	1.93	1	10	4.38	2.47

intersection)	2016	2	6	3.88	1.26	1	12	3.57	2.28
	2017	1	8	4.12	2.85	1	11	3.71	2.34
	2018	1	8	4	2.34	1	8	3.84	2.21
	2021	1	9	3.66	3.27	1	14	4.02	2.56
	2022	1	7	3.71	2.13	1	11	4.33	2.06
	2023	1	7	3.55	1.66	1	10	3.53	1.93
Left Turn	2012	1	16	7.87	6.26	1	17	6.79	4.23
Crashes	2013	2	15	6.55	4.82	1	16	6.74	3.98
	2014	2	14	6.62	3.58	1	18	7.94	4.48
	2016	1	17	6.77	6.05	2	25	9.07	5.52
	2017	1	16	7.37	5.23	1	21	8.55	4.5
	2018	1	18	7.44	5.12	1	25	8.55	5.72
	2021	1	25	6.77	7.44	2	26	9.25	6.05
	2022	2	20	8.25	6.38	1	21	8.67	4.56
	2023	1	17	6.44	5.50	1	22	8.12	5.20
Rear End	2012	3	12	6.77	3.07	1	18	5.74	3.73
Crashes	2013	1	11	7.22	3.45	2	23	7	4.38
	2014	1	16	7.37	4.92	2	21	7.61	4.54
	2016	2	14	7.22	3.73	1	17	7.65	4.56
	2017	2	20	7.88	5.57	2	17	7.23	3.49
	2018	3	13	7	3.27	1	19	6.6	3.51
	2021	1	14	6	4.35	1	15	6.07	3.89
	2022	1	11	5.11	3.21	1	14	5.39	3.04

	2023	2	8	5.25	1.83	1	10	4.84	2.39

Note PD = Property Damage; FI = Fatal and Injury, Min = Minimum, Max= Maximum, Sd= Standard Deviation

3.2.2 Data Analysis

A mixed-methods approach was employed to assess the safety efficacy of RLCs in the COP. This approach integrated qualitative methods such as a survey and discussions with quantitative analysis data at RLC intersections.

Empirical Bayes Method

This study employed the Empirical Bayes method to assess the impact of RLC implementation through a before-and-after study design. The EB method is a statistical technique commonly used in the analysis of before-and-after studies, particularly in the field of road safety research. Many previous studies on RLC effectiveness have used this method to address the issue of regression-to-the-mean bias, which can occur when evaluating the effectiveness of interventions based solely on observed changes in outcomes over time (Ahmed and Abdel-Aty, 2015; Baratian-Ghorghi et al., 2016; Hu et al., 2011). Other methods including the Naïve Before-After study design, and the Full-Bayes (FB) method were considered for the analysis. However, the Naïve Before-After study was not used as this method does not account for the regression to the mean (RTM) and the site selection effect as well as local and regional changes (Geedipally and Consulting, 2014). Further, the FB method was not used due to the complexity of the method and the computation time required to get the results (Lord et al., 2021).

In the context of road safety studies, such as evaluating the impact of RLC implementation, the EB method works by combining information from the observed data with historical trends to estimate the expected number of events (e.g., red-light violations or crashes) in the absence of the intervention. This expected count serves as a baseline against which the observed changes can be compared, allowing for a more accurate assessment of the intervention's effect. The EB method typically involves a hierarchical Bayesian framework, where hyperparameters representing the distribution of treatment effects are estimated based on the observed data. These hyperparameters capture variability in treatment effects across different intersections or study units, accounting for uncertainty in the effect estimates. Incorporating comparison sites into the before-after analysis is based on two assumptions (Hauer, 1997):

1. External factors influencing safety have undergone similar changes from the before to the after period in both groups.
2. The alteration in external factors affects both the treatment and comparison groups equally.

Thus, the reference group has similar characteristics as those in the treatment group. The EB method with a reference group helps ascertain whether a reduction in crashes can be attributed to the presence of RLCs or if this trend is also observed in non-RLC locations. In this study, there are two distinct analyses: one comparing crashes before and during camera implementation, and another comparing crashes during camera operation to those after the camera ban. It is important to note that these analyses are separate and cannot be directly compared.

Conducting an EB before and after (i.e., Before & During, During & After) study involves several steps, including the utilization of these reference/comparison groups (Geedipally and Consulting, 2014; Lord et al., 2021).

1. Develop Safety Performance Function

In this step, a negative binomial model (NB) is developed using the data from non-RLC intersection (reference groups). The response variable is the total number of crash incidents per year and the independent variable is traffic volume (average annual daily traffic). The NB model is commonly used in the process of developing safety performance functions (SPFs). This preference arises because the NB model effectively handles the overdispersion parameter that quantifies the degree of variability which is crucial to calculating the weight factor essential for the EB method (ALTurki, n.d.; Washington and Shin, 2005). The model is used to estimate the long-term mean of site based on the characteristics of data collected for the reference group. The negative binomial model is estimated using the following relationship:

$$\mu_i = \exp\,(x'\beta_i + \varepsilon_i) \qquad (1)$$

where μ_i is the long-term mean for site i (in crashes/year); β_i is a vector of estimable parameter; x' is a vector of independent variable, where ε_i is an error term with mean 1 and variance α. The term α refers to the dispersion parameter of negative binomial model.

2.Estimate the expected number of crashes in the before period.

Using the SPF developed in step (1), the expected number of crashes for the before period at each treatment site is estimated. The EB for the before period is given as follows:

$$\mu_{i_{EB}} = \frac{(\emptyset + y_{i_b})}{(\emptyset/\mu_{ib} + t_{ib})} \qquad (2)$$

Where $\mu_{i_{EB}}$ is the EB estimate for site i (in crashes/year); μ_{ib} is the model output of the NB model for site i for the before period; $y_{i_b}$is the number of crashes in the before period for site; $t_{ib}$is the number of years in the before period; and $\emptyset$ is the inverse of dispersion parameter α.

3.Calculate r_{tf}

The r_{tf} is calculated by the ratio of traffic flow after the treatment by the traffic flow before the treatment to adjust for the differences in traffic flow.

$$r_{tf} = f(A)/f(B) \qquad (3)$$

4.Calculate the predicted value for the after period.

$$\pi_i = r_{tf} * \ t_a * \ \mu_{i_{EB}} \qquad (4)$$

Where r_{tf} & $\mu_{i_{EB}}$ are calculated in eq (3) and eq (1) and t_a is the number of years in the after period.

5.Calculate the estimated value for the after period.

The estimated value for the after period is the observed number of crashes in the after period which is given by:

$$\lambda = \sum_{i=1}^{n} \lambda_i \qquad (5)$$

6.Calculate the safety index.

The safety index is denoted by θ.

$$\theta = \lambda / \pi \qquad (6)$$

Where π is the predicted value for the after period which is also calculated in eq (4).

Surveys and Discussions

A survey was developed and distributed to engineers and law enforcement officers in the valley via email to collect comprehensive information on the success and challenges of automated enforcement in the metro Phoenix region. The survey questions were designed to gather comprehensive insights on RLR and speed enforcement programs in Phoenix. The survey explored respondent's perceptions of why drivers engage in these unsafe behaviors, assess whether RLR and speeding are significant issues in the COP, and measure awareness of enforcement measures. The questions also sought opinions on the effectiveness of RLCs in improving safety before, during, and after their operation, as well as any additional benefits or drawbacks identified. By addressing both general opinions and professional perspectives, the survey aimed to provide a thorough evaluation of the impact and effectiveness of the photo enforcement programs. Subsequently, the data from this survey was analyzed to develop an understanding of the success or unsuccess of automated enforcement in the greater Phoenix region. Additionally, discussions were held with experts who had extensive experience working in the photo enforcement program across various departments to understand the success or lack of success of automated enforcement in the metro Phoenix region, and the reasons for these outcomes. This included retired police officers with years of involvement in the program, police traffic program supervisors, and traffic engineers. These professionals, representing city and neighboring police departments, as well as transportation and street departments, provided valuable insights into the success and challenges of automated enforcement.

3.3 Results

The result of this chapter consists of three sections: the results of the photo enforcement program evaluation survey, the summary of the discussions, and the results of the before-after crash analysis. The first part provides detailed findings from the crash analysis based on the RLC intersections and non-RLC intersections in Phoenix. The second part of this section discusses professionals' opinions on the RLC programs and, in some instances, the RLC program in the COP. The third part provides a summary of the discussions with the professionals currently or previously involved in RLC programs.

3.3.1 Crash Analysis

The EB analysis was conducted separately for injury severity and its two categories (*Property Damage/No Injury* and *Fatal and Injury*), as well as for angle collision, left-turn collision, and rear-end collision, along with their respective injury severity categories for the RLCs installed in the year 2015.

Table 3.3 Injury Severity and Collision Type Analysis for Before and During Period

Crash Type	Injury severity/ collision Manner	Total crashes (Before)	Total crashes (During)	EB predicted number of crashes in the during period (had there been no treatment)	Actual change in crash rate (%)	Predicted change in crash rate (%)
Overall	PDO	1390	1391	1485	8.4(-)	0.37(-)
	FI	955	744	965	28.7(-)	7.51(-)
Angle Collision	Total	112	104	179	11.79(-)	1.602(-)
	PDO	62	68	65	4.41(+)	0.19(-)
	FI	50	36	51	31.50(-)	3.08(-)
	Total	175	187	179	1.51(+)	2.83(-)

Left Turn Collision	PDO	101	115	105	8.12(+)	1.23(-)
	FI	74	72	76	7.62(-)	2.54(-)
Rear End Collision	Total	185	199	190	1.37(-)	5.83(-)
	PDO	126	154	132	16.16(+)	0.54(-)
	FI	59	45	58	27.53(-)	6.6(-)

Table 3.4 Injury Severity and Collision Type Analysis for During and After Period

Crash Type	Injury severity/ collision Manner	Total crashes (During)	Total crashes (After)	EB predicted number of crashes in the after period (had there been no treatment)	Actual change in crash rate (%)	Predicted change in crash rate (%)
Overall	PDO	1439	1536	1713	15.62(-)	6.02(-)
	FI	781	576	834	42.3(-)	15.47(-)
Angle Collision	Total	125	120	135	14.43(-)	3.65(-)
	PDO	81	80	89	11.63(-)	1.88(-)
	FI	44	40	45	19.41(-)	9.12(-)
Left Turn Collision	Total	261	231	286	21.13(-)	2.35(-)
	PDO	154	150	171	13.32(-)	1.09(-)

	FI	107	81	124	44.06(-)	14.45(-)
Rear End Collision	Total	259	188	275	35.24(-)	5.28(-)
	PDO	196	148	212	32.63(-)	3.511(-)
	FI	63	40	62	43.36(-)	12.24(-)

Notes: PDO= Property damage only/No injury; FI= Fatal & injury

First, the crash rate is calculated using this formula for before, during and after period:

$$Intersection\ Crash\ Rate\ (R) = \frac{1000{,}000 * C}{365 * N * V} \qquad (7)$$

Where, R= Crash rate for the intersection as crashes per million entering vehicles (MEV)

C= Total number of intersection crashes in the study period

N= Number of years of data

V= Traffic volume entering the intersection daily

The analysis is performed for two categories which are shown in Table 3.3 and Table 3.4. The analysis was divided into two categories based on data availability and reliability: "Before and During" and "During and After." In both tables, the total number of crashes does not match, and this discrepancy is highlighted to prevent any confusion. In both categories, the During period spanned 2016–2018. However, four locations had cameras installed before 2015 (the designated installation year). These four intersections were excluded from the Before/During analysis to maintain consistency in the Before period and avoid bias, but they were included in the During/After analysis. The following illustrates how crash rates were calculated in both periods.

1.Crash Rate for Before and During Analysis

In Table 3, both the actual and predicted changes in crash rates for the Before and During Analysis are presented. The actual change in crash rate measures the difference in the crash rate between the Before and During period. This reflects the observed effect of the intervention (the implementation of the RLCs). The formula for calculating the actual change is as follows:

$$\text{Actual change in crash rate (\%)} = \left(\frac{Crash\ Rate\ (During) - Crash\ Rate\ (Before)}{Crash\ Rate\ (Before)}\right) * 100 \qquad (8)$$

The predicted change in crash rate reflects the expected change in the crash rate during the "During" period, had the treatment or intervention not occurred. This is based on the predicted crash rate, which was calculated using the EB (Empirical Bayes) method, and compares it to the baseline crash rate in the "Before" period. The predicted change is calculated using the formula:

$$\text{Predicted change in crash rate (\%)}$$

$$= \left(\frac{EB\ Predicted\ Crash\ Rate\ (During) - Crash\ Rate(Before)}{Crash\ Rate\ (Before)}\right) * 100 \qquad (9)$$

2.Crash Rate for During and After Analysis

In Table 3, both the actual and predicted changes in crash rates for the During and After Analysis are calculated. The actual change in crash rate measures the difference in the crash rate between the During and After periods. This reflects the observed effect of deactivating the RLCs. The formula for calculating the actual change is as follows:

$$\text{Actual change in crash rate (\%)} = \left(\frac{Crash\ Rate\ (After) - Crash\ Rate\ (During)}{Crash\ Rate\ (During)}\right) * 100 \qquad (10)$$

The predicted change in crash rate reflects the expected change in the crash rate during the "After" period, had the deactivation not occurred. This is based on the predicted number of crashes, which was calculated using the EB (Empirical Bayes) method, and compares it to the baseline crash rate in the "During" period. The predicted change is calculated using the formula:

$$\text{Predicted change in crash rate (\%)}=\left(\frac{EB\ Predicted\ Crash\ Rate\ (After)-Crash\ Rate(During)}{Crash\ Rate\ (During)}\right)*100 \quad (11)$$

Changes in Injury Severity

The results of the before-and-during analysis are presented in Table 3.3. It is evident that property damage/no injury crashes have decreased by 8.4% compared to the before period. By contrast, the EB-predicted reduction is 0.37%, indicating that, had cameras not been installed, the predicted PDO crash counts would have remained higher than what was observed. Additionally, fatal and injury crashes have decreased by 28.7% during RLC operation, indicating the effectiveness of cameras in reducing crash severity whereas EB-predicted reduction is 7.51%, again suggesting a stronger observed improvement with cameras. Similarly, in the during-and-after analysis, the results presented in Table 3.4 continue to demonstrate a decrease in both property damage/no injury and fatal/injury crashes even after the camera ban. PDO crashes decreased by 15.62% (actual), while the EB-predicted decrease is 6.02%, the observed decline is more pronounced than the model's prediction. Fatal and injury crashes decreased by 42.3% whereas the EB-predicted change at 15.47%. The larger drop in the actual data indicates a lingering positive effect of the cameras, even post-ban. It is noteworthy that predicted crashes in those intersections without cameras initially have also decreased, albeit at a rate nearly three times lower than the actual rate. This suggests some residual effects of the cameras even after the ban.

Changes in Angle Crashes

The analysis of angle crashes before and during RLC implementation reveals an overall decrease of 11.79% in angle crashes whereas the EB model predicts a 1.60% decrease if RLCs had not been installed. Upon closer examination of injury severity, it is observed that although property damage has slightly increased by 4.41% but the EB model predicts a slightly 0.19% decrease. Fatal and injury crashes have significantly reduced by 31.5% during the RLC period contrasted with a predicted 3.08% reduction as indicated in Table 3.3 underscoring the effectiveness of the cameras in reducing severe crashes. However, in the during-and-after analysis, as indicated by the findings in Table 3.4, there is a continued decline in overall angle crashes and its severity even following the discontinuation of RLC implementation.

Changes in Left Turn Crashes

The findings for left turn crashes appear to differ from those of angle crashes. Table 3.3 reveals a slight increase of 1.51% in overall left turn crashes during RLC operation, with property damage and injuries also experiencing an 8.12% rise during this period. However, an interesting observation is that the predicted change in crash rate from before to during shows a 2.83% decrease in overall left turn crashes and a 1.23% decrease in property damage during the period, suggesting a slight uptick in left turn crashes in RLC intersections. Conversely, fatal and injury crashes indicate a 7.62% reduction during the camera operation period and the EB model 2.54% reduction, suggesting the RLCs were beneficial for more severe collisions even though total left-turn crashes rose slightly. The results from Table 3.4 present a stark contrast, indicating a decrease in both total left turn crashes and its severity following the ban on cameras.

Changes in Rear End Crashes

Various studies have addressed the increase in rear-end crashes associated with RLC cameras. In the before-and-during analysis, the findings regarding rear-end crashes were intriguing. The results indicate a slight reduction of 1.37% in rear-end crashes during RLC operation. However, upon examining the predicted numbers, it becomes apparent that rear-end crashes were more prevalent at intersections with RLC cameras, resulting in a predicted crash rate reduction from before to during of 5.83% for the same intersection if there were no cameras present significantly higher than the rate during RLC operation. The occurrence of rear-end collisions is notably more frequent, especially with property damage severity increasing by 16.16% during the camera operation period, while fatal and injury incidents decreased by 27.53%. In line with previous collision patterns, the results of the during-and-after analysis mirror those of before, indicating a decrease in overall rear-end collisions and a reduction in injury severity following the RLC ban.

3.3.2 Survey on Photo Enforcement Program

This section presents the findings of the survey conducted to collect the professional insights of engineers and law enforcement officers in the Valley regarding the COP photo enforcement program and other similar programs. The survey, distributed to 73 individuals, received responses from 26 participants representing a diverse range of institutions and various cities and towns. In this survey, the respondents referenced active RLCs and speed cameras in Scottsdale, Paradise Valley, Mesa, Chandler, and Tempe, as well as the inactive RLCs and speed cameras in Phoenix and El Mirage.

Prevalence and Causes of RLR and Speeding in the Valley

- The survey indicated that RLR and excessive speeding are considered major or somewhat of a problem in the Valley. The following were identified as the reasons for the running red light and excessive speeding behavior:

- Respondents agreed that red-light running and speeding are major or somewhat significant problems in the Valley.

- The survey revealed that most RLR incidents and excessive speeding are tied to conscious decisions by drivers, with aggressive, distracted, and impaired driving also cited as contributing factors.

- Roadway and vehicle characteristics, coupled with perceptions of minimal enforcement, exacerbate speeding behavior.

Awareness and Perceptions of Enforcement Measures

The following were significant takeaways from the respondents about awareness of enforcement programs and whether these initiatives are perceived as adequate or effective in addressing traffic safety concerns:

- Respondents discussed active and inactive red-light camera programs in multiple jurisdictions (Scottsdale, Paradise Valley, Mesa, Chandler, Tempe, Phoenix, and El Mirage).

- The survey gathered professional perspectives on how well the public understands existing enforcement measures and whether such measures are considered optimal or lacking.

- Many respondents felt more consistent or more visible enforcement could further discourage RLR and speeding.

Effectiveness of RLCs in Improving Safety

The following were takeaways when considering the effectiveness of photo enforcement programs in reducing violations and crashes:

- Survey participants generally agreed RLR was a safety problem at intersections targeted by RLCs before camera installation.

- Most felt that RLCs reduced RLR violations and improved safety while they were active, although some respondents lacked detailed before-and-after data.

- Opinions on the post-deactivation period were mixed; some believed RLR issues returned, while others cited insufficient data to draw firm conclusions.

- Respondents broadly agreed that RLCs helped lower the frequency of fatal and serious injury crashes.

Photo Enforcement Impact on Crashes and Driver Behavior

The following were takeaways when considering the impact of automated photo enforcement programs on driver behavior based on professional opinions:

- Respondents attributed reductions in RLR-related crashes to the presence of RLCs.

- Injury and fatal crashes remained a concern overall, but there was strong support that photo enforcement mitigated severe outcomes.

- Many indicated drivers were more cautious at RLC-equipped intersections, with citations serving as a major deterrent.

Other Benefits of RLCs

While other benefits, such as RLC aiding criminal investigations, were mentioned, RLCs primary benefit was unanimously considered safety improvement. The survey results suggest a consensus among practitioners that RLR and excessive speeding are concerns in the Valley. Photo enforcement programs were seen as effective tools in improving safety at intersections, reducing crashes, and influencing driver behavior positively. The findings underscore the importance of continued enforcement efforts.

3.3.3 Discussions on the Photo Enforcement Program

Discussions conducted with four professionals experienced in photo enforcement programs revealed several key insights into their effectiveness and challenges. The professionals, from the cities of Phoenix and Scottsdale, included two retired police officers with over five years of experience in photo enforcement, as well as a senior traffic engineer and a police traffic program supervisor. Discussion with each individual lasted approximately thirty minutes. The discussions collectively provide a rich evaluation of photo enforcement programs, highlighting several critical aspects that contribute to their overall effectiveness and challenges. One of the primary benefits of these programs is the potential significant improvement in road safety, with reports of substantial reductions in crashes, such as a nearly 50% decrease in Paradise Valley since 1987. This long-term benefit underscores the programs' potential to enhance public safety. However, the implementation and operation of photo enforcement programs are not without challenges. Processing violations can be a lengthy process, often taking up to 60 days from the time of violation to the issuance of citations. This highlights the need for efficient administrative processes to manage the volume of cases. Additionally, issues such as driver awareness, particularly for newcomers to areas with RLCs, and the public's ability to access violation videos, present ongoing challenges.

Financial considerations also play a crucial role in the sustainability of these programs. Costs associated with vendor contracts, technological upgrades, and staff payments must be carefully managed to ensure the program's viability. Public perception and media portrayal significantly influence the success of photo enforcement programs. Strong public and council support, as seen in Paradise Valley and Scottsdale, is essential. However, media framing of these programs as intrusive can negatively impact public opinion, emphasizing the need for clear communication about the safety benefits and operational transparency. Effectiveness is further demonstrated by the programs' ability to serve multiple purposes beyond safety, such as identifying suspects and allowing police to focus on more critical tasks. This multi-faceted utility reinforces the value of photo enforcement as a tool for law enforcement. Legislative and strategic considerations also play a vital role, with challenges in establishing and expanding programs often rooted in legislative hurdles. Strategic site selection, such as prioritizing school zones, enhances the safety impact, while automated enforcement and maintaining points on licenses ensure ongoing compliance.

Public education and community engagement emerge as crucial elements in garnering and maintaining support for photo enforcement programs. Initiatives like Safe Routes to School help raise awareness and foster community backing, while ongoing communication addresses public concerns and misconceptions. Data-driven decision-making, supported by detailed statistics on citations, violations, speeds, and collisions, is essential for evaluating program effectiveness and making informed adjustments. Scottsdale's approach of using data to select intersection locations and deploy mobile units exemplifies this strategy. It was noted from the discussions that there is a consistent emphasis on safety benefits, with reduced crashes cited as a critical positive outcome. In summary, the discussions provide a comprehensive understanding of photo enforcement programs, highlighting their safety benefits, operational and legislative challenges, financial considerations, public perception, and the importance of community engagement and data-driven decision-making. The common theme for a successful photo enforcement program is strong public support and council backing. The positive impacts of photo enforcement go beyond safety, addressing various law enforcement tasks. Overall, the discussions highlight the multifaceted nature of automated enforcement, its positive impacts on safety, and the ongoing challenges in implementation and public perception. These insights are invaluable for evaluating and improving the implementation and effectiveness of such programs in various contexts.

3.3.4 Interpretation of Findings

The crash analysis findings demonstrate the effectiveness of RLCs in mitigating injury severity and reducing various collision types. Firstly, during RLC operation, property damage crashes decreased by 8.4%, and fatal and injury crashes decreased by 28.7%. Notably, angle crashes decreased by 11.79%, with a substantial reduction in their fatal and injury severity by 31.50%. These results align with previous studies indicating a reduction in angle crashes during RLC operation (Huang et al., 2006; Kitali et al., 2021; Persaud et al., 2005; Retting and Kyrychenko, 2002). Yet, it is noteworthy to see the decrease in angle crashes even after the termination of RLC cameras. While there was no significant impact on overall left turn crashes, there was a slight increase of 1.51%. However, the severity of left turn crashes decreased, with fatal and injury incidents declining by 7.62%. Conversely, property damage/no injury left turn crashes increased by 8.12%. Similarly for left turn as well, the crashes decrease in the after period which is after the ban of RLC. Regarding rear end crashes, a marginal reduction of 1.37% was observed.

However, empirical Bayesian estimates revealed a greater decrease of 5.83% during RLC operation, indicating a lower occurrence of rear end crashes at intersections with or without cameras. Nevertheless, the estimated change in crash rate of 5.83% exceeded the observed reduction, suggesting a higher prevalence of rear end crashes at RLC intersections compared to non-RLC intersections. Additionally, property damage/no injury incidents in rear end crashes increased by 16%. It's often observed that rear-end collisions tend to increase when RLCs (RLCs) are in operation, a trend consistent with previous studies (Claros et al., 2017; F. Llau et al., 2015; Saffarzadeh Parizi, 2023). In this case, rear-end collisions decreased after the camera ban. This decline in rear-end, angle, and left-turn collisions following the ban could be influenced by various factors, possibly including the effects of COVID-19, as the post-ban period spans from 2021 to 2023, a time of gradual return to normalcy.

Furthermore, the decrease in crashes post-ban could be linked to factors such as economic recession, market downturn and several other factors following the termination of the camera program which also aligns with a similar trend from one of the previous study findings (Pulugurtha and Otturu, 2014). It is also plausible that drivers adapted to the RLC enforcement program and subsequently drove more cautiously within the COP. These are all assumptions that require further investigation. However, it was found that although the cameras were deactivated in 2019, they remained present at some intersections till 2023 without operating. This indicates that the presence of RLCs (RLCs), even when deactivated, had a lasting impact in reducing crashes. Although it was known that some RLCs remained physically present but non-operational following deactivation in 2019, some remained physically present at intersections as late as 2023. Detailed records identifying which intersections retained the equipment versus those where it was dismantled, and the specific timing of those changes were not available. This absence of detailed data limited the ability to distinguish between intersections where enforcement infrastructure was visibly present versus completely removed. It is noted that that the continued physical presence of non-operational cameras may have influenced driver behavior, potentially diminishing the observed effects of deactivation at those locations compared to intersections where cameras were fully removed. As such, interpretation of crash outcomes should consider the possibility of differential behavioral responses based on camera visibility. Future research with more granular data on camera status could offer a clearer understanding of how the visibility of enforcement infrastructure, even when inactive, affects driver behavior and safety outcomes.

3.4 Chapter Summary and Implications

The survey results provide detailed support for the crash analysis findings by highlighting professionals' views on the effectiveness of RLCs in improving traffic safety. Survey respondents noted a significant decline in RLR incidents and crash severity during the active enforcement period, corroborating the crash analysis that showed a 28.7% reduction in fatal and injury crashes. Discussions with professionals also underscored a nearly 50% reduction in crashes in areas like Paradise Valley, aligning with the crash analysis' findings of decreased property damage and injury crashes. Additionally, both survey and interview insights into the persistent safety concerns and challenges with program deactivation align with the crash analysis. These qualitative insights enhance the understanding of the quantitative data, emphasizing the role of RLCs in maintaining traffic safety and reducing crash severity. Future studies could delve into understanding the factors that impact the effectiveness of RLCs. Moreover, conducting model analyses could provide deeper insights into the influence of various factors on this effectiveness.

The study examined the impact of RLC programs on intersection safety through an application in the COP and a comprehensive approach involving surveying, gathering professional opinions, and crash data analysis. The current literature provides a foundation by illustrating the general effectiveness of RLCs in various cities, particularly in reducing severe crashes such as right-angle collisions. In Phoenix, data analysis revealed a 28.7% reduction in severe crashes at intersections with RLCs, alongside a 5.83% increase in rear-end collisions. This highlights the trade-off between decreasing more dangerous crash types and increasing less severe ones. Despite the mixed results, the overall safety benefit of RLCs is significant, as indicated by the continued reduction in crashes even after the program's termination. Professional opinions further support the effectiveness of RLCs in improving driver behavior and reducing violations, though challenges remain, including public perception and the financial sustainability of such programs. Although the results of this study align with previous research, providing evidence of reductions in severe crashes during RLC operation, the integrated methodology used in this study offers a more comprehensive perspective on the long-term effectiveness of RLC programs, particularly after deactivation. By combining quantitative crash analysis with professional insights, this study goes beyond simply replicating prior findings and instead provides valuable context for interpreting the effectiveness of automated enforcement in improving road safety. Moreover, the inclusion of data from multiple periods (before, during, and after deactivation of camera operations) strengthens the understanding of RLCs' sustained impact on intersection safety, which has not been fully addressed in prior studies.

Based on the findings, the following recommendations are proposed to enhance the overall success of RLC:

- Detailed Analysis of Location-Specific Factors: It is essential to conduct a detailed analysis to identify why certain locations do not benefit as expected from RLC operations. Factors such as traffic patterns, intersection design, and enforcement issues may influence the performance of RLCs. Understanding these factors can help optimize camera placements and improve the program's effectiveness.

- Assessment of the Duration of Impact: Ongoing monitoring is crucial to determine how long the safety benefits of RLC programs persist at specific locations. The impact of RLCs may diminish over time, and evaluating the duration of their effectiveness will ensure that the program continues to deliver sustained benefits. Regular assessments will help refine the strategy and ensure long-term safety improvements.

- Staff Training and Understanding: Proper training and understanding of the operational and enforcement needs of the RLC program are fundamental to its success. This includes both technical staff who manage the cameras and law enforcement officers who process violations. Ensuring staff are well-equipped to manage and support the system will help improve the efficiency and reliability of the program.

- Transparent Public Communication: Transparent and ongoing communication with the public is necessary to maintain support for the RLC program. Engaging with the community, addressing their concerns, and clearly communicating the safety benefits of the program will help build trust and ensure its long-term success.

- Investigate Dilemma Zones and Driver Behavior: The timing of violations in relation to dilemma zones, where drivers may be unsure whether to stop or proceed, should be investigated. If drivers speed up to avoid tickets, it could lead to more dangerous driving behavior. Studying and addressing these zones will help mitigate unintended consequences and ensure that RLCs are used effectively to improve safety, not to promote riskier behavior.

The study emphasizes the importance of using data-driven strategies for traffic safety, incorporating public education to address perceptions, and conducting ongoing evaluations to refine and enhance intersection safety measures. The findings advocate for a balanced approach to implementing traffic enforcement technologies, ensuring they contribute positively to road safety while addressing any unintended consequences.

3.5 Acknowledgments

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Chapter 4: Public Perception of Red Light Cameras

This chapter presents the methodology, analysis, and findings from a comprehensive study examining public perceptions of red-light camera enforcement across two distinct policy environments: Arizona and New York. The chapter investigates how perceptions of fairness, transparency, and safety influence overall support for automated enforcement programs, while also assessing the role of demographic and contextual factors such as age, gender, driving frequency, and policy stability. Through the development of composite indices and the application of advanced statistical modeling, including ordinal logistic regression and structural equation modeling, the study identifies the psychological and contextual mechanisms shaping acceptance of automated enforcement.

The analysis provides an in-depth understanding of how individuals evaluate the legitimacy and effectiveness of RLCs, emphasizing fairness and transparency as key determinants of trust and support. By comparing two contrasting enforcement contexts (i.e., New York's long-standing, stable program and Arizona's more contested and variable experience) the findings contribute to a nuanced understanding of how policy continuity and communication influence public attitudes. Ultimately, this chapter seeks to inform evidence-based strategies for designing, implementing, and communicating automated enforcement programs that are both effective and publicly legitimate.

4.1 Introduction

Road traffic injuries represent one of the most urgent global transportation safety concerns, with the World Health Organization (2023) reporting nearly 1.19 million deaths annually. Intersections are particularly hazardous conflict points within roadway networks, where the violation of traffic signals, especially red-light running, has been identified as a major contributor to severe crashes, including angle and side-impact collisions with high fatality risk (Mohd Radzi et al., 2025). Despite decades of engineering and enforcement interventions, RLR remains a persistent and complex problem, influenced by behavioral, demographic, technological, and policy-related factors.

Automated enforcement technologies such as RLCs have been increasingly implemented to deter violations and improve intersection safety. Evidence of their effectiveness is mixed but promising. Cheng et al. (2025) demonstrated that advanced camera systems with machine learning capabilities achieved significant and sustained crash reductions compared to conventional enforcement or no cameras, primarily through enhanced detection, continuous monitoring, and long-term deterrence (Cheng et al., 2025). Yet, other studies note increases in rear-end crashes or null effects, underscoring the need to account for roadway context, signal timing, and program design in evaluating effectiveness.

Beyond technical outcomes, RLC programs intersect with broader concerns about legitimacy, fairness, and equity. Kennedy et al. (2024) note that automated ticketing systems can reduce police-driver interactions and thus potential discriminatory encounters, but they may also exacerbate disparities in fine burdens across minority and low-income communities (Kennedy et al., 2025). Public acceptance of such technologies often hinges on whether they are perceived as enhancing safety rather than serving as revenue tools (Higgins et al., 2011; Kennedy et al., 2025). Prior research consistently finds that perceptions of fairness, transparency, and legitimacy are central to acceptance, often more influential than safety statistics alone.

The U.S. provides a unique lens for examining these dynamics, as state-level contexts for RLCs vary considerably. New York has one of the longest and most stable automated enforcement histories, with New York City pioneering camera adoption in the 1990s and subsequently expanding programs. Arizona, by contrast, has experienced a fragmented and contested trajectory, with programs intermittently adopted, suspended, or discontinued in various jurisdictions. This divergence offers a valuable comparative setting to study whether policy stability versus policy volatility shapes public perceptions of safety, fairness, and legitimacy.

Against this backdrop, the chapter examines public perceptions of RLCs across Arizona and New York, focusing on awareness, safety beliefs, fairness and revenue concerns, transparency, and overall support. Using survey data from over 550 respondents and advanced statistical modeling, the chapter investigates both the direct and mediated pathways through which perceptions of fairness, trust, and transparency influence support for automated enforcement. By situating findings within contrasting policy contexts, the study provides insight into how enforcement stability affects public attitudes and contributes to ongoing debates about the role of automated enforcement in traffic safety.

4.1.1 Policy Context and Rationale for State Selection

Rationale for Comparing New York and Arizona

New York and Arizona were selected as comparative case study states because they present contrasting trajectories of red-light camera (RLC) adoption and governance. New York has one of the longest and most stable histories of automated traffic enforcement in the United States, with sustained legislative support and incremental expansions of authority since the 1990s. By contrast, Arizona's experience with RLCs has been intermittent, contested, and locally variable, with programs being adopted, suspended, and reinstated in different cities over time.

Studying public perception in these two distinct contexts provides a unique opportunity to examine how policy stability versus policy volatility may shape beliefs about safety, fairness, and legitimacy of automated enforcement. In particular, the comparison allows for investigation into whether long-standing, institutionalized programs (e.g., New York City's system) foster greater acceptance and trust than jurisdictions where enforcement is frequently debated or discontinued (e.g., Phoenix and other Arizona cities).

Red-Light Camera Policy in New York State

New York City became the first U.S. city to operate an RLC program in 1994, following state authorization under Vehicle & Traffic Law. Over the past three decades, state legislation has repeatedly extended and expanded the scope of RLC programs, authorizing additional intersections and new jurisdictions. Recent updates have further expanded authorization across multiple counties, including parts of the Hudson Valley(NYC, 2024).

The NYC program began with a cap of 50 intersections and has steadily grown to encompass several hundred intersections, making it one of the largest automated enforcement systems in the country (NYCDOT, 2024). Violations carry a $50 fine, no driver's license points are assessed, and liability rests with the registered vehicle owner through a mailed Notice of Liability (NYC DOT, 2011.).

Red-Light Camera Policy in Arizona

Unlike New York, Arizona law allows local jurisdictions to implement photo enforcement but prohibits its use on state highways (Arizona Senate Research Staff, 2022). Cities such as Phoenix, Scottsdale, and Tempe have adopted programs, but state statute imposes strict requirements on signage and visibility.

Violations typically result in fines of about $250 and add two points to the driver's license, classifying them as moving violations that may affect insurance premium. Phoenix discontinued its RLC program at the end of 2019 but approved a $12 million contract in 2025 to reinstate cameras at key intersections, reflecting a major policy reversal (Liberty Law AZ, 2025).

Table 4.1 Key Differences in Red-Light Camera Policy Contexts: New York vs. Arizona

Policy Feature	New York State	Arizona
Program Start	NYC in 1994 (first in US)	Mid 2000s (city level adoption varies)
Stability	Continuous, expanding since 1994	On-off programs, bans/ reinstalls
Fine Amount	$50	~$250 (varies by city)
Driving Points	No driver's license points	2 license points (moving violation)
Liability	Vehicle owner	Vehicle owner (Contest possible)
Scope	Hundreds of intersections in NYC; programs in other countries	City-level only; banned on state highways
Political Climate	Expansions backed by state law	Frequent debate, legislative challenges

Table 4.1 presents the policy contrast which is central to the survey. New York's long-standing,

widely institutionalized program provides an environment where residents are accustomed to RLCs and may see them as normalized aspects of traffic enforcement. By contrast, Arizona's intermittent adoption and contentious politics surrounding automated enforcement suggest that residents may perceive RLCs as less legitimate, more punitive, or more closely tied to revenue generation. These differences provide a natural comparative framework for analyzing how policy context moderates public perceptions of automated enforcement.

4.2 Data Collection

The survey consisted of 30 structured questions that captured public perceptions of RLCs across multiple domains: awareness and understanding, perceived safety benefits, fairness and enforcement, clarity and transparency of policies, and overall support for automated enforcement technologies. The full survey questionnaire is provided in Appendix A.

The survey was developed in Qualtrics following an extensive review of prior literature on automated enforcement programs (Aldossari et al., 2023; Council et al., 2005; McCartt and Eichelberger, 2012). The questions were designed to measure factors consistently identified in the literature as shaping acceptance of RLCs, including beliefs about safety benefits, concerns about fairness and revenue motives, policy clarity, and willingness to support enforcement expansion. A combination of Likert-scale, categorical, and open-ended questions was used to capture both quantitative and qualitative perspectives. Two attention check questions were embedded to detect low-quality responses (e.g., "Traffic lights use a specific color for the STOP signal. To show you are paying attention, please select 'Green' as your answer"). Participants who failed either check questions were excluded from the sample. A screening question at the start excluded participants who indicated they did not know what a red-light camera was. Those respondents were compensated for their brief participation but did not proceed further in the survey. This research received approval from the University of Arizona Institutional Review Board (IRB).

4.2.1 Survey Administration

The questionnaire was distributed online through Qualtrics and administered via Prolific, a recruitment platform with access to a large and diverse participant pool. Data collection took place between May and June 2025. Eligibility criteria required participants to be at least 18 years old and current residents of either Arizona or New York. Unlike some prior studies, respondents were not required to hold a driver's license, reflecting the understanding that perceptions of automated enforcement extend beyond drivers to include pedestrians, cyclists, and community members exposed to enforcement programs. The rationale was that public perceptions of automated enforcement are not limited to licensed drivers; pedestrians, cyclists, and other road users may also form strong views about RLCs based on community discourse, news, or indirect experiences. Participants received compensation based on Prolific's fair payment calculator: \$1.35 for completing the full questionnaire (average completion time ≈ 8 minutes) and \$0.14 for screened-out respondents (average time ≈ 30 seconds) (Prolific, 2025). The target sample size was 600 individuals, evenly divided between the two states.

The minimum required sample size was calculated using the standard formula based on Israel's research paper (Israel, 1992). Sample size calculations indicated that 385 responses per state would be required for a 95% confidence level with a ±5% margin of error. After excluding incomplete responses, screened-out respondents, and those who failed attention checks, the final sample consisted of 557 respondents. While the achieved totals (277 in Arizona and 280 in New York) fall slightly below this threshold, they were found to be sufficient to yield margins of error of approximately ±6% at 95% confidence. Alternatively, under the 90% confidence criterion, which requires only 271 responses for the same margin of error, both state samples meet the recommended standard. This ensures that the results remain statistically valid for comparative analysis of public perceptions across the two states.

The final sample included 49.7% and 50.3% from Arizona and New York. Demographic questions were asked at the beginning of the survey to contextualize perceptions and evaluate representativeness. These included: age (continuous, in years), gender (man, woman, non-binary/other), frequency of driving and primary mode of transportation. Due to the small number of non-binary respondents (n = 10), they were excluded from the analysis.

4.3 Methodology

4.3.1 Construction of Composite Indices

To capture underlying dimensions of public perceptions toward red-light camera enforcement, two composite indices were created: the Fairness-Trust Index (FTI) and the Transparency-Clarity Index (TCI). These indices aggregate multiple questions into continuous scales, enabling more robust statistical modeling of perceptions.

Fairness-Trust Index (FTI)

The FTI was designed to measure respondent's trust in the fairness, legitimacy, and effectiveness of RLCs. It was constructed from four survey questions addressing:

- Fairness of implementation: Whether cameras are applied without bias toward specific drivers or communities

Revenue concern (reverse-coded): Concern that cameras are used primarily for revenue generation. (Responses were reversed so that higher values reflected greater trust rather than higher concern.)

- Justification of citations: Whether tickets issued by cameras are viewed as justified

- Comparative effectiveness: Perceived effectiveness of cameras relative to traditional police enforcement

Responses were coded on a five-point ordinal scale (1-5). Because the FTI combines several conceptually related questions into a single measure, internal consistency was assessed using Cronbach's α. Reliability testing ensures that each survey questions measure the same latent construct and can be meaningfully aggregated. Cronbach's α is a standard reliability statistic that measures how well a set of items captures a common underlying construct, with values above 0.7 generally considered acceptable (Jansseens et al., 2008; Taber, 2018). The Cronbach's α coefficient for the FTI indicated acceptable reliability of $\alpha = 0.76$, which justified averaging them into a single index. This suggests that the item measure a coherent underlying construct and can be meaningfully aggregated into a composite index. The final FTI score was calculated as the row-wise mean of the four items, with higher values indicating stronger perceptions of fairness and trust for each survey respondent.

Transparency-Clarity Index (TCI)

The TCI was constructed to evaluate respondent's perceptions of transparency and clarity in communication about red-light camera enforcement. Two components were included:

- Perceived clarity: How clear and accessible respondents found the information regarding policies and operational guidelines

- Exposure to official communications: Whether respondents had read or seen official reports/statements explaining that cameras are used for safety rather than revenue. Responses were coded as: Yes = 5, Not sure = 3, No = 1.

Because this index consisted of only two related but distinct items, Cronbach's α was not emphasized. Instead, the items were harmonized to a numeric scale and averaged to create the TCI (range 1–5). Higher scores reflect greater perceived transparency and clarity.

4.3.2 Ordinal Logistic Regression (OLR)

To assess the factors influencing public support for RLCs, this study employed ordinal logistic regression (OLR), also known as the proportional odds model (McCullagh, 1980). This approach is appropriate because the dependent variable respondents' level of support was measured on an ordered categorical scale (i.e., Oppose, Neutral, Support), where categories have a natural ranking but the distances between them are not assumed to be equal.

The proportional odds model estimates the log-odds of being at or below a given response category as a linear function of predictor variables. For an ordinal outcome with j ordered categories, the model can be expressed as equation (12):

$$\log\left(\frac{P(Y\leq j)}{P(Y>j)}\right) = \theta_j - X\beta, \quad j = 1, \dots, J-1 \tag{12}$$

Where Y is the ordinal outcome, θ_j are threshold (cutpoint) parameters, $\boldsymbol{X}$ is the vector of explanatory variables, and β represents the regression coefficients.

Exponentiating the coefficients yields odds ratios, which indicate the change in odds of belonging to a higher support category associated with a one-unit increase in the predictor. Odds ratios greater than one signify increased likelihood of support, while values less than one signify decreased likelihood. Predictors included demographic characteristics (age, gender, state of residence, and driving frequency), awareness measures (knowledge of cameras in the state or local community, self-rated understanding), and perception indices (Fairness-Trust Index, Transparency-Clarity Index, and perceived safety benefits). This allowed the model to assess both contextual and perceptual influences on respondent's attitudes toward automated enforcement.

A key assumption of the proportional odds model is that the estimated relationships between predictors and the outcome are constant across all thresholds (i.e., the proportional odds assumption). This assumption holds that the effect of each predictor on the dependent variable is consistent across all thresholds of the ordered outcome (McCullagh, 1980). In other words, the estimated coefficients (β) remain the same whether the comparison is between "Oppose vs. Neutral/Support" or between "Oppose/Neutral vs. Support." This assumption makes the model more parsimonious, as one set of coefficients describes relationships across all cumulative logits.

To evaluate whether this assumption was satisfied in the present analysis, I conducted the nominal test in R, which is analogous to the Brant test (Brant, 1990). The test compares the proportional odds model to a less restrictive model in which coefficients are allowed to vary across thresholds. A statistically significant result would indicate violation of the proportional odds assumption, suggesting that the effect of one or more predictors differs across outcome cutpoints. In this study, the test showed no significant violations for most predictors, supporting the validity of the OLR specification. However, age and gender did not meet the proportionality assumption. For this reason, I estimated a partial proportional odds (PPO) model, which relaxed the proportionality constraint for these two predictors while retaining it for others. This ensured valid estimation and interpretation of all effects.

4.3.3 Structural Equation Modeling of Public Perceptions

To investigate the psychological mechanisms underlying public support for RLCs, a Structural Equation Modeling (SEM) framework was applied. SEM is a multivariate statistical technique that integrates aspects of factor analysis and path analysis, enabling simultaneous estimation of direct, indirect, and total effects among multiple constructs (Byrne, 2013; Kline, 2016). Unlike standard regression models, which evaluate one outcome at a time, SEM captures sequential pathways (e.g., legitimacy → safety beliefs → support) and accounts for both measurement and structural components. This makes SEM particularly well-suited for transportation policy research, where perceptions of fairness, transparency, and safety are conceptually interdependent (de Oña et al., 2013).

The conceptual model hypothesized that legitimacy perceptions (Fairness–Trust Index, FTI) exert both direct and mediated effects on public support for RLCs. Two sequential mediating pathways were tested: (i) safety beliefs, and (ii) transparency (Transparency–Clarity Index, TCI) leading to safety beliefs.

Formally, the system of equations can be written as shown in equation (13-15):

$$\mathrm{TCI} = \alpha_1 + \beta_1\,\mathrm{FTI} + \varepsilon_1 \tag{13}$$

$$\mathrm{Safety} = \alpha_2 + \beta_2\,\mathrm{TCI} + \beta_3\,\mathrm{FTI} + \varepsilon_2 \tag{14}$$

$$\mathrm{Support} = \alpha_3 + \beta_4\,\mathrm{Safety} + \beta_5\,\mathrm{FTI} + \varepsilon_3 \tag{15}$$

Where,

FTI = Fairness–Trust Index,

TCI = Transparency–Clarity Index,

Safety = belief that RLCs reduce red-light-running crashes,

Support = respondent support for RLCs,

Thus, the indirect effect of FTI on Support via Safety is given by equation (16):

$$\mathrm{Indirect}_{FTI\rightarrow Safety\rightarrow Support} = \beta_3 \times \beta_4 \tag{16}$$

and the sequential indirect effect via TCI and Safety is calculated by equation (17):

$$\mathrm{Indirect}_{FTI\rightarrow TCI\rightarrow Safety\rightarrow Support} = \beta_1 \times \beta_2 \times \beta_4 \tag{17}$$

The total effect of FTI on Support is the sum of its direct and indirect components shown in equation (18):

$$\text{Total}_{FTI \rightarrow Support} = \beta_5 + (\beta_3 \times \beta_4) + (\beta_1 \times \beta_2 \times \beta_4) \tag{18}$$

Measurement of Constructs

Fairness–Trust Index (FTI): Composite of four survey questions regarding perceived fairness, concern about revenue motives, justification of citations, and effectiveness relative to police enforcement (PSQ18, PSQ19, PSQ20, PSQ21) Internal consistency was acceptable (Cronbach's $\alpha = 0.77$).

Transparency–Clarity Index (TCI): Derived from two questions regarding clarity of policies and recall of official communications (PSQ24, PSQ25).

Safety Belief: Measured by agreement with the statement that RLCs reduce red-light-running crashes.

Support: Respondent's stated support, opposition, or neutrality toward RLCs in their community.

SEM models were estimated using the lavaan package in R (Rosseel, 2012), employing maximum likelihood with robust (MLR) standard errors. Model fit was evaluated using multiple fit indices, including:

- Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), where values ≥ 0.90 indicate acceptable fit (Hu and Bentler, 1999).
- Root Mean Square Error of Approximation (RMSEA), where values ≤ 0.08 indicate reasonable fit (Steiger, 1990).
- Standardized Root Mean Square Residual (SRMR), where values ≤ 0.08 indicate a good fit (Hu and Bentler, 1999).

To assess whether structural relationships differed between Arizona and New York, a multi-group SEM was conducted. This allowed the estimation of path coefficients for each state separately while testing whether constraining parameters to equality significantly reduced model fit. By comparing constrained and unconstrained models, it was possible to evaluate whether the effects of fairness, transparency, and safety on support varied across policy contexts.

4.4 Results

4.4.1 Descriptive Statistics and Bivariate Analysis

Welch two-sample t-tests were conducted to compare perceptions across Arizona and New York. For the Safety Belief Index, no significant difference was found between the two states ($t = –0.49$, $df = 555$, $p = 0.628$). Respondents in Arizona (M = 3.45) and New York (M = 3.50) reported nearly identical levels of perceived safety, with the 95% confidence interval (–0.23, 0.14) including zero, confirming the lack of meaningful differences. Similarly, the Fairness–Trust Index (FTI) showed no significant state-level difference (t = –0.74, df = 552.78, p = 0.458). Mean values were nearly identical (Arizona: M = 3.30; New York: M = 3.35), suggesting that perceptions of fairness and legitimacy are consistent across the two policy contexts. In contrast, a significant state difference was observed for the Transparency–Clarity Index (TCI) (t = –2.68, df = 554.52, p = 0.008), with New York respondents rating transparency higher (M = 2.79) than those in Arizona (M = 2.53). This difference indicates that residents of New York, where enforcement programs have been longer-standing and more institutionalized, are more likely to perceive RLC policies as transparent and clearly communicated (Figure 4.1).

Figure 4.1 Transparency Clarity Index (TCI) by State. (Note: Lower TCI is observed in Arizona; larger TCI observed in New York)

Results across both parametric and non-parametric tests revealed mixed gender patterns. Participants identifying as non-binary were excluded from the analysis due to the small sample size. For both fairness and safety perceptions, no statistically significant differences were observed between men and women. However, significant gender differences emerged for transparency. Men reported significantly higher TCI scores ($M = 2.82$) compared to women ($M = 2.54$), ($t = 2.78$, $df = 519.09$, $p = 0.006$, 95% CI: 0.08, 0.47). A Wilcoxon test confirmed this result ($p = 0.021$), indicating that women perceived RLC programs as less transparent than men (Figure 4.2). This suggests a potential gendered dimension in how automated enforcement programs are perceived in terms of clarity and openness. To further explore these relationships, a two-way ANOVA (linear regression with interaction) tested the joint effect of state and gender on transparency perceptions. The main effect of state was marginally significant ($\beta = 0.27$, $SE = 0.15$, $t = 1.83$, $p = 0.068$), with New York residents showing somewhat higher TCI values. The main effect of gender was also marginal ($\beta = –0.24$, $SE = 0.14$, $t = –1.71$, $p = 0.088$), with women rating transparency lower. However, the interaction between state and gender was not significant, indicating that the effect of state on transparency perceptions does not differ between men and women.

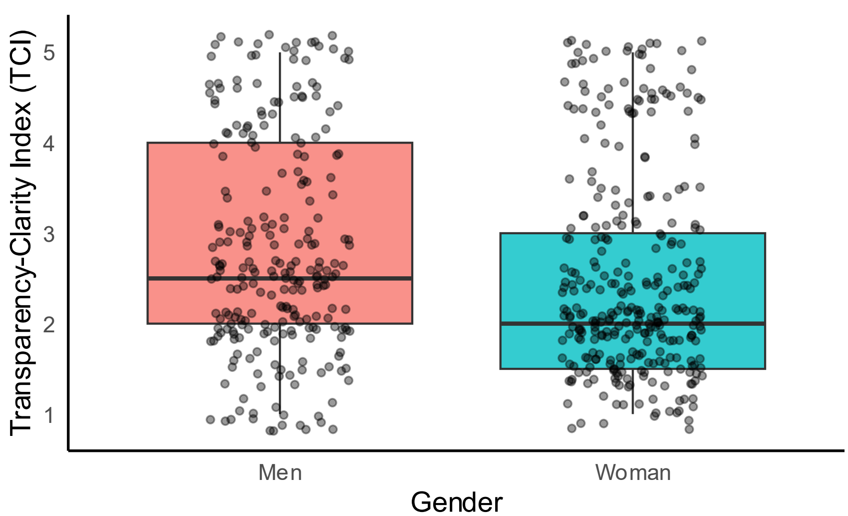

Figure 4.2 Transparency-Clarity Index (TCI) by Gender

Support for RLCs was significantly associated with both gender and overall safety perceptions. A chi-squared test revealed gender differences in levels of support ($\chi^2 = 8.18$, $df = 2$, $p = 0.017$). A stronger association was observed between safety perceptions and support ($\chi^2 = 320.75$, $df = 4$, $p < 0.001$). ANOVA further confirmed that higher levels of support were linked with significantly greater fairness and transparency scores (Figure 4.3).

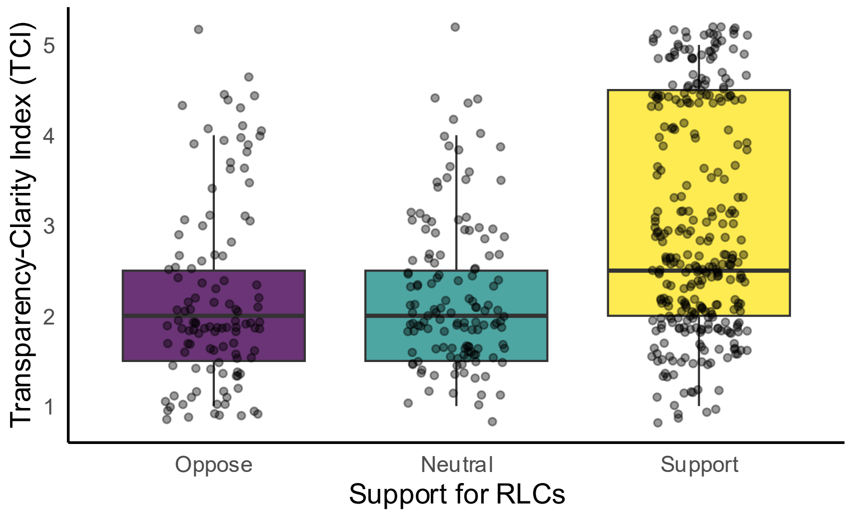

Figure 4.3 Transparency-Clarity Index (TCI) by Support Levels

Exposure to official reports or communications explaining that RLCs are implemented for safety rather than revenue also had a strong impact, as shown in Figure 4.4. Respondents who reported having seen such communications assigned significantly higher transparency scores, with explained variance exceeding that of demographic variables.

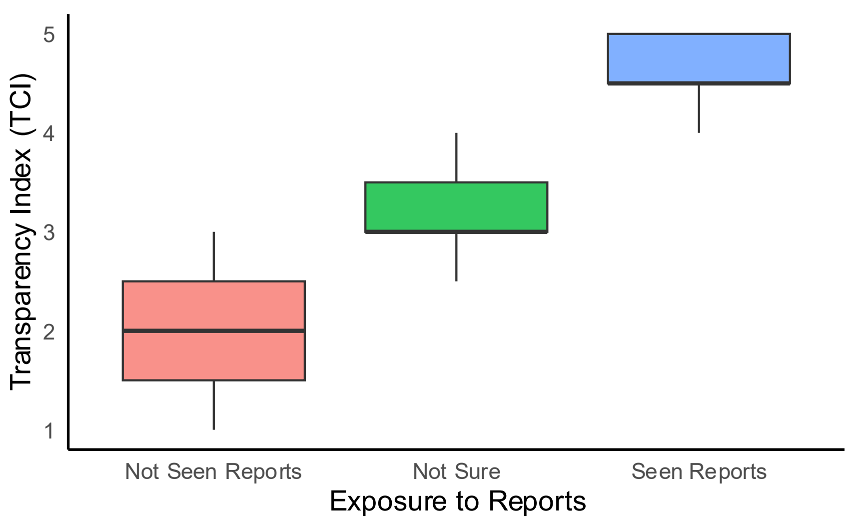

Figure 4.4 Transparency Clarity Index (TCI) by Exposure to Reports

Finally, Spearman's rank correlation revealed a significant positive association between the

Fairness-Trust Index and Transparency-Clarity Index, as shown in Figure 4.5, suggesting that respondents who perceived the system as more transparent were also more likely to view it as fair and legitimate.

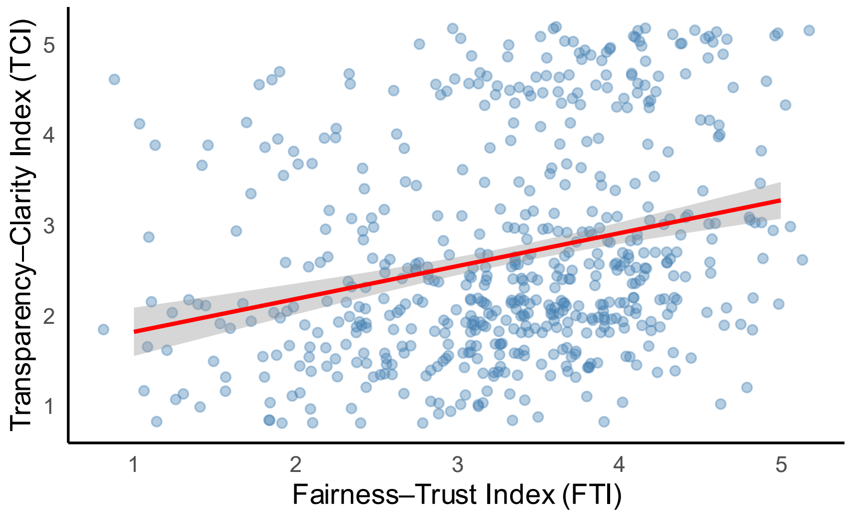

Figure 4.5 Correlation between Fairness and Transparency

4.4.2 Ordinal Logistic Regression Results

Two composite measures were developed to capture broader perceptions of automated enforcement. Both demonstrated good reliability (FTI: Cronbach's α = 0.76, 95% CI [0.73, 0.79]; TCI: Cronbach's α = 0.72, 95% CI [0.68, 0.76]). Mean values indicated moderately positive views on fairness (M = 3.33, SD = 0.87) and more mixed or neutral perceptions of transparency (M = 3.29, SD = 0.92) (Table 4.1).

Table 4.2 Reliability and Descriptive Statistics for Composite Indices

Index	Cronbach's α (95% CI)	Mean (1-5)	Standard Deviation
FTI	0.76 [0.73, 0.79]	3.33	0.87
TCI	0.72 [0.68, 0.76]	3.29	0.92

The proportional odds assumption was evaluated using a nominal effects test. Results indicated significant violations for age ($\chi^2(1) = 10.18$, $p = 0.001$) and gender ($\chi^2(1) = 5.55$, $p = 0.018$), suggesting that the effect of these predictors differed across thresholds of support. No other predictors showed significant violations (all $p > 0.10$). Thus, the proportional odds assumption was generally supported for most predictors, with the exception of age and gender. To address these violations, a partial proportional odds (PPO) model was estimated, relaxing the proportionality constraint for age and gender but retaining it for all other predictors. A likelihood ratio test confirmed that the PPO model fit significantly better than the proportional odds model (LR $\chi^2(2) = 15.95$, $p < 0.001$). Table 4.2 presents odds ratios (ORs) with 95% confidence intervals for predictors constrained under the proportional odds assumption.

Table 4.3 Ordinal Logistic Regression Results Predicting Support for Red-Light Cameras

Index	Odd Ratios (OR)	95% Confidence Interval	P-Value
Understanding (Linear)	0.34	0.13-0.87	0.018
RLC in Area (linear)	1.78	1.16-2.72	0.007
Safety Reduces Crashes (linear)	16.8	6.3-44.6	<0.001
Fairness–Trust Index (FTI)	9.7	6.5-14.6	<0.001
Transparency–Clarity Index (TCI)	1.52	1.19-1.93	<0.001
Aware of RLCs in State	1.10	0.42-2.87	0.85
State (NY vs AZ)	1.14	0.72-1.81	0.56

*Odds ratios quantify the multiplicative change in the odds of stronger support associated with a one-unit increase in each predictor. For example, an OR of 1.5 indicates a 50% increase in the odds of higher support, whereas an OR of 0.6 indicates a 40% decrease. In this study, fairness–trust perceptions had an OR ≈ 9.7, suggesting that higher fairness perceptions strongly predicted greater support for RLCs.

Several predictors were significant, as shown in Table 4.2. Fairness and trust perceptions emerged as the most influential predictors of support for RLCs. Specifically, a one-unit increase in the FTI was associated with a more than ninefold increase in the odds of supporting RLCs (OR = 9.69, $\beta = 2.27$, SE = 0.21, $p < 0.001$). Perceptions that RLCs reduce crashes also exerted a strong influence: those who agreed that cameras help reduce red-light running crashes had odds of support approximately 17 times higher (OR = 16.85, $\beta = 2.82$, SE = 0.50, $p < 0.001$). TCI was another significant predictor, with each unit increase associated with a 53% increase in the odds of support (OR = 1.53, $\beta = 0.42$, SE = 0.12, $p < 0.001$). Similarly, respondents who reported that cameras were installed in their communities were significantly more supportive (OR = 1.78, $\beta = 0.58$, SE = 0.22, $p = 0.007$). Interestingly, higher self-reported understanding of camera operations predicted lower odds of support (OR = 0.34, $\beta = -1.09$, SE = 0.46, $p = 0.018$), suggesting that greater familiarity with enforcement procedures may correspond to heightened skepticism.

Other predictors, including state of residence (i.e., Arizona vs. New York), driving frequency, and awareness of state-level RLC use, were not significant when fairness, safety, and transparency perceptions were controlled. These null findings suggest that support is not driven by broad contextual or exposure-based factors but rather by evaluative judgments of legitimacy and effectiveness.

The partial proportional odds result also revealed threshold-specific effects for age and gender. At the “oppose vs. neutral/support” threshold, older respondents were more likely to move out of opposition ($\beta = 0.026$, SE = 0.012, $p = 0.038$), though this trend reversed at the “neutral vs. support” threshold ($\beta = -0.018$, SE = 0.010, $p = 0.063$). For gender, women were marginally less likely than men to shift from opposition to neutrality ($\beta = -0.615$, SE = 0.33, $p = 0.061$), but no difference was found in the transition from neutrality to support ($p = 0.317$).

The analysis results indicate that support for RLCs is shaped primarily by perceptions of fairness, trust, safety, and transparency, while demographic characteristics like age and gender exert influence only at specific stages of the support continuum. Broader contextual factors such as state of residence or driving frequency did not significantly explain variation in support.

4.5 Demographic and Contextual Predictors of Red-Light Camera Perceptions

To examine how demographic and contextual factors shape perceptions of RLCs, a series of logistic and ordinal regression models were estimated. Predictors included age, gender, state of residence (i.e., Arizona vs. New York), and driving frequency, with outcomes covering understanding of enforcement, revenue concerns, fairness, effectiveness, policy clarity, and awareness of local RLC presence. Results for significant predictors ($p < 0.05$) are summarized in Table 4.3.

Table 4.4 Logistic and Ordinal Regression Results for Demographic and Contextual Predictors of Red-Light Camera Perceptions

Outcome	Predictor	Odd Ratios (OR)	Lower Confidence Interval (CI_low)	Higher Confidence Interval (CI_high)	P-Value
Understanding	State: New York	1.50	1.10	2.03	0.011
Understanding	Drive frequency (linear)	0.26	0.16	0.41	0.000
Revenue Concern	Gender: Woman	0.67	0.49	0.90	0.009
Revenue Concern	State: New York	1.49	1.10	2.02	0.009

Revenue Concern	Drive frequency (linear)	0.53	0.33	0.86	0.011
Justification of Citations	Drive frequency (linear)	1.67	1.02	2.74	0.041
Effectiveness	State: New York	1.80	1.32	2.45	0.000
Clarity of Policies	Gender: Woman	0.73	0.54	0.99	0.043
Clarity of Policies	State: New York	1.39	1.02	1.89	0.036
Support if Evidence	Drive frequency (linear)	1.89	1.12	3.17	0.016
Expand Automated Enforcement	Age (years)	0.99	0.98	1.00	0.044
Awareness of RLCs in Area	Age (years)	0.99	0.97	1.00	0.036
Awareness of RLCs in Area	State: New York	2.35	1.64	3.36	0.000

Awareness of RLCs in Area	Drive frequency (linear)	0.49	0.29	0.81	0.005

*Note: Drive Frequency (5-point Likert Scale), Reference State: Arizona, Reference Gender: Man

For binary outcomes (e.g., awareness of RLCs in the area, support for expansion of automated enforcement), logistic regression models were used. Each model included the predictors age, gender, state of residence and driving frequency. Odds ratios with p-values were extracted, and results were filtered to retain only predictors significant at the 5% level.

The regression analyses identified several significant demographic and contextual predictors of perceptions and attitudes toward RLCs. State of residence emerged as a consistent factor across multiple outcomes. Respondents from New York compared to Arizona were:

- more likely to report higher understanding of how RLCs operate (OR = 1.50, $p = 0.011$)
- more confident in the effectiveness of RLCs relative to traditional police enforcement (OR = 1.80, $p < 0.001$)
- and more likely to view program policies as clear (OR = 1.39, $p = 0.036$)

At the same time, New York respondents were also more likely to express concern that cameras might be used primarily for revenue generation rather than safety (OR = 1.49, $p = 0.009$). These findings suggest that New York's longer and more stable enforcement history has not only increased awareness and legitimacy perceptions but also heightened sensitivity to revenue-related criticisms.

Gender differences were also observed. Women were less likely than men to express concern about revenue motivations (OR = 0.67, $p = 0.009$), yet they were also less likely to perceive clarity in policies and guidelines (OR = 0.73, $p = 0.04$). This dual pattern suggests that women may view automated enforcement as less financially exploitative but also experience greater difficulty in accessing or interpreting policy-related information.

Driving frequency strongly shaped perceptions. Respondents who drove more frequently were:

- less likely to report a strong understanding of how RLCs operate (OR = 0.26, $p < 0.001$)
- less likely to view RLCs as primarily revenue-driven (OR = 0.53, $p = 0.011$)
- but more likely to perceive citations as justified (OR = 1.67, $p = 0.041$)

In addition, frequent drivers were significantly more supportive of RLCs when evidence of safety effectiveness was provided (OR = 1.89, $p = 0.016$). These findings suggest that while frequent drivers may be less engaged with policy details, their greater exposure to enforcement fosters a stronger sense of legitimacy and openness to evidence-based arguments.

Age effects, while modest in size, were also significant. Older respondents were less likely to support expanding automated enforcement to other traffic violations (OR = 0.99, $p = 0.04$) and less likely to report awareness of cameras in their area (OR = 0.99, $p = 0.04$). This indicates that younger individuals are slightly more open to the broader use of automated technologies and may also be more attuned to their presence in local environments.

Finally, state-level differences were again apparent in awareness of cameras in local communities. Respondents in New York were more than twice as likely as those in Arizona to report the presence of cameras in their area (OR = 2.35, $p < 0.001$), while frequent drivers were less likely to indicate awareness (OR = 0.49, $p = 0.005$). Taken together, these results demonstrate that both policy context and individual demographics play a critical role in shaping how automated enforcement is perceived. The stability and visibility of New York's red-light camera program appear to have reinforced perceptions of clarity, effectiveness, and presence, while also intensifying concerns about revenue use. At the same time, gender, driving exposure, and age introduce nuanced differences in legitimacy, clarity, and support that underscore the importance of tailoring communication and policy strategies to diverse groups.

4.5.2 Structural Equation Model Results

To further investigate the mechanisms linking fairness, transparency, safety perceptions, and support for RLCs, a SEM was estimated. This approach allowed for simultaneous assessment of both direct and indirect pathways, providing insight into how perceptions interact to shape overall acceptance.

Model fit indices indicated limited overall fit (e.g., CFI = 0.68; RMSEA = 0.35–0.49). This outcome was expected given the reliance on composite indices and single-item measures rather than multi-indicator latent constructs. Nevertheless, the path coefficients were stable and statistically significant, supporting substantive interpretation of the relationships.

Direct Effects

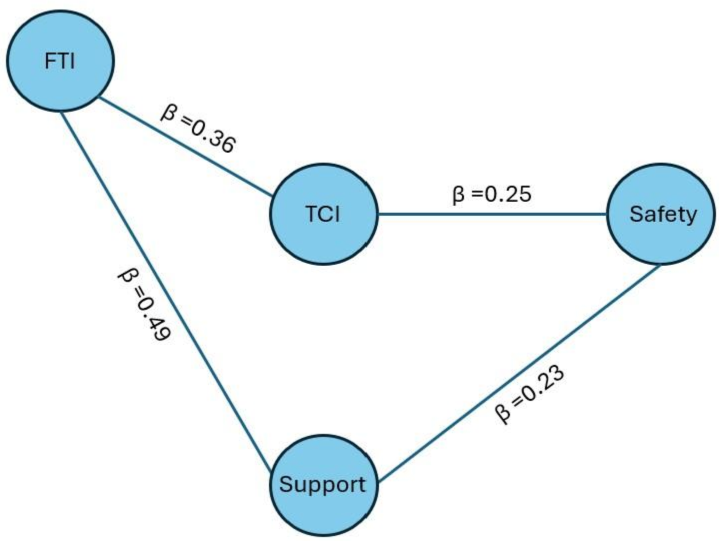

Figure 4.6 Structural Equation Model of Relationships Among Fairness, Transparency, Safety Beliefs, and Support for RLCs

Figure 4.6 visually represents the SEM and the standardized path coefficients among the key latent constructs (FTI, TCI, Safety, and Support). Among the latent constructs, the Fairness Trust Index (FTI) showed the largest standardized effect on support. The standardized coefficient for the path FTI → Support was $\beta = 0.49$, $p < 0.001$, indicating that respondents who perceived RLCs as fair, justified, and not primarily revenue-driven were substantially more likely to support their continued use. Safety beliefs also played an important role. The direct path from Safety Belief → Support was $\beta = 0.23$, $p < .001$ (Table 4.4). This indicates that even beyond fairness perceptions, believing that cameras reduce crashes increased the likelihood of supporting them. This suggests that improving public understanding of the safety benefits of RLCs through educational or awareness campaigns could further enhance support. Additional relationships were also significant. Fairness perceptions strongly predicted transparency (FTI → TCI, $\beta = 0.36$, $p < 0.001$), and transparency in turn predicted safety perceptions (TCI → Safety, $\beta = 0.25$, $p < 0.001$). These results suggest a sequential pathway in which fairness enhances perceptions of transparency, which then reinforce safety beliefs.

Indirect Effects

The sequential indirect pathway FTI → TCI → Safety → Support was small but statistically significant ($\beta = 0.02$, $p = 0.001$). This indicates that fairness indirectly bolsters support through improved transparency and strengthened safety perceptions When combined with direct effects, the total effect of FTI on support was $\beta = 0.51$, $p < 0.001$, confirming that fairness serves as the central driver of public acceptance.

Explained Variance

The SEM accounted for a substantial proportion of variance in support ($R^2 = 0.50$), while transparency and safety each explained more modest shares of their respective outcomes ($R^2 = 0.07$ for TCI; $R^2 = 0.07$ for Safety). These findings highlight fairness as the most influential construct shaping support, with transparency and safety acting as important but secondary mediators.

Multi-Group Analysis

A multi-group SEM was conducted to examine whether these relationships differed between Arizona and New York. Results revealed nearly identical patterns in Arizona and New York. For example, the FTI → Support path was 0.48 in both states, while the Safety → Support path remained at 0.23. These results suggest that despite stark differences in policy history; New York with a long-standing and stable RLC program, and Arizona with contested and intermittent implementation, the psychological mechanism underlying public support remains robust. Across both environments, fairness perceptions are the strongest determinant of acceptance, with transparency and safety shaping support indirectly.

Table 4.5 Structural Equation Model Results: Direct, Indirect, and Total Effects on Support for RLCs

Path	Standardized β	P-Value	Interpretation
FTI → Support	0.49	< 0.001	Fairness Strongly boosts support
Safety → Support	0.23	< 0.001	Safety beliefs independently add support
FTI → TCI	0.36	< 0.001	Fairness improves transparency perception
TCI → Safety	0.25	< 0.001	Transparency fosters safety belief
Indirect (FTI → TCI → Safety → Support)	0.02	0.001	Small but significant sequential mediation
Total FTI → Support	0.51	< 0.001	Fairness drives both direct + indirect support
R^2 (Support)	0.50		Half of support explained
R^2 (Safety)	0.07		Transparency explains some safety beliefs
R^2 (TCI)	0.07		Fairness explains some transparency

4.6 Discussions

This study examined public perceptions of RLCs across two distinct policy environments in Arizona and New York using survey data, composite indices, regression models, and SEM. Several important findings emerged that contribute to both the theoretical understanding of automated enforcement and the practical design of policy interventions.

4.6.1 Core Drivers of Support

Across both states, perceptions of fairness and legitimacy were the most influential predictors of support for RLCs. The Fairness–Trust Index (FTI) consistently emerged as the strongest determinant, both directly and indirectly influencing support through its associations with transparency and safety. This confirms earlier findings that legitimacy and fairness are central to public acceptance of automated enforcement (Kennedy et al., 2025; McCartt and Eichelberger, 2012), extending this evidence by showing that fairness can outweigh demographic and contextual influences.

Beliefs about safety effectiveness also independently shaped support. Respondents who believed that RLCs reduce crashes were far more likely to support their use, aligning with prior research demonstrating that perceived effectiveness is a key condition for acceptance (Aldossari et al., 2023; Council et al., 2005). Transparency, while not the strongest predictor, played a meaningful mediating role: respondents who perceived greater clarity and communication about enforcement were more likely to view RLCs as safety-enhancing and legitimate.

4.6.2 Demographic and Contextual Influences

Although fairness and safety were the dominant predictors, several demographic and contextual variables added nuance. Age showed modest effects, with older respondents less supportive of expanding automated enforcement and less aware of cameras in their communities. Gender influenced perceptions of transparency, with women consistently reporting lower clarity in policy communication. These findings echo broader research suggesting gendered differences in trust toward government communication (Cheng et al., 2025).

Driving frequency also shaped perceptions. Frequent drivers were more skeptical about fairness and transparency but were more likely to view citations as justified and to support RLCs when strong evidence of safety benefits was presented. This suggests that routine exposure to enforcement may generate both critical perspectives and greater legitimacy when effectiveness is demonstrated.

Contextual differences between states were especially evident for transparency and awareness. New York respondents reported higher understanding of camera operations, stronger perceptions of effectiveness, and greater awareness of local camera presence compared to Arizona respondents. However, they were also more likely to express concern about revenue motives. This duality suggests that policy stability enhances legitimacy and visibility but simultaneously increases scrutiny, as residents of long-standing programs may be more attuned to potential shortcomings.

4.6.3 Psychological Mechanisms of Acceptance

The SEM analysis reinforced fairness as the central psychological driver of support, explaining half of the variance in attitudes toward RLCs. Importantly, the mechanism was consistent across both states, indicating that the pathways linking fairness, transparency, safety, and support are robust regardless of policy context. This finding suggests that while state histories shape baseline perceptions of transparency and awareness, the psychological logic of support operates similarly in both stable and contested environments.

4.6.4 Policy Implications

The findings have several implications for policy and practice. To begin, the findings underscore that public support for red-light camera programs depends less on technical performance alone and more on how policies are communicated, implemented, and perceived as fair. To enhance legitimacy and acceptance, policymakers should adopt targeted educational and communication strategies that clearly convey the safety rationale behind RLCs. For instance, public awareness campaigns explaining how cameras are selected, how violation revenues are reinvested in safety improvements, and how effectiveness is monitored could improve perceptions of fairness and transparency. These campaigns should be designed with accessibility and audience diversity in mind, using multiple media formats and languages to reach different demographic groups.

Another key policy approach is the establishment of transparent reporting systems, requiring jurisdictions to publish annual summaries of RLC locations, citation volumes, revenue allocations, and crash reduction outcomes. Such transparency not only supports accountability but also directly addresses concerns that cameras are primarily revenue driven.

Additionally, equitable enforcement frameworks for example, limiting camera placement in historically overburdened neighborhoods and ensuring consistent signage and public notice before deployment can help build trust across communities. Policymakers might also consider pilot demonstration programs or community-based advisory panels that include residents in evaluating site selection and reviewing outcomes.

Finally, long-term success depends on stability and consistency in enforcement policy. States with established, continuous programs (like New York) show higher awareness and legitimacy, while volatile or inconsistent enforcement (like Arizona) risks public confusion and distrust. Maintaining continuity, while integrating routine public engagement and education, can ensure that automated enforcement remains both effective and publicly supported.

Chapter 5: Psychological and Operational Barriers to Public Electrical Vehicle Fleet Adoption

This chapter investigates the transition to electric vehicle fleets within public agencies, with an emphasis on both operational realities and workforce perspectives. With sustainability and feasibility as guiding concerns, this chapter examines how agency personnel including fleet managers, operations staff, mechanics, and field personnel perceive the opportunities and challenges of electrification. Based on 86 survey responses across Minnesota agencies, supplemented by five follow-up interviews, the research analyzes both psychological factors (such as risk perception, trust in technology, and range anxiety) and practical barriers (including charging infrastructure, cold-weather performance, and maintenance demands). The chapter not only evaluates patterns across roles and responsibilities but also interprets how workforce readiness, training needs, and organizational context shape the trajectory of fleet electrification. The results highlight that while agencies recognize the long-term benefits of EV adoption, significant concerns remain regarding reliability, cost, and implementation, underscoring the need for workforce engagement and tailored planning. Within the broader scope of this dissertation, this study demonstrates that technological transitions in transportation require more than infrastructure investment or policy mandates; they depend on the acceptance, capacity, and adaptability of the workforce responsible for implementation.

5.1 Introduction

With the ever-changing climate and the necessity for sustainable systems (UNDESA, 2024), electric vehicles have been increasingly popular amongst the public as a way to reduce emissions (Woo et al., 2017). Emissions from standard gas vehicles have played a large role in the negative impact transportation has had on the environment (Haroon et al., 2025; U.S. Environmental Protection Agency, Office of Transportation and Air Quality, 2023). One potential solution to this problem, specifically in the form of sustainable transportation via car, is seen as fully electric vehicles and plug-in hybrid vehicles (PHEVs) (Zheng et al., 2020). As of 2014, one of the largest adopters of EVs were public agencies that utilize agency-owned vehicles that are used for work purposes (Sierzchula, 2014). While they have expanded significantly since that date, they are still not widely adopted across all sectors, particularly at the regional and local government levels. Despite the growing availability of EV models and supportive federal and state-level incentives, many public agencies continue to face a range of barriers to full EV fleet integration. These include high upfront costs, limited charging infrastructure, concerns about vehicle range, and institutional resistance to change (Di Foggia, 2021; Mahdavian et al., 2021). Additionally, psychological factors such as range anxiety, risk aversion, and lack of familiarity with new technologies may further hinder adoption among fleet managers and decision-makers (Farhar et al., 2016; Rainieri et al., 2023). Understanding these barriers, both practical and perceptual, is critical to developing effective policies and implementation strategies that support sustainable fleet transitions.

To date, no studies have been identified in the United States that specifically investigate this combination of psychological and infrastructural barriers in the context of electric vehicle fleet adoption by regional and local public agencies. Most existing research has focused on individual consumer behavior or national-level policy analysis, leaving a critical gap in understanding the unique challenges faced by government fleet managers. To address this gap, this study contributes to the current literature by focusing on the factors influencing public agency EV fleet adoption, with a particular emphasis on regional and local agencies in the state of Minnesota. Specifically, a mixed-methods approach was employed, beginning with the development and administration of a survey, followed by a structured interview protocol. These methods enabled a comprehensive examination of both the barriers hindering EV fleet adoption and the factors supporting it. The paper is organized as follows: first, a literature review provides background and context. Next, the materials and methods section details the survey design, participant recruitment, and interview methodology. This is followed by the results section, which presents key findings. The discussion section interprets these results in the context of broader policy considerations. Finally, the conclusion summarizes the main insights and offers actionable recommendations based on the study’s findings.

5.2 Material and methods

This chapter employed a mixed-methods approach (i.e., surveys, analysis, interviews) to explore the human factors involved in transitioning to EV fleets. Surveys and interviews were conducted with agency employees who either currently use or are planning to use EVs for various purposes to gain a deeper understanding of the human factors influencing EV adoption among employees managing agency vehicles in Minnesota.

Minnesota provides an ideal setting for this investigation due to its diverse climatic conditions, with distinct winter and extreme summer that influence vehicle performance, maintenance, and operational decisions. The state also features a mix of urban, suburban, and rural transportation agencies, offering a comprehensive perspective on the challenges and opportunities of EV adoption across different contexts. In addition, Minnesota's active investment in sustainability initiatives and the support of the Minnesota Local Road Research Board make it a relevant case for studying institutional readiness and workforce adaptation in the transition to EV fleet.

The interactive online survey was conducted via the Qualtrics platform and distributed by email, which provided detailed insights into employees' professional perspectives on EVs. The survey was disturbed by the Minnesota Local Road Research Board via email across local and regional public transportation agencies throughout the state in July and August of 2024. A full list of the questions of the survey can be found in Appendix A. Overall, the survey examined common attitudes towards EV adoption, concerns related to their use, and expectations regarding performance, convenience, and benefits. Table 5.1 summarizes the roles and experience levels of the 86 survey participants, with fleet managers, operation managers and engineers making up the majority. Most of the participants had five to eight years of experience, reflecting a well-informed sample of response pool.

Table 5.1 Average Years of Experience and Number of Respondents by Role

Role	Average Years of Experience	No of Respondents
Fleet Manager	5.00	18
Operations Manager	8.00	18
Engineer	6.50	15

Public Works Director	8.00	12
Other	4.25	8
Field Staff	6.12	6
Mechanic	8.00	4
Maintenance	8.00	3
Inspector	8.00	2

Following the survey, to gather more in-depth information, a series of 15-minute virtual interviews were conducted with five key stakeholders responsible for managing or using agency fleets in Minnesota. These individuals were identified among the survey respondents. These five individuals represented different agencies, from rural and urban environments, and at different levels of their career and experience. One participant had served as a fleet manager in a large urban city, overseeing vehicle procurement and maintenance across multiple departments. Another was a fleet manager in a mid-sized suburban community, focused primarily on administrative fleet operations. A third interviewee had worked as an operations manager for a rural county, managing public works activities over a broad geographic area. A fourth participant was a county engineer in a very rural and expansive county, with responsibilities centered on infrastructure planning and heavy equipment. The final interviewee was a newly appointed fleet manager in a rapidly growing outer-ring suburb, bringing prior EV experience from a different municipality and operating within a changing political and organizational environment. These individuals varied in job function, jurisdiction size, tenure, and organizational context, offering a range of perspectives on agency operations and planning. The specific questions asked during the interview portion of the study consisted of the following:

- How does your agency currently view the adoption of electric vehicles (EVs)? What are your main concerns or hesitations about this transition?
- What are your expectations regarding the performance, usability, and reliability of EVs

compared to the traditional vehicles your agency currently uses?

- In your view, what are the main factors that would support or hinder the successful integration of EVs into your agency's vehicle fleet? For example, government incentives and robust charging infrastructure can support integration, while high initial costs and insufficient charging stations can impede it.

- How important do you consider incentives or supportive policies in influencing your and your colleagues' willingness to adopt EVs for agency-related tasks? Why or why not?

- Can you share any insights or experiences that highlight the potential using EVs within your agency that you believe are important for our understanding of EV adoption? What about challenges?

- How do you think EV adoption could contribute to achieving your agency's sustainability and environmental goals, it at all?

For the interview portion of the study, the Institutional Review Board protocol was submitted and was determined to not be human subjects research. The interviews were scheduled via email and were conducted with two members of the project team. Following each interview, the notes taken for each interviewee were sent to each individual to ensure that their responses were reflective of their thoughts, and to offer an opportunity for them to provide any additional details. Overall, these interviews offered more nuanced responses and additional insights through open-ended questions, further elucidating the specific concerns and professional perspectives unique to the user group.

5.3 Analysis

In addition to a general investigation of the results, this chapter employed quantitative methods to explore existing demographic and experience-level factors relating to perception about EV fleet transitions. To identify ordered EV attitude associations with participant-specific characteristics, including percentage of EVs in a fleet, role type, years of experience in role, gender identity, and whether a participant had received EV training, ordinal logistic regression modeling was performed. This technique was utilized to preserve the ordered survey response options (Very Negative, Somewhat Negative, Neutral, Somewhat Positive, Very Positive) provided to respondents in order to effectively predict relative attitude outcomes. Associations between size of fleet and percentage of EVs in a fleet were established through logistic regression modeling. While there was no significant correlation apparent between respondents' EV training and their reported safety concerns, this relationship was modeled with linear regression methods. Logistic, ordinal, and linear regression modeling methodologies have been well-established as effective methods for predicting associations across a diversity of outcome formats and have been performed extensively in related transportation research, including related EV and safety studies (Asare and Mensah, 2020; He et al., 2022; Ling et al., 2021).

5.4 Results

The results section of this report is divided into three key parts: a descriptive analysis of the survey findings, a quantitative analysis of the survey findings on the human factors involved in transitioning to an EV fleet, and a summary of key insights from stakeholder interviews. The first part delves into professionals' perspectives on the human factors influencing the shift to EV fleets within Minnesota state agencies. The second part summarizes the interviews with professionals who specifically use agency vehicles, offering deeper insights into their experiences and concerns regarding the adoption of EVs.

5.4.1 Descriptive survey results

The survey gathered responses from 86 employees across multiple agencies in Minnesota. Among the participants, 21% were fleet managers, 7% were field staff, 21 were operations managers, and 4% were mechanics. The remaining 47% included engineers, directors of public works departments, supervisors, maintenance directors, and other key roles. More than half of the respondents have been for more than 6 years in their current role. Additionally, over half of the respondents use an agency vehicle daily, while 2% have never used one. In terms of gender, 87\% of the respondents identified as male and 10% as female.

Among 86 survey respondents from agencies across 37 counties and 27 cities, 21 individuals reported operating EVs, with EVs comprising 1–10% of fleet vehicles in most cases. The majority of these EVs were passenger cars or light-duty vehicles. Attitude towards EV transition were mixed, with 33% of respondents expressing neutral views, 25% holding positive views, and 42% holding negative views. Respondents with EVs in their fleet or prior EV experience tended to express more favorable attitudes.

Survey responses revealed that perceived benefits of EVs included fuel cost savings (55%), environmental benefits (36%), and technological innovation (23%), as displayed in Figure 5.1. Only 7% felt EVs improved the driving experience. Key concerns included driving range limitations, availability and speed of charging infrastructure, high initial costs (63\%), cold weather performance, and uncertainty surrounding maintenance and battery disposal. Respondents who have never worked with or don't have EVs in their fleet tend to express neutral or negative feelings, while those who have experience with EVs or include them in their fleet report more positive feelings. The neutral stance appears to stem from various factors, although there is an understanding of the benefits associated with electric vehicles.

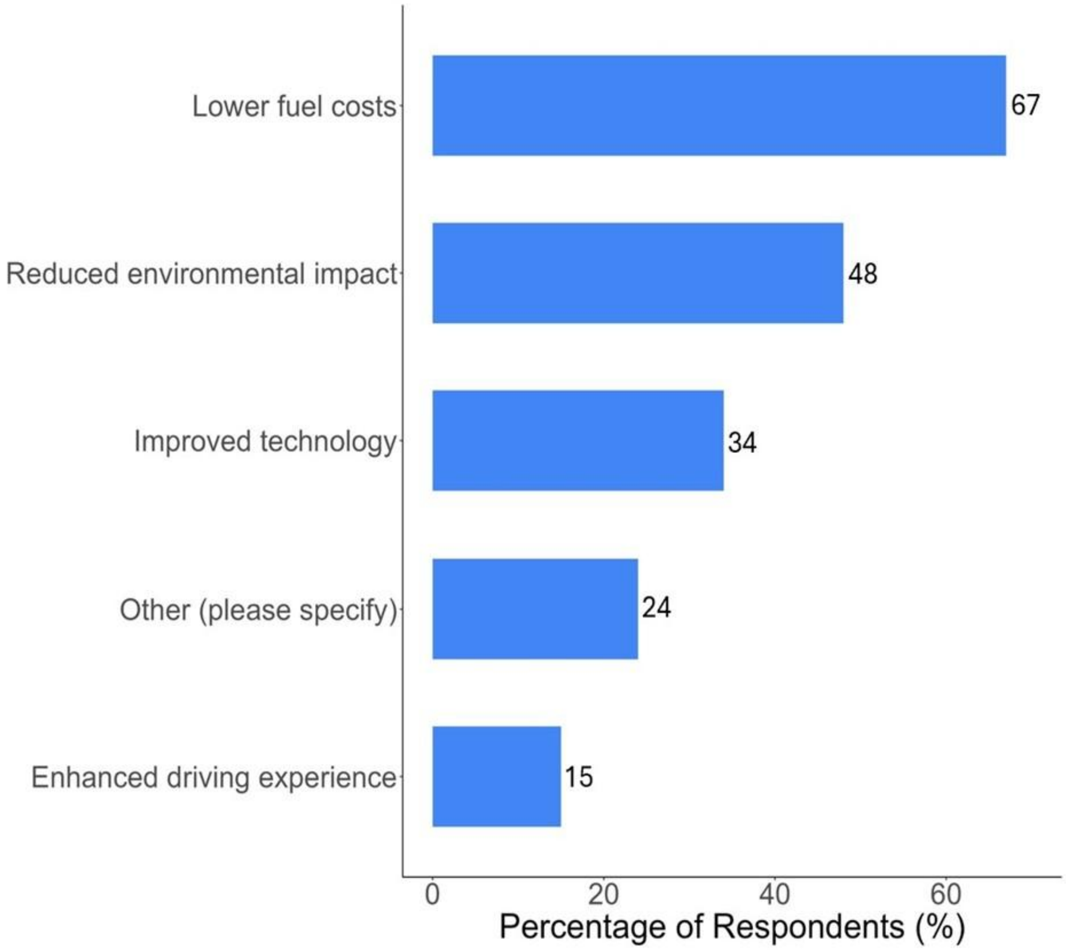

Figure 5.1 Perceived Benefits of Electric Vehicles Among Survey Respondents

Concerns about EV adoption

Limited driving range was a commonly cited concern for those considering EVs, particularly for long-distance travel, also shown in Figure 5.2. Also noted as concerns are the time it takes to charge an EV and the availability of charging stations. Unlike traditional vehicles, which can refuel quickly, EV drivers may struggle if charging stations are not conveniently located.

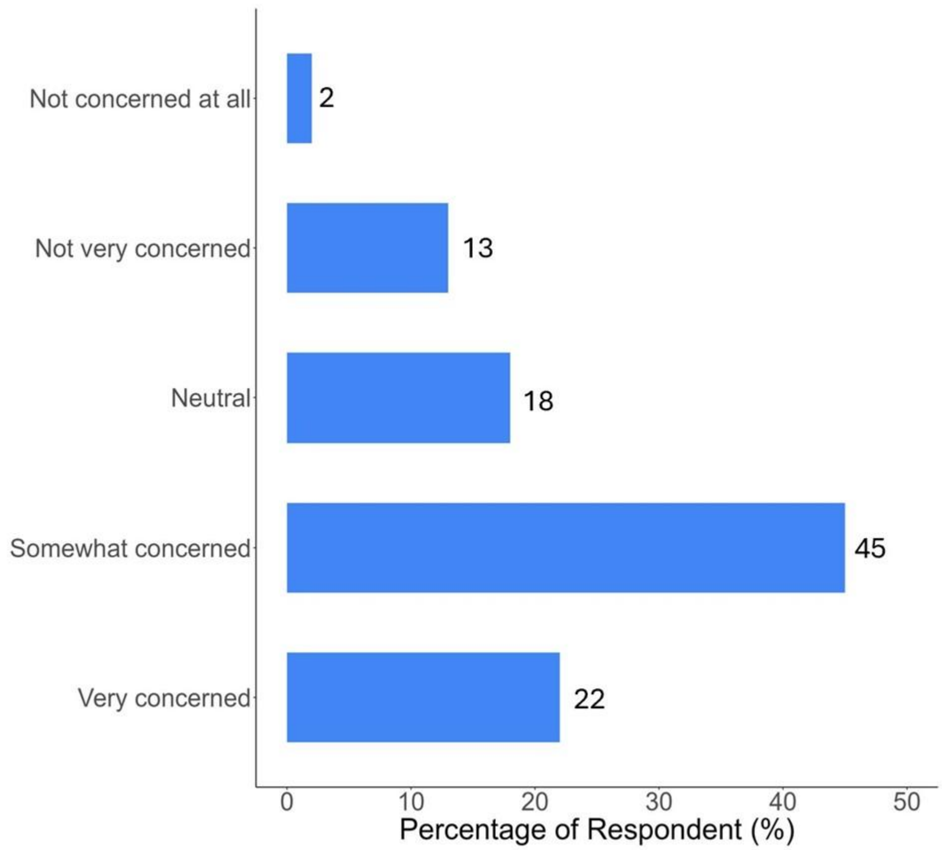

Figure 5.2 Key Concerns About Electric Vehicles Among Respondents

Additionally, 63% of respondents thought that the higher initial cost of EVs could be a deterrent, as technology continues to evolve, potentially making the resale value uncertain. Maintenance and repairs pose further challenges, as skilled technicians and mechanics specialized in EVs may not be readily available, making it difficult for agencies to manage these tasks efficiently.

Open-ended survey responses reveal a wide range of concerns and challenges associated with electric vehicles. Environmental issues are prominent, with worries about battery disposal, pollution from mining for battery materials, and the challenges of recycling EV components. Cold weather performance is also a significant concern, particularly in regions like Minnesota, where respondents question the reliability and power retention of EVs in freezing conditions. Infrastructure and power supply limitations are another critical issue, with doubts about the current grid's ability to support widespread EV adoption, especially during extreme weather.

Respondents also cited high battery replacement costs, the reliability of public charging stations, and the time required for charging as key challenges. Operationally, EVs are perceived as having limited driving range and power, particularly for larger vehicles, and there is concern about the dependence on foreign sources for raw materials. Additionally, the lack of technical expertise for EV maintenance and repair, coupled with the cost and feasibility of upgrading infrastructure, adds to respondents' hesitancy. Other concerns include the quietness of EVs posing potential noise hazards, the complexity of new technology, and uncertainties about resale value and overall investment payback. These varied concerns highlight the practical, environmental, and economic factors that influence the decision to adopt EVs.

Reliability of EVs compared to traditional vehicles

Further, respondents expressed varying levels of concern about the reliability of EVs: 45% are somewhat concerned, 22% are very concerned, and the remaining 33% are either neutral or not particularly concerned, as shown in Figure 5.3. Respondents expressed a variety of concerns regarding the reliability of electric vehicles compared to traditional vehicles. A major concern is cold weather performance, with worries about reduced battery life, charging efficiency, and the ability to maintain heat during winter operations, especially for heavy-duty vehicles. Maintenance and repair challenges were also highlighted, including the need for specialized training and certified technicians, as well as the availability of parts, particularly in rural areas. Additionally, limited charging infrastructure and long charging times were frequently mentioned, with rural respondents emphasizing the impracticality of using EVs for long shifts without sufficient support. Environmental concerns about battery production, disposal, and long-term costs were raised, along with uncertainty about the overall reliability of EVs due to their relative newness. While some respondents reported positive experiences with EVs, many expressed cautions, especially in demanding or emergency scenarios, citing the need for more data and time to fully assess their long-term performance.

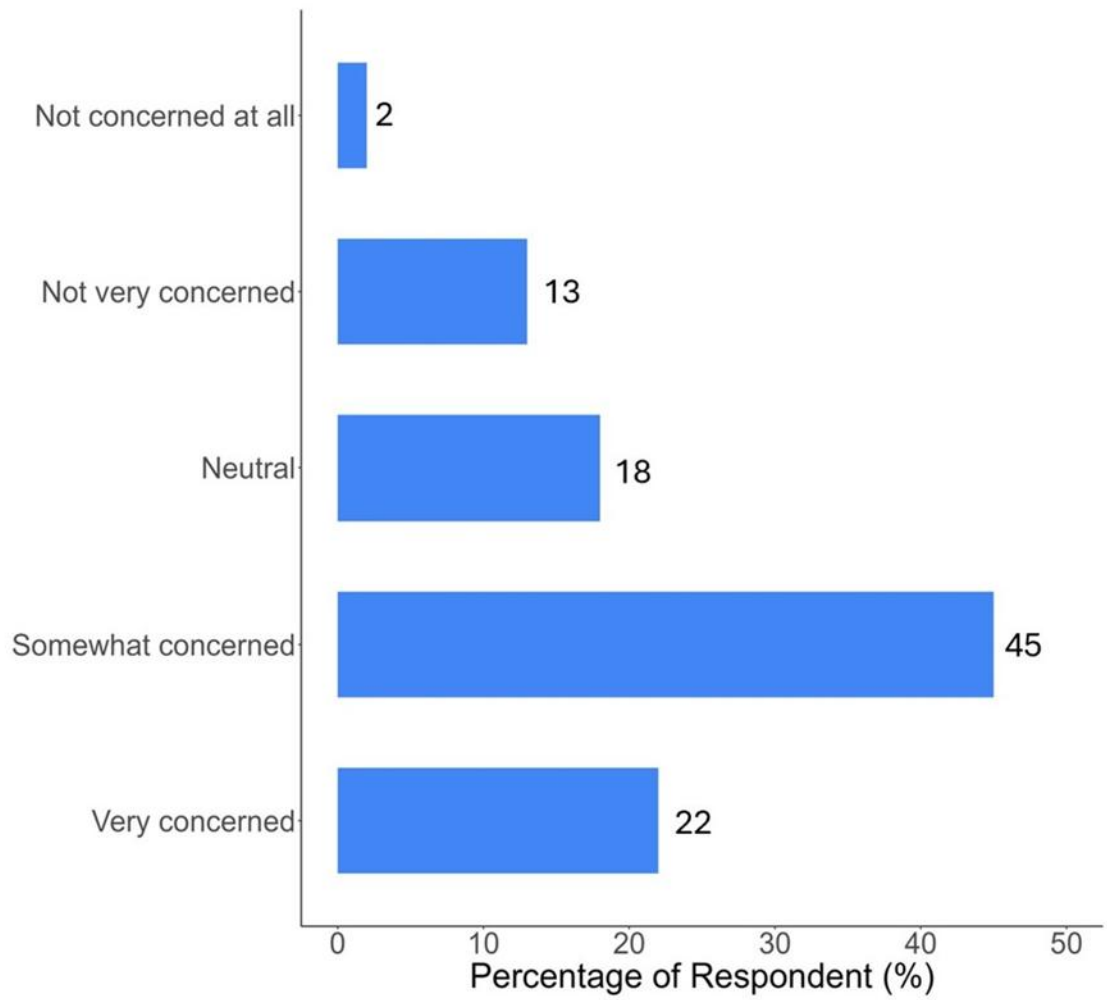

Figure 5.3 Survey Responses on Sentiments Toward the Reliability of Electric Vehicles Compared to Traditional Vehicles

Safety of EVs

While more than half of the respondents (58%) have no concerns about the safety of EVs, 42% expressed some concerns regarding their safety. The most prominent worry is the risk of battery fires, especially during charging or following a collision. Many noted that these fires can be more challenging to extinguish compared to traditional vehicle fires, posing significant risks to first responders and those nearby. There were also concerns about the increased weight of EVs, which could lead to more severe damage in crashes, particularly for pedestrians and cyclists. Additionally, some respondents highlighted potential safety risks for mechanics working with high-voltage systems and the long-term effects of battery disposal.

Other concerns included the potential for stalling, the safety of touchscreen interfaces, and the impact of harsh conditions like road salt on vehicle components. Overall, while the chances of severe incidents are viewed as low, the consequences of such incidents are perceived as potentially severe, prompting concerns about preparedness and safety protocols. These concerns underscore the need for continued advancements in EV safety measures, enhanced training for emergency responders and mechanics, and robust safety standards to mitigate risks associated with battery technology and vehicle operation. Many respondents believe EVs are as safe as, or safer than, gasoline vehicles, especially due to lower tailpipe emissions. While some initially had concerns about cold-weather reliability, they feel these issues have been addressed over time. Advancements in technology and safety training have further reinforced the view that EVs are as secure as traditional vehicles. Overall, there is also a sense of confidence in EV safety.

Training, feedback, and key considerations for transitioning to EVs

Regarding training before using EVs at work, 68.6% of respondents reported that they have not yet used an EV in this capacity. Additionally, 16.3% stated they received no training prior to using an EV at work, while 2.3% indicated they had received training but had not yet used an EV in their job. Finally, 10.5% confirmed they had received training before using an EV in their work. Some respondents expressed a desire for a hands-on training session, informational workshops, detailed user manuals, and online resources and videos as shown in Figure 5.4. They emphasized the importance of practical solutions and learning from organizations with EV experience, as well as showcasing the benefits of heavy-duty and medium/light-duty EVs through real user experiences and financial savings. The majority of respondents are familiar with aspects such as battery life, charging time, range per charge, and the environmental benefits of EVs. However, there is less familiarity with maintenance requirements and the overall cost of ownership when considering the technical characteristics of EVs.

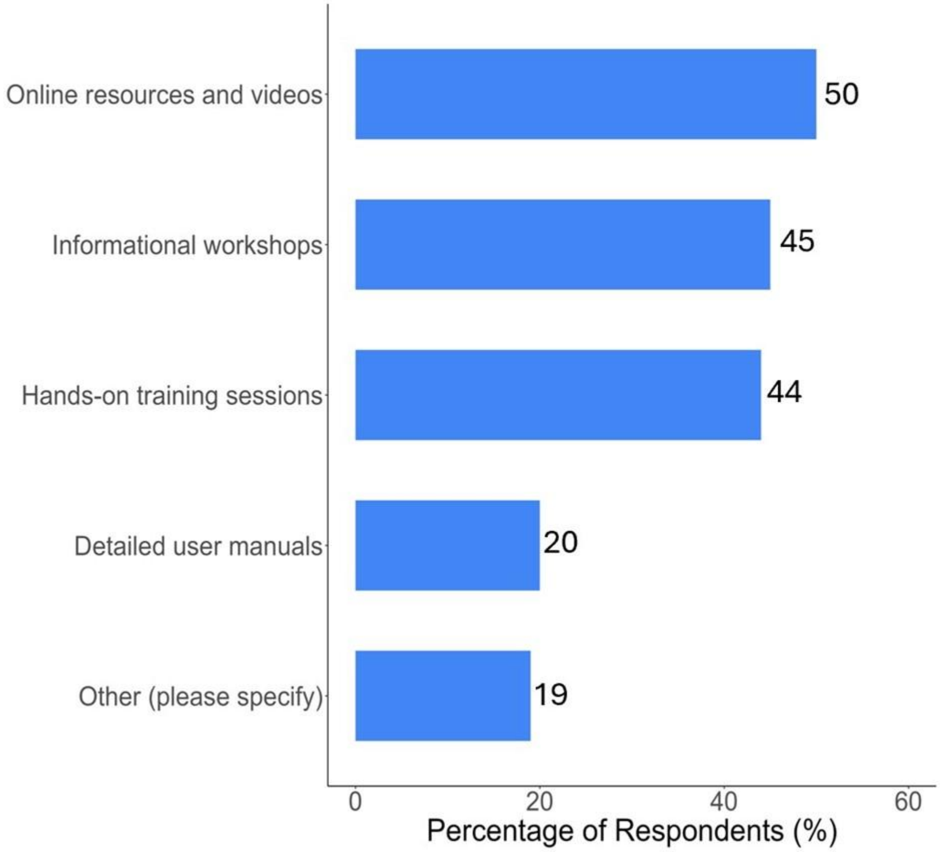

Figure 5.4 Preferred Support and Training Resources for Transitioning to Electric Vehicles

More than half of the respondents believe it is important for the agency to consider employee feedback when transitioning to EVs, as shown in Figure 5.5.

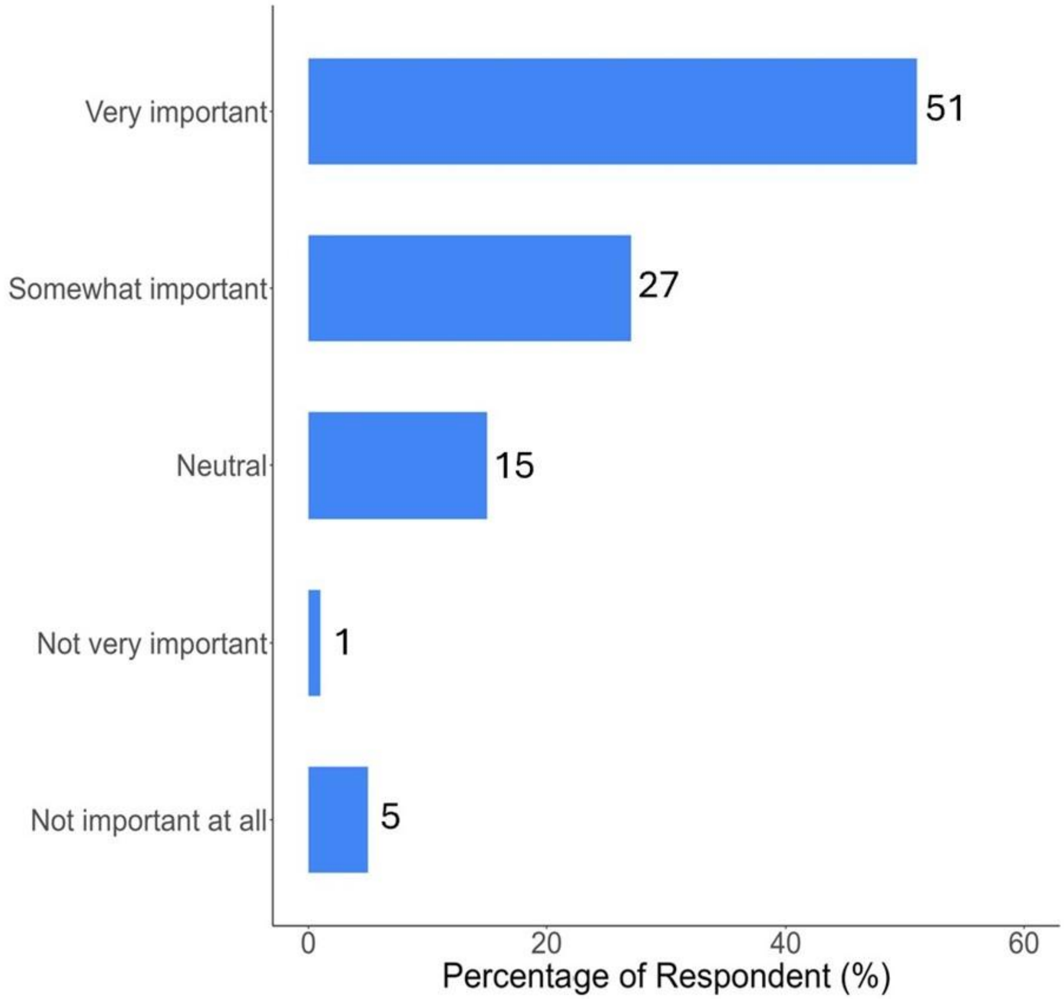

Figure 5.5 Survey Responses on Employee Feedback Consideration for Transitioning to Electric Vehicles

Figure 5.6 results align with the broader discussion of EV adoption challenges and considerations. Specifically, it highlights the features most desired by users, which include longer battery life (top priority at nearly 80% of respondents), faster charging times, and more charging stations. These factors correspond to concerns about the current limitations of EV technology and infrastructure. Fewer respondents chose advanced navigation systems, indicating that functional features like battery life and charging are more immediate concerns. Respondents provided a range of thoughts on transitioning to EVs within their agencies. Key considerations included ensuring that EVs meet user needs, addressing the political and financial implications of EV adoption, and the importance of staff acceptance and involvement in the transition process. Some highlighted the need for scalable charging infrastructure, while others expressed concerns about the current costs and technology limitations, particularly for specialized vehicles. Overall, there is a mix of cautious optimism and skepticism, with some advocating for gradual adoption as technology and infrastructure improve.

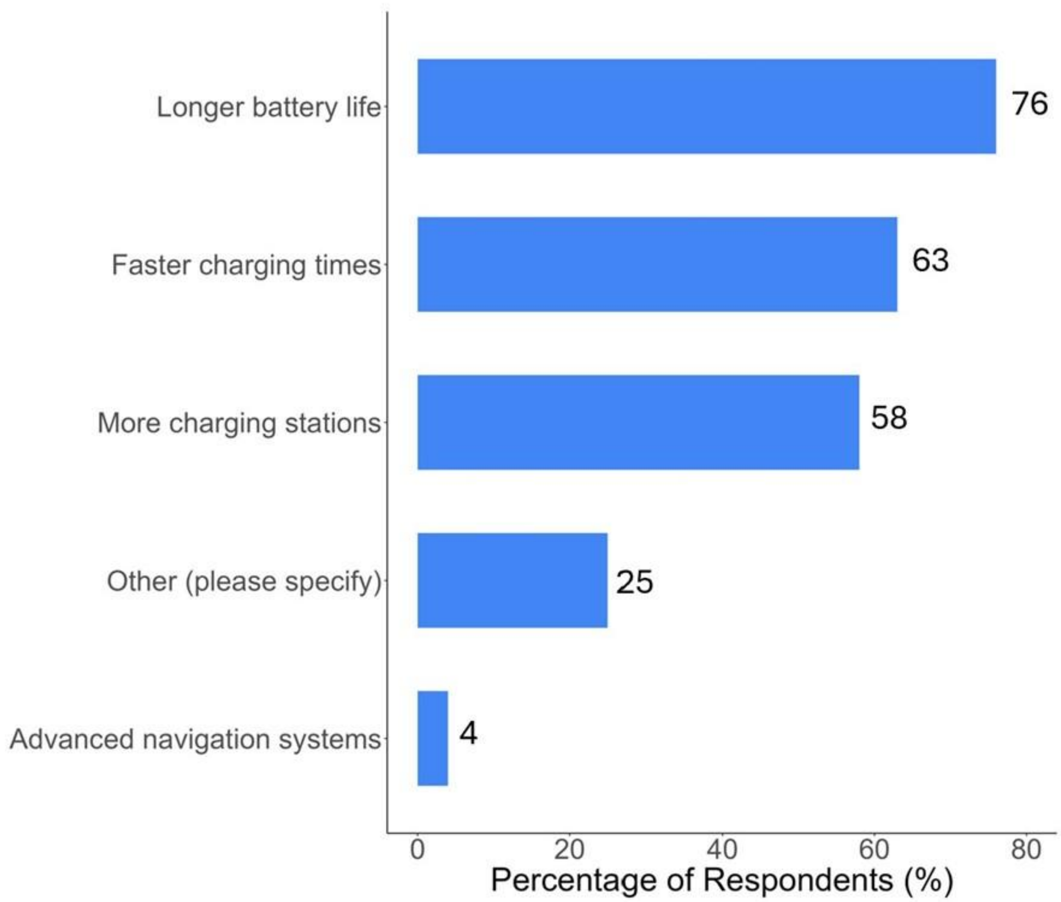

Figure 5.6 Desired Features for Agency Electric Vehicles to Enhance Work Efficiency

Perspective on transitioning to EVs

Fleet managers, operations managers, field staff, and mechanics were asked specific questions in the survey based on their distinct job titles to capture their unique perspectives and challenges regarding EVs. Their insights provide a comprehensive view of the issues and strategies related to managing and maintaining EV fleets. The results of these discussions are presented in this section:

Challenges in managing electric fleet (fleet managers' perspectives):

Managing a fleet of EVs presents several challenges compared to traditional vehicles. Key issues include the significant costs and logistics associated with installing and maintaining charging infrastructure, as well as ensuring sufficient electrical grid capacity. High initial costs and battery replacement expenses are also concerns. There is a need for specialized staff training due to a lack of existing knowledge and experience with EVs. Performance issues such as limited range, reliability in extreme weather, and battery life are highlighted, along with concerns about reduced vehicle trade-in values. Additionally, managing charging locations, times, and ensuring drivers are well-informed about EV capabilities are operational challenges. Overall, these factors contribute to a more complex management scenario for EV fleets.

Strategies effective for encouraging the adoption of EVs (operations managers' perspectives):

To encourage the adoption of EVs within agencies, several effective strategies have been identified. Grant funding and substantial rebates can help offset the initial costs, while demonstration programs allow staff to experience EVs firsthand, addressing reservations and showcasing their practical benefits. Expanding charging infrastructure and improving battery technology are crucial to supporting widespread adoption. Providing data on the benefits and performance of EVs can strengthen the case for their use. Engaging with local electric providers and increasing EV visibility can also drive interest. Additionally, offering training to employees can build trust in EV technology, facilitating a smoother transition. Overall, a mix of financial incentives, practical experiences, infrastructure improvements, and education is essential for promoting EV adoption.

Key challenges in EV maintenance (mechanic and field staff perspectives):

Concerns about the repair and upkeep of EVs center on the high costs of battery replacement and the environmental impact of battery disposal. Respondents also mentioned the significant expense of specialized equipment and training needed for EV maintenance, as well as worries about vehicle range and frequent charging requirements. Additionally, responses indicate a general uncertainty or lack of involvement in EV maintenance, with many respondents unsure about the specific challenges or noting similarities to maintaining traditional vehicles, aside from the fuel system. Overall, there is a limited understanding of the unique maintenance demands of EVs.

5.4.2 Quantitative results

To build on the descriptive findings, regression analysis was employed on the survey responses to explore the factors influencing EV adoption and readiness across agencies. As shown in Table 5.2, logistic regression demonstrated that a larger fleet size was significantly associated with a higher percentage of EVs in the fleet, reflecting the economy of scale that allows larger agencies to absorb costs, manage infrastructure, and streamline operational transitions more easily. Furthermore, as shown in Table 5.3, which examines the relationship between EV-specific training and respondents' reported safety concerns, the results yielded no significant relationship, indicating that training alone may not impact safety concerns.

Table 5.2 EV Adoption vs. Fleet Size

Variable	Estimate	Standard Error	t Value	Pr(>|t|)
(Intercept)	-0.635	0.454	-1.397	0.166
Fleet Size (numeric)	0.030	0.0049	5.999	$3.98 * 10^{-8}$***
Residual Standard error: 2.047 on 91 degrees of freedom				
Multiple R-squared: 0.283, Adjusted R-squared: 0.276				

Table 5.3 Interest in EV Training vs. Safety Concerns

Variable	Estimate	Standard Error	z Value	Pr(>|t|)
(Intercept)	-1.838	0.407	-4.518	$6.26 * 10^{-6}$***

Fleet Size (numeric)	0.164	0.603	0.273	0.785
Dispersion Parameter: 1 (Binomial)				
Residual Standard error: 74.02 on 88 degrees of freedom				
Residual deviance: 73.94 on 87 degrees of freedom				

Ordinal logistic regression modeling revealed significant associations between respondents' attitudes about EV fleet transition as shown in Table 5.4.

Table 5.4 EV Attitude Predicted by Number of EVs Owned

Variable	Estimate	Standard Error	t Value
EVs Owned	0.3788	0.0893	4.241
Thresholds (Intercept)			
Very Negative | Somewhat Negative	0.164	0.603	0.273
Somewhat Negative | Neutral	0.0908	0.2518	0.3604
Neutral | Somewhat Positive	1.7293	0.3290	5.2559
Somewhat Positive | Very Positive	2.9760	0.4307	6.9105
Residual Deviance: 258.90			

Predicting relative perception of EV transition by the percentage of EVs present in the fleet, analyses revealed a significant positive association, with each percentage point increase in EV presence leading a 0.379 increase in the odds of having a more positive attitude towards EV transition.

As shown in Table 5.5, ordinal logistic regression results indicate that participation in EV training is significantly associated with more positive attitudes toward EVs. Specifically, respondents who reported receiving training were more likely to express favorable views about the EV transition, with a positive coefficient of 1.879 ($t = 3.14$, $p < 0.01$) compared to those who had not received training.

Table 5.5 EV Attitude Predicted by EV Training Experience

Variable	Estimate	Standard Error	t Value
Training Received (training_YN)	1.879	0.5984	3.14
Thresholds (Intercept)			
Very Negative | Somewhat Negative	-1.8316	0.3256	-5.6260
Somewhat Negative | Neutral	-0.2730	0.2261	-1.2074
Neutral | Somewhat Positive	1.2442	0.2696	4.6143
Somewhat Positive | Very Positive	2.4093	0.3812	6.3209
Residual Deviance: 261.71			

In contrast, role types, denoted in the indicated categories (i.e., Fleet Manager, Mechanic, Operations Manager, Field Staff, Maintenance, Engineer, Inspector, and Public Works Directors) exhibited markedly negative relationships, as shown in Table 5.6. Field Staff was selected as the reference category due to its consistent significance across models and its utility as a comparison group representing a large portion of the participant population. Fleet Management exhibited a negative relationship (-1.825) with EV attitudes, with respondents within this role being more likely to hold negative perceptions about the EV transition than Field Staff. The direction of these associations held true across the remaining roles, with respondents identifying with Operations Management (-2.502), Mechanics (-2.941), Engineers (-2.295), Inspector (-2.532), and Public Works Director (-1.718) roles being significantly less likely than Field Staff to report more positive attitudes about EVs.

Table 5.6 Ordinal Logistic Regression Results: EV Attitude Predicted by Job Role (Excluding "Other"; Reference Category: Field Staff)

Variable	Estimate	Standard Error	t Value
Engineer	-2.295	0.8728	-2.63
Fleet Manager	-1.825	0.7990	-2.28
Inspector	-2.532	1.3573	-1.87
Maintenance	-18.512	690.3056	-0.03
Mechanic	-2.941	1.1567	-2.54
Operations Manager	-2.502	0.8224	-3.04
Public Works Director	-1.718	0.8609	-2.00
Thresholds (Intercept)			
Very Negative | Somewhat Negative	-4.3391	0.8077	-5.37
Somewhat Negative | Neutral	-2.4880	0.7373	-3.37
Neutral | Somewhat Positive	-0.8976	0.6942	-1.29
Somewhat Positive | Very Positive	0.5123	0.6729	0.76
Residual Deviance: 229.51			

Regression results predicting attitudes about EVs demonstrated a significant difference between male and female perceptions, as shown in Table 5.7. Those identifying as male were significantly less likely (-1.407) than those identifying as female to hold positive attitudes about EVs.

Table 5.7 Ordinal Logistic Regression Result: EV Attitudes Predicted by Gender Identity

Variable	Estimate	Standard Error	t Value
Gender: Male (vs. Female)	-1.407	0.6619	-2.13
Thresholds (Intercept)			
Very Negative | Somewhat Negative	-3.3304	0.7073	-4.71
Somewhat Negative | Neutral	-1.7136	0.6506	-2.63
Neutral | Somewhat Positive	-0.3604	0.6321	-0.57
Somewhat Positive | Very Positive	0.7332	0.6305	1.16
Residual Deviance: 258.30			

5.4.3 Interview results

Five interviews were conducted with professionals who provided in-depth insights into their survey responses and beyond. All participants had experience managing agency vehicles and were responsible for fleet operations. The group included four fleet managers and one operations manager. Among the interviewees, two represented agencies with existing EVs, comprising 1-10\% of their fleets. The remaining three were from agencies without EVs, with one of these agencies currently exploring EV adoption. The following details the key takeaways from these interviews.

Interviewees cited infrastructure challenges, particularly the lack of rapid charging and the impracticality of installing chargers in underground garages as major obstacles. Concerns about cold-weather performance, safety, and the difficulty of sourcing qualified maintenance personnel were also common. Financial uncertainty, including questions about total cost of ownership and battery replacement, were seen as barriers to broader adoption.

However, interviewees also noted positive expectations. EVs were expected to require less maintenance, reduce idling, and perform well in administrative or urban contexts. Training for drivers and mechanics was viewed as essential, and some participants supported integrating training into procurement contracts.

Policy preferences were also clear: participants favoured incentives, such as grants or low-cost charger installation, over mandates. Agencies emphasized the importance of integrating EV adoption into long-term capital planning and allowing for gradual, locally tailored transitions. Leadership priorities and community support were seen as key enablers.

5.5 Discussions

This study provides a comprehensive view of the organizational and logistical considerations that influence the transition to EV fleets within Minnesota's public agencies. The results underscore the complexities of EV adoption, including the organizational structures, role capacities, and material constraints that shape how these decisions are made and carried out.

Differences in perception across roles highlight the nuanced dynamics that shape technology adoption throughout the public sector. Field staff, the ultimate users of EVs, reported more favorable views compared to management and technical roles such as mechanics. Their views may be shaped by how familiar they are with EVs, as previous research shows that more exposure and experience tend to lead to more positive attitudes (Riedner et al., 2019). This divergence may reflect a division in perceived burdens and benefits of EV adoption. While field staff may focus on daily usability, upper-level management are more aware of the long-term operational costs and infrastructure demands of extensive EV adoption. These role-based patterns suggest that EV policies must be responsive not only to technical constraints but also consider perceptions across a diversity of professional capacities.

The strong association between EV-specific training and favorable perceptions underscores the importance of workforce education in promoting technological change. Beyond information dissemination, effective training demonstrates that management supports EV transition, which could ease uncertainty and concerns surrounding EV adoption. However, since EV training did not lead to fewer safety concerns, future initiatives should directly target employees' deeper fears, such as risks of battery fires, emergency procedures, and the long-term durability of these systems.

The diversity of concerns presented across role types and agencies reinforces the need for a multifaceted approach to EV implementation. While barriers such as limited charging infrastructure, range anxiety, and higher upfront costs have been previously cited in research on EV adoption, this study offers novelty by distinguishing between unique challenges experienced across individual roles (Sierzchula, 2014; Slowik et al., 2019). Fleet and operations management positions each emphasized strategic obstacles, including garage equipping, grid capacity, and planning for long-term costs. Field staff and mechanics, however, highlighted usability and maintenance concerns, potentially shaped by insufficient training. These findings reinforce previous literature, which demonstrates that successful EV adoption depends on aligning organizational change with workforce realities (Hardman et al., 2018).

Roles without direct experience with EVs often held neutral or negative views, emphasizing the importance of hands-on usage. Similarly, past studies emphasize that exposure to EVs can lead to more favorable attitudes (New York City Pilot Project, 2013). While our findings follow this trend, we find that familiarity with EVs increases acceptance, but does not resolve concerns about reliability, safety, or cold-weather performance. Considering Minnesota's climate, cold-weather concerns are especially relevant, and mirror similar challenges with EV implementation in cold regions (Tal et al., 2014). Climate-specific concerns suggest that agencies must pursue strategies adapted to specific regions in order to address unique weather limitations.

Chapter 6: Quantifying Wildlife Vehicle Crash Risk: An Exploratory Approach Applied in Tucson, Arizona

This chapter presents the methodology, analysis, and findings from a comprehensive study examining wildlife-vehicle collisions in the City of Tucson, Arizona. This chapter specifically explores how roadway characteristics, environmental features, and human activity patterns influence the spatial distribution and likelihood of WVCs. Using a grid-based spatial framework, multiple geospatial datasets including wildlife observations, crash records, roadway networks, and land use layers such as parks and water bodies were integrated to evaluate patterns of collision risk across the region. Through the application of spatial and statistical modeling techniques, including binary logistic Regression and mapping, the study identifies key environmental and infrastructural factors associated with areas of elevated risk.

The analysis provides a detailed understanding of how transportation infrastructure and landscape context interact to shape wildlife-vehicle conflict patterns. It also presents a reproducible approach for other cities to begin to investigate their own WVC risks, even in cases of little available data. By combining observed data with modelled predictions, the chapter highlights a framework to show spatial hotspots of collision likelihood and clarify the underlying mechanisms that contribute to these risks. Ultimately, this chapter demonstrates a transferable analytical framework that cities can use to evaluate their own wildlife-vehicle collision risks. By outlining an approach that integrates spatial data, environmental factors, and roadway characteristics, the study provides a practical model that can be reproduced in other urban contexts to inform mitigation and coexistence strategies.

6.1 Introduction

The interaction between transportation infrastructure and the natural environment has long been recognized as a defining element of sustainable mobility and safety planning. As roadway networks expand and human activity extends into previously undisturbed habitats, these systems increasingly influence ecological processes and wildlife behavior. One of the most prominent and persistent outcomes of this interaction is the occurrence of wildlife-vehicle collisions events that pose risks not only to human safety but also to ecological integrity and species survival (Ament et al., 2008; Huijser et al., 2008; Wilkins et al., 2019).

From a transportation safety perspective, WVCs represent a unique category of crashes that bridge human, infrastructural, and environmental systems. Unlike other collision types primarily explained by roadway design or driver behavior, WVCs involve an additional layer of ecological complexity, influenced by factors such as habitat connectivity, seasonal movement, and resource availability. This dual dependence on transportation and environmental conditions makes WVCs particularly complex to analyze and mitigate. As demonstrated by Gunson et al. (2011) and Morelle et al. (2013), collisions are rarely random but instead cluster spatially in areas where roadway features intersect with wildlife movement corridors and resource-rich habitats (Gunson et al., 2011; Morelle et al., 2013).

Recent studies increasingly emphasize the need to integrate ecological and engineering perspectives when assessing WVC risk. Research has explored the influence of roadway characteristics including design speed, traffic volume, and functional classification (Lao et al., 2011; Roy and Ksaibati, 2022) as well as environmental features such as forest edges, riparian corridors, and proximity to protected areas (Ha and Shilling, 2018; Llagostera et al., 2022). Human and demographic factors, including land use and population density, have also been shown to shape collision patterns, particularly in transitional zones between urban and natural environments (Cherry et al., 2019; Laflamme et al., 2024). Despite these advancements, knowledge gaps persist in understanding how these determinants interact in arid, urban-rural fringe contexts, where water resources and fragmented landscapes strongly influence wildlife movement. This study addresses part of that gap by relying on datasets that are commonly collected and widely available across jurisdictions, prioritizing future transferability of the modeling approach for other cities facing similar data limitations.

The present study seeks to address some of these gaps by examining WVCs within Tucson, an arid urban-rural fringe context that is rarely represented in the literature. The analysis emphasizes roadway (distance to roads, road density), environmental (distance to parks, distance to water), and population variables, bringing them together in a single spatial framework. By identifying where risk clusters emerge across this landscape, the study contributes both to local transportation safety planning and to the broader evidence base on how WVC predictors operate in urban-desert environments.

Research in road ecology has long emphasized the need for transferable, scalable methods that can be applied across different cities, regions, and ecological contexts. A major barrier to achieving this has been the inconsistency of datasets across jurisdictions, including differences in crash reporting practices, spatial resolution, and the availability of environmental or infrastructural layers. These challenges are especially evident in urban areas, where high-resolution data are essential to capture the complexity of built environments and human–wildlife interactions. As van der Ree et al. (2011) note, advancing the field will require integrated and well-replicated approaches that allow multiple road projects across states or countries to be studied collectively (van der Ree et al., 2011) . This chapter contributes to that broader goal by developing a reproducible, grid-based spatial framework that can be adapted by other cities despite variation in data quality and availability.

6.2 Methodology

6.2.1 Data Collection

Wildlife-Vehicle Collision Incidents

Tucson, Arizona, was selected as the study area because it encompasses a mix of urban, suburban, and natural landscapes where roadways intersect major wildlife habitats, making it an ideal setting to examine human-wildlife interactions within a rapidly growing metropolitan region. Wildlife-vehicle collision data were obtained for the period 2001-2024 for City of Tucson from Arizona Crash Information System (ADOT, 2024). These data were converted into spatial layers using the XY Table to Point tool in ArcGIS Pro, with the coordinate system defined as GCS_WGS_1984. The resulting point shapefile provided the geographic distribution of collision incidents across the study area and served as the primary response variable in subsequent spatial analyses.

Roadkill Observations

Roadkill data from 2006 to 2025 were obtained through the Sonoran Desert Protection Coalition, which manages an iNaturalist portal for recording wildlife roadkill observations (Sonoran Desert Protection Coalition, 2012). Similar to the WVC dataset, the tabular data was converted into point features using XY Table to Point in ArcGIS Pro and assigned the same GCS_WGS_1984 coordinate system for spatial consistency. These data complemented the WVC crash records by capturing a broader range of human-wildlife conflict events, including those not reported as vehicle crashes but still indicative of animal movement and mortality near roadways.

Geographic Features Influencing Human–Wildlife Interaction

Hydro-Ecological Features

To represent the region's hydro-ecological characteristics, multiple datasets were integrated to provide a comprehensive view of both natural and anthropogenic water features (Pima County Geographic Information Systems (GIS) Library, 2008; Pima County GIS, n.d.; Pima County Regional Flood Control District, 2025). The analysis began with Pima County, Arizona flood hazard zones and shallow groundwater layers, where shallow groundwater was defined as being 50 feet or less below the surface. These layers were merged to capture areas with higher hydrologic influence.

Recognizing that these data alone did not fully characterize the hydrological network, additional sources were incorporated to represent linear channels, washes, and arroyos with key pathways for intermittent and ephemeral flow in arid regions. Data were obtained from the Arizona Department of Environmental Quality (ADEQ) and the Federal Emergency Management Agency (FEMA)(Arizona Department of Environmental Quality, 2023; United States Department of Agriculture, Farm Production & Conservation, n.d.), including:

- Flood Insurance Rate Map (FIRM) surface water features, depicting stream channel inverts used for rate map interpretation, and
- ADEQ Flow Regimes, which classify perennial, intermittent, and ephemeral streams.

Despite these sources, noticeable data gaps remained when compared against NAIP 2021 and 2022 orthophotos. These omissions primarily involved manmade water features, such as reservoirs, artificial lakes, and golf course ponds. To address this, aerial imagery (NAIP 2021 and

2022) across Pima County was used to hand-delineate missing open water surfaces visible excluding swimming pools and fountains.Small ornamental features such as swimming pools and fountains were excluded. The final hydro-ecological layer thus integrated both natural and anthropogenic surface water features relevant to wildlife movement.

Roadway Network

Roadway data were obtained from Pima County and the City of Tucson, each contributing complementary information (City of Tucson, 2024; Pima County Information Technology Department - GIS, 2025). The Pima County dataset provided major arterials and highways, including lane count attributes, whereas the City of Tucson dataset supplied detailed coverage of local and residential streets but lacked lane count data.

To estimate roadway width, each lane was assumed to be ten feet wide, and the total width was calculated by multiplying lane count by lane width (NACTO, 2013). For road segments without lane count information, a default of two lanes (reflecting a standard two-way configuration) was assigned. In areas where both datasets overlapped, Tucson features were clipped to preserve the richer Pima County attributes. For Tucson streets without lane data, a two-lane assumption was again applied to ensure continuity across the network.

Speed limit information was joined to the road network where available. Missing values were assigned a default of 25 mph, consistent with residential speed regulations in Tucson (Bieber, 2025; City of Tucson, 1982). All derived roadway geometries and width estimates were visually validated using NAIP 2021-2022 aerial imagery to ensure geometric accuracy relative to on-the-ground conditions.

Parks and Protected Lands

Park features were compiled from City of Tucson Parks and Pima County protected lands datasets (City of Tucson, 2025; Pima County GIS, 2025). The City's dataset primarily included recreational parks, while the Pima County data encompassed protected parcels managed for biological and ecological preservation. The two datasets were cross-checked against regional open-space inventories to confirm coverage and attribute consistency. Together, they represented both recreational green spaces and ecologically significant conservation areas relevant to wildlife movement and habitat connectivity.

Establishing Zones of Influence

To operationalize the spatial relationship between wildlife incidents and environmental features, zones of influence were delineated around key geographic elements. A baseline distance of 500 U.S. survey feet was selected, reflecting the typical block length in Tucson's urban street grid (Tucson Traffic Engineering Division, 1987). This buffer distance aligns with urban design standards that shape circulation and connectivity patterns affecting both human and wildlife movement.

Using ArcGIS Pro Buffer Analysis tools, 500-foot buffers were generated separately for parks and water features (Cooksey, 2012; Gallagher, 2021; Hastings, 2023). Parameters included side type: full, end type: round, method: geodesic, and dissolve type: all, ensuring accurate and continuous coverage around each feature.

During preliminary analysis, the research team observed that the road network density within the study area was substantially higher than that of parks or hydro-ecological features. Applying the same 500-foot buffer to roads produced disproportionately large coverage areas, obscuring spatial variation and overlapping much of the study region. As a result, subsequent modeling accounted for road influence through derived measures of road density and distance to nearest roadway rather than equivalent buffer zones, ensuring more meaningful representation of exposure across spatial units.

In total, the integrated spatial database combined wildlife collision records (2001–2024), roadkill observations (2006–2025), hydro-ecological and water features, roadway network data, and park and protected land boundaries. Each dataset was harmonized to a common coordinate system (GCS_WGS_1984) and verified through visual cross-validation using high-resolution NAIP imagery. Wildlife-vehicle collision data are known to be incomplete due to inconsistent reporting requirements, limited documentation of minor incidents, and variation in how agencies classify wildlife-related crashes. As highlighted by Jørgensen et al. (2025), underreporting can distort analyses of WVC predictors and obscure the true influence of environmental and roadway factors (Jørgensen et al., 2025). To address these limitations in the Tucson context, this study incorporates additional spatial datasets, including roadway characteristics, land-use features such as parks and water bodies, and hydro-ecological layers, to help approximate the conditions associated with collision risk. Using these complementary datasets strengthens the analysis by providing environmental and infrastructural context that compensates for known gaps in crash reporting. These data collectively provide the foundation for the spatial modeling and hotspot analysis described in the subsequent sections.

Table 6.1 List of Data

Data	Data Sources	Description
Wildlife-Vehicle Collision Incidents	Arizona Crash Information System (ADOT)	Crash records for 2001–2024 within City of Tucson; geocoded from ACIS and used as primary response variable.
Roadkill observations	Sonoran Desert Protection Coalition (iNaturalist Portal)	Wildlife roadkill reports for 2012, 2016-2024 from community observations and iNaturalist records managed by SDPC.
Population	IPUMS NHGIS and U.S. Census Bureau (ACS 5-year estimates)	Annual block-group estimates for 2000–2024 harmonized to 2020 boundaries using NHGIS crosswalks and ACS data.
Roadway Network	Pima County Information Technology Dept – GIS and City of Tucson Open Data	Street centerlines, lane counts, and speed limits for Tucson and Pima

		County; width estimated assuming 10 ft lanes.
Parks and Protected Lands	City of Tucson & Pima County GIS	Recreational parks and protected parcels representing open-space networks and habitat areas.
Hydro-Ecological Features	Pima County GIS Library, ADEQ, FEMA, and USDA NAIP Imagery	Flood hazard zones, shallow groundwater, flow regimes, and surface water features (merged natural and man-made sources).

6.3 Data Analysis

6.3.1 Population Estimation for Tucson Block Groups (2000–2024)

To develop a continuous, spatially consistent population dataset for Tucson block groups from 2000 through 2024, decennial census counts and American Community Survey (ACS) estimates were integrated and harmonized to 2020 Census block group boundaries (IPUMS NHGIS, 2025). This step was essential to ensure that all demographic, environmental, and crash datasets were aligned to a uniform spatial framework for subsequent spatiotemporal analyses.

Population counts for the years 2000, 2010, and 2020 were first collected from the U.S. Census Bureau. The 2000 population data were obtained from the National Historical Geographic Information System (NHGIS) (IPUMS NHGIS, 2025), while the 2010 and 2020 population data were extracted using the tidycensus package (Walker, 2024), referencing variables P001001 (2010 Census) and P1_001N (2020 Census). Because census block group boundaries change between decades, population counts were adjusted to 2020 boundaries using official geographic crosswalk files from NHGIS. Specifically, 2000 block groups were reallocated to 2010 boundaries using area-weighted population factors, and the 2010 block groups were subsequently reallocated to 2020 boundaries using population-based weights provided by NHGIS crosswalks. This two-step translation (2000→2010→2020) ensured that all historical data were normalized to consistent 2020 geometries.

After reallocation, population totals from 2000, 2010, and 2020 were linearly interpolated to estimate annual block group populations between census years. The interpolation used all available anchor years to produce continuous estimates from 2000 through 2020. These interpolated data were then spatially clipped to the Tucson study boundary, proportionally adjusting population counts for block groups that only partially intersected the city limits based on the ratio of clipped to full area. This resulted in annual population estimates within the Tucson boundary at the 2020 block group level for 2000–2020.

To extend population estimates beyond the 2020 Census, five-year ACS data were used to anchor population counts for 2021, 2022, and 2023. ACS estimates were retrieved for Pima County block groups using the variable B01003_001 (total population) via the tidycensus API. These data were spatially transformed to match the Tucson boundary and adjusted proportionally for partial overlaps using the same area-based correction approach as with the census years. The 2021–2023 ACS block group estimates were then combined with the interpolated 2000–2020 data to create a continuous population series from 2000 through 2023.

A linear regression model was then applied to each block group using the 2021–2023 ACS population values to project the population for 2024. The regression-based approach allowed a smooth continuation of recent growth trends while ensuring non-negative population values across all units. The final dataset, spanning 2000–2024, provides annual population estimates for all Tucson block groups standardized to 2020 boundaries. These data were stored as a GeoPackage for use in subsequent analyses involving crash and wildlife observation modeling.

This approach harmonizes decennial census and ACS data using officially validated crosswalks, maintains spatial consistency across changing geographic definitions, and produces a temporally continuous population series suitable for longitudinal modeling of human-wildlife interactions and transportation safety within the Tucson region.

6.3.2 Grid-Based Spatial Framework Development

To analyze the spatial relationships between built environment features, wildlife presence, and crash occurrences across Tucson, a grid-based spatial framework was developed using the R programming language and several geospatial libraries (R Core Team, 2024). Population data from 2000 to 2024 were obtained in polygon format and transformed into a uniform projected coordinate system (UTM Zone 12N). The geometries representing 2020 census block groups served as the base boundary for defining the study area. A uniform 1 km × 1 km grid was then created to ensure consistent spatial resolution and to facilitate the integration of multiple datasets such as population, parks, water bodies, and transportation networks within standardized units. Each grid cell was assigned a unique identifier, and its total area was recorded to support later calculations.

Population estimates were spatially interpolated from census block groups to the grid cells using an area-weighted approach. For each year, the overlapping area between a block group and a grid cell was determined, and the population was proportionally distributed according to the fraction of that overlap relative to the total area of the block group. This method produced continuous annual population estimates across all grid cells between 2000 and 2024, allowing for normalization of crash or roadkill events by population density.

Spatial layers representing parks, water bodies, and road networks were integrated into the same coordinate system to ensure spatial consistency. Roadway features were enhanced by estimating realistic road widths based on available lane counts, shoulder assumptions, or recorded widths. Variable-width buffers were applied to represent the physical extent of paved surfaces and overlapping road segments were merged to avoid double-counting. These processed layers provided a foundation for deriving environmental predictors such as the percentage of grid area covered by roads, parks, or water bodies, as well as the minimum distance from each grid centroid to the nearest road, park, or water feature. Average posted speed limits for road segments within each grid were also calculated to represent exposure risk.

Crash records from 2001 to 2024 and roadkill observations from 2012 and 2017–2024 were then geocoded and intersected with the grid framework. When events overlapped multiple grid cells, fractional weights were applied to ensure that each event was counted proportionally based on its spatial extent. This resulted in annual counts of crashes and roadkill events per grid cell.

Two longitudinal panel datasets were created from these processed layers: one combining crash counts, population, and built environment predictors for 2000-2024, and another combining roadkill counts with the same spatial predictors for 2012-2024.

This process produced a harmonized, fine-scale spatial database that enabled detailed modeling of the factors influencing both human and wildlife-related crash risks. The grid-based design provided a consistent unit of analysis, allowing for temporal comparison, population normalization, and direct assessment of how environmental and infrastructural features contribute to traffic safety and wildlife-vehicle conflict patterns in Tucson.

6.3.3 Comparison of Spatial Units: Census Blocks and 1-km Grid

To examine the spatial relationship between crash and roadkill events, analyses were conducted using two different spatial aggregation frameworks: census block groups and a uniform 1-km grid. Although both approaches revealed areas of overlapping risk, the spatial patterns differed due to variations in boundary definition, resolution, and aggregation effects.

Census block groups are administrative units defined primarily by population distribution, whereas the 1-km grid applies uniform, equal-area cells across the study area. This distinction reflects the Modifiable Areal Unit Problem (MAUP), where statistical relationships and spatial patterns depend on the choice of aggregation scale. In the census-based analysis, hotspot patterns were influenced by population density and jurisdictional boundaries, while the grid-based approach provided smoother and more continuous spatial representations aligned with roadway corridors and environmental features.

Differences in spatial resolution also contributed to variation in event density. Census block groups vary greatly in area from small, compact polygons in the urban core to large rural tracts at the periphery creating inconsistencies in how crash and roadkill events are aggregated. The uniform grid, with its constant cell size, ensured consistent spatial resolution and enabled direct comparison of event densities, resulting in clearer identification of high-risk corridors throughout the region.

Because census boundaries are designed for demographic representation, they emphasize human exposure rather than physical risk. As a result, the census-based results partially reflect areas of higher residential density rather than true spatial co-occurrence of crashes and roadkills. The grid-based analysis, in contrast, decoupled population effects and captured the physical locations where these events overlap. Additionally, the grid aggregation reduced zero inflation by pooling neighboring observations, which stabilized the data and slightly increased the observed correlation between crash and roadkill counts. The grid also minimized edge effects caused by administrative boundaries intersecting roadways or habitat areas, allowing for a more accurate spatial depiction of event interactions.

Figure 6.1 and Figure 6.2 illustrate these differences. In the census block map (Figure 6.1), hotspots appear fragmented and concentrated within populated areas. This pattern is driven by the irregular shape and variable size of census block groups, which produce scattered clusters shaped by population boundaries rather than continuous spatial processes. Smaller urban blocks often capture localized crash activity but may underrepresent roadkill events, whereas larger rural blocks dilute event densities. Consequently, the overlap between crash and roadkill hotspots appears uneven, reflecting the influence of administrative rather than geographic boundaries.

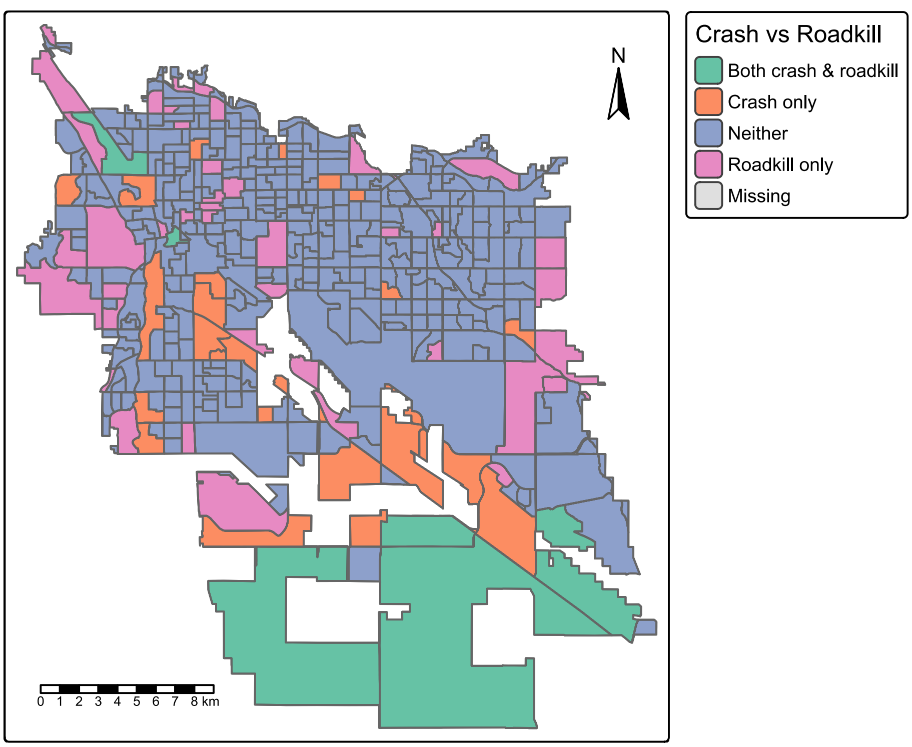

Figure 6.1 Spatial Distribution of Crash and Roadkill Events by Census Block (2018–2024)

In contrast, the 1-km grid map (Figure 6.2) displays a smoother, continuous distribution of events. The equal-area cells align more closely with underlying roadway networks and ecological zones, emphasizing corridors where human and wildlife movement intersect. Hotspots in the grid map extend along major arterials and peripheral regions, capturing spatial risk patterns that the census-based aggregation tends to obscure. The grid approach also reduced the prevalence of zero-event cells, improving visibility of co-occurrence zones and enhancing interpretability.

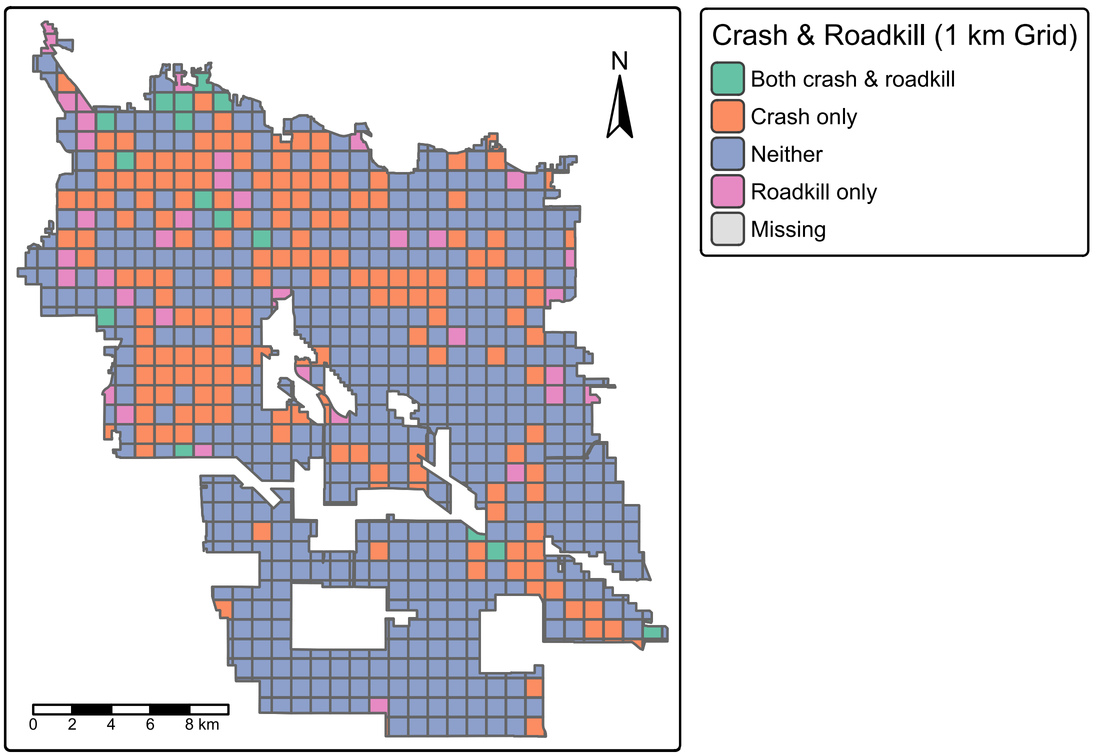

Figure 6.2 Spatial Distribution of Crash and Roadkill Events by 1-km Grid (2018–2024)

Overall, these comparisons highlight the sensitivity of spatial relationships to the choice of areal unit. The census-based aggregation is useful for understanding human exposure and demographic context, whereas the 1-km grid provides a more spatially balanced representation of roadway and environmental risk. Given the objectives of this research is to model spatial risk patterns and identify roadway segments where crash and roadkill events co-occur the 1-km grid system was selected for subsequent modeling and spatial analyses. This uniform structure ensured consistent area representation, minimized boundary distortions, and enhanced the detection of spatial processes underlying transportation and wildlife interactions

6.3.4 Binary Logistic Regression for Crash Likelihood

To assess the influence of built environment and population characteristics on the likelihood of crash occurrences within the 1 km² grid framework, a binary logistic regression model was developed. The analysis used annualized grid-level data derived from the spatial panel described earlier. Each grid cell was coded as either containing one or more crashes (1 = crash present) or having no recorded crashes (0 = no crash) during the study period. This binary outcome variable allowed the modeling of crash probability as a function of multiple spatial predictors.

The explanatory variables included road density (m/m²), percentage of road coverage, percentage of water area, average road speed (mph), population, and percentage of park area. These predictors represent different dimensions of the built and environmental context such as traffic exposure, natural barriers, human activity intensity, and land use characteristics that may influence the spatial distribution of crash events. Before model fitting, all continuous predictors were standardized (mean-centered and scaled by one standard deviation) to allow for direct comparison of coefficient magnitudes and to improve model convergence.

A generalized linear model (GLM) was estimated using a binomial distribution with a logit link function, implemented through the glm() function in R (Salinas Ruíz et al., 2023). The logistic regression estimates the log-odds of a crash occurring within a grid cell as a linear combination of the predictor variables. The fitted model took the following form as shown in equation (19):

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} \qquad (19)$$

Where,

$p_i =$ probability of at least one crash in grid cell i

$X_{1i} - X_{5i}$

$=$ standardized predictors (road density, water area, average speed, population, park area)

$\beta_0 - \beta_5 = \ estimated\ coefficients$

where

p_i is the probability of at least one crash occurring in grid cell i, and the β coefficients represent the effect of each standardized predictor on the log-odds of a crash.

Multicollinearity among predictors was evaluated using the Variance Inflation Factor (VIF) statistic from the car package. All VIF values were below the commonly accepted threshold of 5, indicating minimal redundancy among predictors and supporting model stability (Mahmood, 2024). Variance Inflation Factor diagnostics showed no indication of multicollinearity among predictors, with all VIF values below the commonly accepted threshold of five, confirming that each variable contributed unique information to the model.

To facilitate interpretation, model coefficients were exponentiated to obtain odds ratios and 95% confidence intervals. Odds ratios greater than 1 indicate that an increase in the corresponding predictor is associated with a higher likelihood of a crash, while values below 1 indicate a negative association. These results were visualized through a publication-style forest plot displaying point estimates and confidence intervals for each variable.

Model performance was evaluated using multiple diagnostic measures. Predictive accuracy was assessed through the Receiver Operating Characteristic (ROC) curve, and the Area Under the Curve (AUC) was calculated to quantify model discrimination capability. An AUC value closer to 1.0 indicates better separation between crash and non-crash grid cells. Additionally, McFadden's pseudo R^2 was computed to assess the overall explanatory power of the model by comparing the log-likelihoods of the fitted and null models.

Overall, the logistic regression model provided a robust and interpretable framework for identifying which built environment and population factors most strongly predict the spatial presence of crashes within Tucson's urban grid. The standardized predictors and diagnostic checks ensured the model's validity and comparability across variables, while the odds ratio interpretation allowed clear communication of each variable's relative effect on crash likelihood.

6.4 Results

The model was fitted using a logit link function, where the dependent variable represented the log-odds of a crash occurring in a given grid cell. The results indicated that the model provided a significant improvement in fit compared to the null model, with a reduction in deviance from 3048.4 to 2720.5. McFadden's pseudo R^2 value was approximately 0.11, suggesting that the model explained about 11 percent of the variation in crash presence. Although this value may appear modest, it is considered acceptable for spatial and behavioral models, where variability is inherently influenced by numerous unobserved factors. The overall model performance was satisfactory, with an Area Under the Curve value of 0.785, indicating that the model correctly distinguished between crash and non-crash grid cells nearly 79 percent of the time (Figure 6.3).

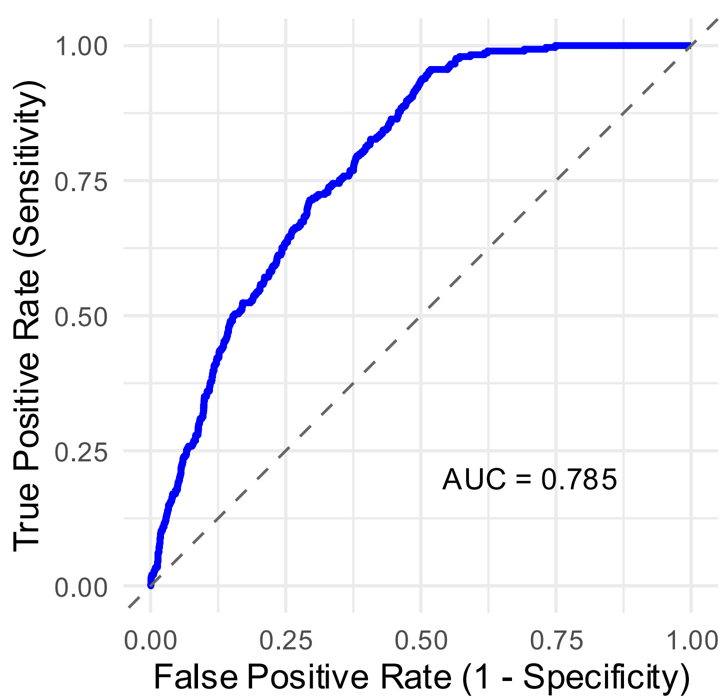

Figure 6.3 ROC Curve for Crash Likelihood Model

Among the predictors, average road speed emerged as the most influential factor. The odds ratio of 3.57 indicated that for each one standard deviation increase in average speed, the odds of a crash occurring increased by approximately 3.6 times, holding other factors constant. This strong association underscores the critical role of speed in determining crash likelihood, reflecting the elevated risks associated with higher operating speeds. Population was also a significant predictor, with an odds ratio of 1.62, suggesting that areas with higher population density had 62 percent greater odds of experiencing a crash. This finding is consistent with exposure theory, which shows that areas with more people and vehicles are more likely to experience traffic conflicts and crashes. Road density exhibited a smaller but statistically significant effect, with an odds ratio of 1.26, implying that denser roadway networks were associated with higher crash probabilities due to greater interaction between vehicles and intersections shown in Figure 6.4.

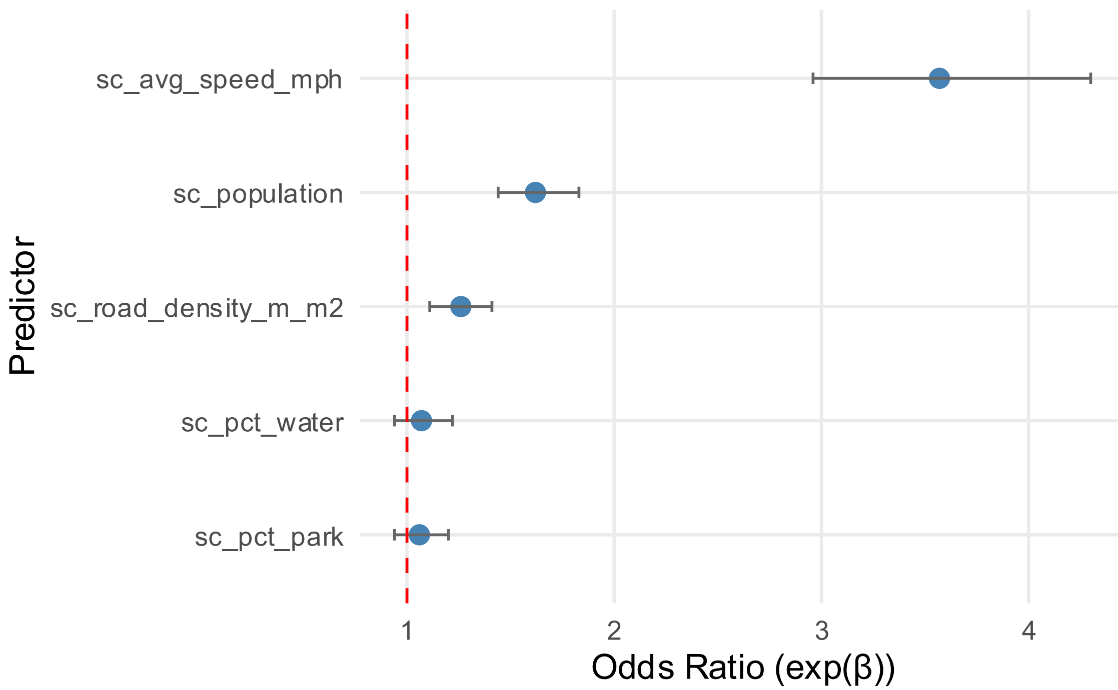

Figure 6.4 Odds Ratios for Crash Presence (Logistic Regression Result)

In contrast, the percentage of water area and park area were not statistically significant predictors of crash presence, with p-values greater than 0.05 as shown in Table 6.1. These results indicate that, once traffic-related and population factors were controlled for, the presence of natural or recreational land uses had no measurable effect on crash likelihood within the grid cells. The model intercept was negative (–5.08), representing the baseline log-odds of a crash occurring under average environmental conditions when all predictors were held at their mean values.

Table 6.2 Odds Ratios, Confidence Intervals, and Significance Levels for Crash Presence Model

Predictor	Odds Ratio (exp β)	95% Confidence Interval	P-Value
Average Speed	3.57	2.96-4.30	<0.001***
% of water area inside the grid	1.07	0.94-1.22	0.29
% of park area inside the grid	1.06	0.94-1.2	0.31
Road Density (m/m^2)	1.26	1.11-1.41	<0.001***
Population	1.62	1.44-1.83	<0.001***

The results collectively highlight that crash occurrence within Tucson is strongly associated with traffic exposure and operational conditions rather than with natural environmental features. Higher average speeds, greater road density, and more populated areas were consistently linked to increased crash likelihood, suggesting that targeted speed management and roadway design interventions may be effective in mitigating crash risk in high-exposure zones. The findings align with broader evidence in transportation safety research that emphasizes the influence of roadway design, speed environment, and urban form on spatial patterns of crash risk.

6.5 Chapter Summary and Implications

This chapter examined wildlife-vehicle collisions and associated crash patterns in Tucson through an integrated spatial and statistical framework. By combining crash, roadkill, and environmental datasets spanning over two decades, the analysis demonstrated how locally available city and state data can be used to assess WVC risk in an arid urban environment. The framework provided a structured, reproducible approach that can be replicated by other agencies using their own datasets to identify local hotspots, prioritize mitigation, and guide the allocation of limited safety resources toward areas with higher wildlife vehicle crash likelihood.

The comparison between census block and 1-km grid aggregation frameworks revealed substantial differences in spatial representation, emphasizing the Modifiable Areal Unit Problem and the importance of scale selection in spatial safety analysis. The 1-km grid framework was ultimately selected for modeling because it provides uniform spatial resolution, reduces boundary distortions, and better captures the physical processes underlying both human and wildlife-related crash occurrences.

While both crash and roadkill data were analyzed to understand spatial overlap and hotspots, the roadkill dataset was comparatively limited in both temporal coverage and reporting consistency. As a result, roadkill observations were used primarily for spatial visualization and exploratory comparison rather than for inclusion in statistical modeling. The crash dataset, which was more complete and consistent annually served as the primary basis for the binary logistic regression analysis.

For Tucson, results from the logistic regression model demonstrated that crash occurrence is strongly influenced by built environment and exposure-related factors, particularly roadway speed, population density, and road density. Natural features such as parks and water areas did not exhibit statistically significant associations once traffic and population factors were accounted for. These results highlight the potential of locally available data and scalable spatial methods to generate meaningful insights even within data-limited contexts.

Overall, this chapter establishes a methodological foundation for the spatial modeling of transportation safety in an ecologically sensitive, arid urban environment. The reproducible grid-based framework developed here not only validates a consistent approach for understanding WVC patterns within Tucson but also provides a transferable platform that can be adapted by other cities and agencies to model wildlife-related incidents, evaluate spatial risk factors, and inform strategies for mitigating human–wildlife conflicts along transportation networks.

Chapter 7: Conclusions & Contributions

7.1 Conclusions of Research Hypothesis

This section is aimed at tying the findings from the research back to the research hypothesis stated in Chapter 1:.

Research Hypothesis 1:

RLCs reduce the severity of crashes and result in reduction in different types of collisions at intersections. Following program termination, overall crash frequencies and severities exhibit shifts that reflect both behavioural adaptation and enforcement gaps.

Chapter 3 analyzed the safety effectiveness of RLCs in the City of Phoenix by comparing crash trends before, during, and after the implementation of the photo enforcement program. The findings showed that intersections with RLCs experienced reductions in severe angle crashes but a relative increase in rear-end collisions which is consistent with behavioural adaptation patterns observed in previous studies. Even after the program ended in 2019, crash reductions persisted, suggesting that other contextual influences such as the broader economic slowdown and changes in driving behavior following years of enforcement which may have contributed to continued safety improvements. Another important observation was that many cameras remained in place for several years after deactivation, which likely reinforced compliance by reminding drivers of possible monitoring.

Overall, these findings support Research Hypothesis 1, indicating that automated enforcement can produce both immediate and residual safety benefits when drivers internalize risk-averse behaviors. The Phoenix case highlights how enforcement visibility, even without active operation, can influence long-term driving patterns. The City of Phoenix's current deliberations about reinstating the program underscore the importance of leveraging past lessons to design data-driven, transparent, and equitable enforcement frameworks. Integrating community feedback, periodic performance evaluations, and public reporting can ensure that future automated enforcement initiatives balance deterrence objectives with public trust and fairness. These insights provide practical guidance for cities reconsidering automated enforcement as part of comprehensive safety strategies.

Research Hypothesis 2:

Public perception of RLCs is influenced by an individual's understanding of safety benefits, fairness in enforcement, and clarity in policies, which together shape support or opposition to their use.

Chapter 4 examined public perceptions of red-light cameras through surveys administered in Arizona and New York, focusing on how beliefs about safety, fairness, and transparency influence support for automated enforcement. The results demonstrated that support for RLCs is strongly associated with individuals' perceptions of safety benefits and fairness in enforcement procedures. Respondents who viewed RLCs as transparent, equitable, and focused on safety were significantly more likely to support their continued use, while those concerned about revenue motives or lack of clarity in violation notices expressed opposition. Structural equation modeling further revealed that fairness and transparency indirectly shaped support through their influence on perceived safety benefits, emphasizing that acceptance of automated enforcement is grounded not only in its outcomes but also in the perceived legitimacy of its operation.

These findings confirm Research Hypothesis 2, indicating that attitudes toward RLCs are shaped by a combination of cognitive (safety belief), procedural (fairness), and communicative (clarity) dimensions. The results highlight that the long-term viability of automated enforcement depends on the public's trust in program governance and communication. Policymakers should therefore prioritize transparency, consistent public education, and equity-driven site selection when designing or reinstating RLC programs. By addressing fairness and communication gaps, agencies can strengthen the social legitimacy of enforcement initiatives and improve compliance without exacerbating public skepticism or inequity.

Research Hypothesis 3:

Adoption of electric vehicles (EVs) in public agency fleets is influenced by workforce attitudes, organizational readiness, and perceptions of operational challenges such as charging accessibility, cold-weather performance, and safety, which together shape the pace and success of fleet electrification and progress toward sustainability goals.

Chapter 5 explored the readiness of public agencies to transition toward electric vehicle fleets, emphasizing the role of workforce attitudes, organizational preparedness, and perceived barriers. Survey and interview results revealed strong conceptual support for electrification but highlighted persistent concerns regarding vehicle performance, charging infrastructure, and maintenance logistics. Field staff and operations personnel expressed particular apprehension about vehicle reliability and charging time, while administrative staff tended to emphasize long-term cost savings and environmental benefits. Regression analysis confirmed that direct exposure to EVs and prior training experience significantly predicted positive attitudes toward adoption.

These findings affirm Hypothesis 3, indicating that EV adoption within public agencies extends beyond financial and infrastructural considerations to include cultural and operational dimensions. Addressing workforce skepticism through targeted training, demonstration programs, and clear operational guidelines can accelerate institutional readiness. The study underscores that technological transitions in the transportation sector require alignment between environmental policy goals and organizational realities. By fostering workforce engagement and feedback mechanisms, agencies can improve the effectiveness and sustainability of their fleet electrification efforts.

Research Hypothesis 4:

Wildlife-vehicle collision (WVC) patterns can be effectively quantified through an integrated spatial framework that leverages locally available data, allowing for the assessment of how built-environment and ecological conditions jointly shape spatial patterns of crash likelihood.

Chapter 6 examined the spatial and environmental factors influencing wildlife-vehicle collisions and general crash patterns within Tucson’s urban and peri-urban areas. The research hypothesis proposed that wildlife–vehicle collision (WVC) patterns can be effectively quantified through an integrated spatial framework using locally available data. The findings support this hypothesis by demonstrating that the developed grid-based framework successfully integrated crash, roadkill, environmental, and demographic datasets to evaluate spatial patterns of WVC risk within an urban–desert context. The approach was effective in identifying areas of elevated risk and clarifying the interactions between roadway, exposure, and environmental factors, confirming the framework’s capability to assess WVC risk using accessible local data sources.

1. **Evaluation of Red-Light Camera Effectiveness through Integrated Quantitative and Qualitative Analysis:**

This research makes a significant contribution by developing a rigorous three-period evaluation framework that examines the before, during, and after operation of RLCs. This framework is integrated with Empirical Bayes estimation to isolate the true safety effects of red-light cameras beyond random crash variation. This approach advances conventional evaluation by capturing the persistence of deterrence even after program termination. The study also introduces the novel concept of distinguishing between camera visibility and activation, revealing that visible but inactive cameras continue to influence driver behavior. Furthermore, the integration of surveys and interviews with transportation professionals and enforcement officers provides rare institutional insight into program operation, administrative barriers, and enforcement practices. Together, these methodological and empirical advancements establish a robust foundation for long-term, evidence-based evaluation of automated enforcement programs.

2. **Behavioural and Perceptual Determinants of Public Support for Automated Enforcement:**

This research makes an important contribution by establishing an analytical framework that identifies fairness, trust, safety, and transparency as the key psychological drivers of public support for red-light camera programs. Using composite indices and advanced modeling approaches, the chapter demonstrates that legitimacy perceptions far outweigh demographic factors in shaping acceptance, even though age and gender influence specific stages of the support process. These finding challenges previous studies in technology adoption that have emphasized demographic predictors as dominant determinants. The results reveal that when individuals perceive enforcement programs as fair, transparent, and focused on safety, their support increases substantially, accounting for nearly half of the variation in attitudes. The research also shows that clear and consistent communication particularly official documents emphasizing safety enhances transparency perceptions. These findings highlight the importance of targeted educational campaigns and communication strategies that address trust and clarity concerns among specific demographic groups, offering a practical pathway for policymakers to strengthen long-term public confidence and sustain automated enforcement initiatives.

3. **Workforce Readiness and Electric Vehicle Fleet Transition Policy:**

This chapter advances understanding of fleet electrification by uncovering how psychological perceptions and operational realities jointly shape public agency readiness for electric vehicle transitions. Through a mixed-methods design combining survey data from agency professionals and interviews with fleet managers, engineers, mechanics, and field staff, the study provides a comprehensive understanding of both attitudinal and logistical challenges shaping EV transitions. The findings reveal that workforce roles, prior exposure to EVs, and targeted training significantly influence attitudes toward adoption, while persistent operational concerns such as charging infrastructure, cold-weather performance, maintenance expertise, and upfront costs continue to hinder large-scale implementation. By differentiating between psychological and operational barriers, the study demonstrates that successful fleet electrification requires not only technical investment and policy support but also organizational adaptability and workforce engagement. The chapter advances current practice by proposing actionable strategies, including tailored hands-on training, demonstration projects, and region-specific planning approaches, to enhance agency readiness and accelerate sustainable EV adoption in the public sector.

4. Reproducible Assets for Policy and Practice:

Across chapters, this dissertation provides reproducible analytical approaches and guidance that bridge research and implementation. These include:

- **Survey instruments and composite indices** for evaluating public perceptions and legitimacy of automated enforcement programs.

- **Frameworks for evaluating automated enforcement programs** that integrate both operational performance and perceived visibility to improve understanding of enforcement impacts.

- **Insights into workforce readiness for electric vehicle (EV) transition**, highlighting role-specific challenges and training priorities that can inform agency planning.

- **Spatial analysis workflows** linking crash and wildlife-risk patterns to potential countermeasures, promoting consistent, data-driven safety assessments.

Together, these approaches enable transparent evaluation, replication, and communication of safety performance, demonstrating how durable safety gains emerge when technical effectiveness is paired with legitimacy, readiness, and spatial precision.

5. **Integrating Ecological and Transportation Data for Crash Risk Analysis at the City Level**

This chapter contributes a reproducible, grid-based spatial framework for analyzing wildlife–vehicle collisions (WVCs) and broader crash risk within urban and peri-urban environments. The framework harmonizes crash, demographic, roadway, and environmental datasets using locally available data sources, enabling consistent evaluation of spatial crash risk at the city scale. By comparing census block group aggregation with a uniform 1-km grid system, the analysis highlights the impact of spatial unit selection on observed crash–roadkill relationships and addresses the Modifiable Areal Unit Problem (MAUP) in safety modeling.

The 1-km grid structure provides a standardized spatial resolution that supports integration across ecological and transportation datasets, allowing for more transparent and scalable modeling of WVC risk. While the Tucson application demonstrated how built-environment and exposure variables can be effectively captured through this framework, the broader contribution lies in establishing a transferable methodological foundation. The framework can be adapted by other cities or agencies to investigate local wildlife-related safety concerns, evaluate data gaps, and inform evidence-based mitigation and coexistence strategies where human development intersects natural habitats.

7.2 Future Directions

Building on the findings across chapters, future research should shift from retrospective evaluations to prospective, policy-linked studies. When jurisdictions modify automated enforcement, those changes create opportunities to estimate effects with stronger causal designs. Intersection-level records should document activation and deactivation dates, signage, equipment presence and removal, and signal timing parameters. Pairing those records with approach speeds, violation counts, and near-miss indicators will make it possible to separate the effect of active enforcement from the effect of visible, non-operational equipment and to understand how deterrence fades or persists over time. These designs can also test how alternatives such as advance warning periods, right-turn policies, and revenue reinvestment communication influence compliance and crash outcomes.

Future research should build upon these findings by integrating survey data with behavioral indicators such as violation records, crash data, and citation trends to more effectively connect public perception with enforcement outcomes. Expanding the scope beyond Arizona and New York to include states that have recently adopted, banned red-light cameras or have never implemented RLCs would provide a broader understanding of how varying policy context and legislative history influence attitudes. Longitudinal approaches such as panel surveys conducted before and after policy changes could capture how perceptions of safety, fairness, and procedural transparency evolve over time. In addition, survey-based experiments could identify which program features, such as notice design, language clarity, or enforcement transparency, enhance public acceptance. Future studies should also incorporate qualitative methods, including interviews and focus groups, to explore fairness and trust dynamics in greater depth. Combining these approaches would support the development of more equitable, transparent, and publicly supported automated enforcement systems.

For fleet electrification, future research should extend this work beyond Minnesota to include a wider range of geographic, climatic, and policy contexts, enabling comparison across regions with different levels of EV readiness and infrastructure. Expanding participation to include a more diverse pool of respondents particularly underrepresented groups such as women, field staff, and technicians would enhance understanding of how perspectives vary across roles and demographics. Larger and more regionally diverse samples could also capture how institutional capacity, funding mechanisms, and environmental conditions influence EV adoption. Additionally, longitudinal studies tracking attitudes and behaviors over time would help reveal how workforce perceptions evolve as agencies gain experience with electric fleets and as technology and infrastructure mature. Combining these approaches would provide a more comprehensive understanding of the human and organizational dynamics shaping the transition to electric vehicle fleets.

Wildlife-vehicle risk analysis will benefit from spatiotemporal modeling and targeted evaluation of countermeasures. Future work should build on the reproducible spatial framework developed in this chapter by applying it to other cities or states to evaluate its adaptability across different ecological and transportation contexts. Using the same analytical structure with locally available data would enable comparative assessments of wildlife–vehicle collision (WVC) risk and provide insights into how regional differences in landscape, policy, and roadway design influence outcomes. Expanding the framework to integrate additional data sources such as camera-trap observations, citizen science reports, habitat connectivity models, and mitigation inventories would enhance its capacity to capture wildlife movement patterns and assess countermeasure effectiveness. Incorporating roadway design features such as fencing, lighting, and shoulder width, along with temporal or climatic variables, could further improve model precision and policy relevance. Collectively, these directions position the framework as a transferable decision-support tool that can guide evidence-based mitigation and promote stronger integration of ecological and transportation safety planning.

Appendix A

Questionnaire Used in Public Perception of Red-Light Cameras Survey

Survey Participants: People residing in New York and Arizona State

1. Do you know what a red-light camera is?
a) Yes, I know what it is.
b) I have heard of it.
c) No, I don't know what it is.

2. What is your age in years?

3. What is your gender?
a) Men
b) Woman
c) Non-binary or other

4. In which state do you currently reside?

5. What is your 5-digit zip code?

6. How often do you drive a vehicle?
a) Daily
b) Several times a week
c) Once a week
d) A few times a month
e) Rarely (once a month or less)
f) Never

7. What is your primary mode of transportation?
a) Personal vehicle

b) Public transit

c) Bicycle

d) Walking

e) Other – please specify

Awareness and Understanding of Red-Light Cameras

8. Are you aware that red-light cameras (RLCs) are used for traffic enforcement in your city?

a) Yes

b) No

9. Does your community or the area where you often drive have red-light cameras installed?

a) Yes

b) No

c) I'm not sure

10. Where have you encountered information about red-light cameras? (Select all that apply)

a) Television/Radio

b) Newspapers/Magazines

c) Social media/Online news

d) Official local government or transportation websites

e) Word of mouth

f) Personal experience (e.g., receiving a citation, seeing one in person)

g) Other (please specify)

11. How would you rate your understanding of how red-light cameras operate?

1 = Not at all knowledgeable

5 = Fully understand their function and related enforcement process

12. In your own words, what do you believe is the primary purpose of red-light cameras?

13. Traffic lights use a specific color for the "STOP" signal. To show that you are paying attention, please select "Green" as your answer.

a) Blue

b) Green

c) Red

d) Yellow

Perceived Safety Benefits

14. Do you believe that red-light cameras improve intersection safety overall?

a) Yes

b) No

c) Not sure

15. Please indicate your level of agreement with the following statement:

“Red-light cameras help reduce crashes caused by red-light running.”

(1 = Strongly disagree; 5 = Strongly agree)

16. What factors contribute to your view on the safety benefits of red-light cameras? (Select all that apply)

a) They reduce dangerous driving behavior.

b) They improve consistent enforcement of traffic laws.

c) They reduce the need for in-person police enforcement.

d) They serve as a reminder to follow traffic rules.

e) I do not believe they improve safety.

f) Other (please specify)

17. If you have any concerns or reservations about the safety benefits of red-light cameras, please explain in at least one sentence.

Perceptions of Fairness and Enforcement

18. To what extent do you agree with the following statement:

“Red-light cameras are implemented fairly and do not target specific drivers or communities.”

(1 = Strongly disagree; 5 = Strongly agree)

19. How concerned are you that red-light camera enforcement might be used primarily as a revenue-generation tool rather than for enhancing road safety?

(1 = Not at all concerned; 5 = Extremely concerned)

20. In your opinion, are the citations issued by red-light cameras justified?

(1 = Never justified; 5 = Always justified)

21. How effective do you believe red-light camera enforcement is compared to traditional police enforcement?

(1 = Much less effective; 3 = About the same; 5 = Much more effective)

22. Please explain in at least one sentence your concerns regarding the fairness or punitive nature of red-light camera enforcement.

Clarity and Transparency of Policies

23. Please select "Red" as your answer to demonstrate that you are paying attention.

a) Blue

b) Green

c) Red

d) Yellow

24. How clear and accessible do you find the information regarding the policies and operational guidelines for red-light cameras in your area?

(1 = Very unclear; 5 = Very clear)

25. Have you read or seen any official reports or public statements explaining that red-light cameras are used for safety rather than revenue collection?

a) Yes, I have seen official communications/reports

b) No, I have not seen official communications/reports

c) Not sure

26. What additional information or policy changes would increase your trust in the red-light camera enforcement system, if any? Please describe in at least one sentence.

Overall Support and Future Perspectives

27. Overall, do you support or oppose the use of red-light cameras in your community?

a) Support

b) Oppose

c) Neutral

28. Which of the following factors have the biggest impact on your opinion about red-light cameras? (Select all that apply)

a) Safety improvements

b) Fairness in enforcement

c) Transparency of policies

d) Concerns over revenue generation

e) Privacy issues

f) Effectiveness compared to in-person police enforcement

g) Other (please specify)

29. If strong evidence showed that red-light cameras significantly reduce crashes, how likely would you be to support their use?

1 = Not likely at all

5 = Extremely likely

30. Do you believe that automated enforcement technologies (such as red-light cameras) should be expanded to include other traffic violations?

a) Yes

b) No

c) Not sure

31. Please share any additional thoughts, experiences, or concerns you have about red-light cameras or automated traffic enforcement in general that you think would be helpful for us researchers to know.

Appendix B

Questionnaire Used in Agencies Survey in Transitioning to EV Fleet in Minnesota

1. What is your current role in your agency?
a. Fleet Manager
b. Field Staff
c. Operations Manager
d. Other (please specify)

2. What is the name of your agency?
a. Fill in the blank

3. How many years have you been in your current role?
a. Less than 1 year
b. 1-3 years
c. 4-6 years
d. More than 6 years

4. How often do you use agency vehicles?
a. Daily
b. Weekly
c. Monthly
d. Rarely (less than once per month)
e. Never

5. What is your age group?
a. 18-29
b. 30-39
c. 40-49
d. 50+

6. Please specify your gender identity.

a. Male

b. Female

c. Non-binary

d. Prefer not to say

e. Other (please specify)

Business Context

7. What is the size of the passenger vehicle fleet at your agency (to your knowledge)?

a. 1-10 vehicles

b. 11-50 vehicles

c. 51-100 vehicles

d. More than 100 vehicles

8. What is the size of the vehicle fleet at your agency (to your knowledge), including all vehicle types?

a. 1-10 vehicles

b. 11-50 vehicles

c. 51-100 vehicles

d. More than 100 vehicles

9. What type of vehicles are in your fleet? (select all that apply)

a. Passenger cars

b. Light commercial vehicles

c. Heavy trucks

d. Specialized vehicles (e.g., construction, emergency)

e. Other (please specify)

10. What percentage of your fleet currently consists of electric vehicles (EVs) to the best of your knowledge?

a. 0%

b. 1-10%

c. 11-25%

d. 26-50%

e. More than 50%

Adoption and understanding of EVs

11. How do you feel about the transition from traditional vehicles to electric vehicles (EVs)?

a. Very positive

b. Somewhat positive

c. Neutral

d. Somewhat negative

e. Very negative

12. What benefits do you associate with using EVs? (Select all that apply)

a. Reduced environmental impact

b. Lower fuel costs

c. Improved technology

d. Enhanced driving experience

e. Other (please specify)

Concerns and Challenges

13. What concerns do you have about using EVs? (Select all that apply)

a. Limited driving range

b. Availability of charging stations

c. Charging time

d. Maintenance and repair

e. Initial cost

f. Other (please specify)

14. How concerned are you about the reliability of EVs compared to traditional vehicles?

a. Very concerned

b. Somewhat concerned

c. Neutral
d. Not very concerned
e. Not concerned at all

15. Please elaborate on your answer to Question 14.
a. Short answer

16. Do you have any concerns about the safety of EVs?
a. Yes (please specify)
b. No (please specify)

Preferences & Expectations

17. What features would you like to see in agency EVs to support your work?
a. Longer battery life
b. More charging stations
c. Faster charging times
d. Advanced navigation systems
e. Other (please specify)

18. How familiar are you with the following technical characteristics of EVs?
a. Battery life and charging times
b. Range per charge
c. Maintenance requirements
d. Total cost of ownership
e. Environmental benefits

(1 - Not familiar at all, 2 - Slightly familiar, 3 - Moderately familiar, 4 - Very familiar, 5 - Extremely familiar)

19. Did you receive any training from your agency before using EVs?
a. Yes, I had training before I used an EV in a capacity at work.
b. No, no training before I used an EV in a capacity at work.

c. Yes, but I haven't used an EV in this capacity at work yet.

d. No, I haven't yet used an EV in this capacity.

20. What type of support or training would help you transition to using EVs?

a. Hands-on training sessions

b. Informational workshops

c. Detailed user manuals

d. Online resources and videos

e. Other (please specify)

21. How important is it for the agency to consider employee feedback when transitioning to EVs?

a. Very important

b. Somewhat important

c. Neutral

d. Not very important

e. Not important at all

22. Please specify any other thoughts you may have to transitioning to EV vehicles are your agency.

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