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Affective risk perception in automotive environments

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AFFECTIVE RISK PERCEPTION IN AUTOMOTIVE ENVIRONMENTS

An Abstract of a Thesis

Submitted

In Partial Fulfillment

Of the Requirements for the Degree

Master of Arts

Dane Atkins

University of Northern Iowa

May 2018

ABSTRACT

Traversing the automotive environment exposes drivers to a risk of property damage, injury, and death. This risk varies across the road network. This research questions whether drivers are capable of accurately perceiving their own exposure to risk in this environment. Analysis begins with an assessment of risk exposure at roadway intersections (as measured in terms of crash frequency, severity, and mixed-weighting methods). This assessment provides risk indices for a cross-section of road intersections across an urban Iowa community. These indices are then used in the development of an experimental visual cognition survey used to record risk perceptions of roadway sites amongst survey respondents. Survey responses record the way in which drivers' perception of risk varies within the automotive environment. Despite limitations in the experimental methods, survey results question the ability of drivers to predict their risk exposure, and therefore contributes to our understanding of risk homeostasis theory.

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This Study by: Dane Atkins

Entitled: AFFECTIVE RISK PERCEPTION IN AUTOMOTIVE ENVIRONMENTS

Has been approved as meeting the thesis requirement for the

Degree of Master of Arts

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Date	Dr. Patrick Pease, Dean of the Graduate College

I dedicate this work
to those who have walked or bicycled
in all or part of their daily trips

to those who have endured
wind, rain, hail, snow, heat, and cold
in the dark and in the light
of the day and of the night

to those who have faced
the speed, power, and terror
of two-tons of careening steel

to those who know what it is
to risk life and limb

to play in traffic

In 2015, only 0.6% of Americans rode a bicycle to work, and only 2.8% of Americans walked to work. A staggering 74.2% of Americans reported having 2 or more automotive vehicles available for personal transportation (United States Census Bureau, 2016).

I owe this work, and more, to my mother, especially for her unwavering support throughout my education and my life, and for her efforts reading and revising my most terrible first drafts.

I thank Dr. David May for his motivation throughout my undergraduate program; without his inspiration I might have procrastinated my dreams.

I would like to recognize Dr. Tim Strauss, Dr. Patrick Pease, Dr. Helen Harton, Dr. Mark Ecker, and Dr. Lisa Millsaps for their time and contributions to this thesis, to my education, and to my profession.

I also recognize Dr. Michael Pawlovich; in addition to the lessons I learned from him at the Iowa Department of Transportation, he provided crucial access to data for this work.

I express my gratitude to the Law Enforcement Officers working across the state of Iowa. They work to keep us safe, day and night, weekend and holiday. While I deal with computers and numbers, they deal firsthand with the realities of automotive crashes.

I also thank the 300 participants of the survey, including users of Reddit.com's subreddits: motorcycles, truckers, flying, gradschool, askacademia, geography, urbanplanning, urbanstudies, and samplesize; as well as users of the forums ADVRider, MTBR, NICOForum, and HondaTechForum. I owe my success to their participation.

Lastly, I thank all of the faculty in the Department of Geography at the University of Northern Iowa for taking a chance on a student dressed in leather and lycra.

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CHAPTER I

INTRODUCTION

On Risk, Perception, and the Automotive Environment

Every day we are confronted with risk: an uncertain probability that exposure to some hazard may cause injury or loss. We navigate the complexity of this risk in one of two ways, either a cognitive analysis or an affective perception. Cognitive analyses require thoughtful deliberation and critical reasoning to reach a carefully calculated estimate of risk (Loewenstein, Weber, Hsee, & Welch, 2001). However, many of our individual evaluations of risk are necessarily made quickly and subconsciously, suggesting that these risk analyses are dominated by emotion and intuition; this quick calculation of risk is described as an affective perception of risk (Slovic & Peters, 2006). There is often a striking divergence between our cognitive analysis and our affective perception of risk (Loewenstein et al., 2001).

The divergence between cognitive analysis and affective perception is especially intriguing in scenarios for which methods of expert analysis of risk are well established. This phenomenon occurs frequently in the context of automotive transportation safety. Drivers broadly self-report themselves as possessing above-average driving skills (Wohleber & Matthews, 2016), and also underestimate their risk of collision while driving (McKenna, 1993). Although these and similar studies are informative, they fail to address the uneven spatial distribution of crash risk in the automotive environment (Dezman et al., 2016). Some road sites are particularly dangerous, demonstrating

elevated levels of crash risk. This spatial heterogeneity of crash risk has prompted development of numerous statistical methods to identify these dangerous roadway sites, often referred to as crash hotspots (Hauer, 1996; Lord & Mannering, 2010). Given these considerations, this research questions whether the individual affective risk perception of roadway sites demonstrates concordance with the empirical assessment of crash risks.

The Risk of Being Wrong

There are countless sources of risk when navigating the automotive environment. In addition to the red-light runners and the reckless, distracted, inexperienced, and intoxicated drivers, there are the risks of mechanical failures, such as tire blowouts, brake failures, seized engines, and locked transmissions. There is also the risk posed by nature, from wildlife and weather conditions like snow, ice, rain, fog, wind, and the daily cycle of darkness. There are yet more risks, though less common, posed by road debris or from roadway structural failures. Lastly, there is our own inexperience, inability, and inattentiveness that poses additional risk to ourselves and others. We evaluate these risks cognitively before ever starting the car, but after, we rely on our affective perception to update our assessments based on the dynamic conditions we observe when traversing the high-speed and high-risk automotive environment.

The cost of a bad decision on the road varies from minor fender benders to life-altering injuries and death. In 2015, automobile collisions killed 35,092 people in the United States (including 5,376 pedestrians and 817 bicyclists), an increase of 7% from 2014 (Insurance Institute for Highway Safety, 2017). This mortality rate makes the

automobile the thirteenth leading cause of death in the United States, and the eleventh leading cause of death in Iowa (Centers for Disease Control, 2015; Iowa Department of Transportation [IaDOT], 2016a). Non-fatal collision data is infrequently aggregated at the national level, but in Iowa alone, there were 54,589 collisions and 19,103 reported injuries during 2015 in a population of just 2.2 million licensed drivers (IaDOT, 2016b). In 2005, the National Highway Traffic Safety Administration found that automotive crashes were the leading cause of death for all individuals aged 3 through 33 (United States Department of Transportation [USDOT], 2005). Automotive collisions remain a leading cause of death for Americans (USDOT, 2015b). The automotive environment poses a significant risk to drivers, passengers, and non-participants alike.

Rationale for Study

Calls for increased automotive safety are generally well regarded and uncontested. Debate continues, however, as to how best to establish safety objectives, and further, which programs might meet such objectives. There is strong support for utilizing technological innovations and for increasing regulatory enforcement, however, these programs typically prove to be prohibitively expensive (Elvik, 1999). Focusing instead on driver behavior could increase safety for all road users and all travel modes.

Compounding the cost of safety intervention is the drastic rise in automotive reliance, especially in the United States. Compared to 1980, the average driver travels 30% more miles per year; coupled with the increasing number of drivers, this contributes to a doubling of total annual vehicle miles travelled (USDOT, 2014). United States

drivers travel over 3 trillion miles per year, while tolerating near 100 fatalities per day. Travel demand management programs, aimed at reducing automotive reliance, may offset societal exposure to automotive risks, but are unlikely to eliminate the social and economic costs of automotive collisions (Giuliano, 1992; Winters, 2000).

Mention of transportation safety concerns can be traced back to the early 20th century, garnering attention from transportation's earliest regulatory agencies. In those early days, safety was only a casual concern; safety was secondary to economic productivity during the rapid transition from railroad commerce to interstate trucking and bussing industries (George, 1935). Since then, public road mileage has increased less than one million miles, while vehicle miles travelled have tripled (Figure 1). The increasing density of automotive traffic and the increasing potential for traffic collisions motivates the ongoing review of transportation safety concerns.

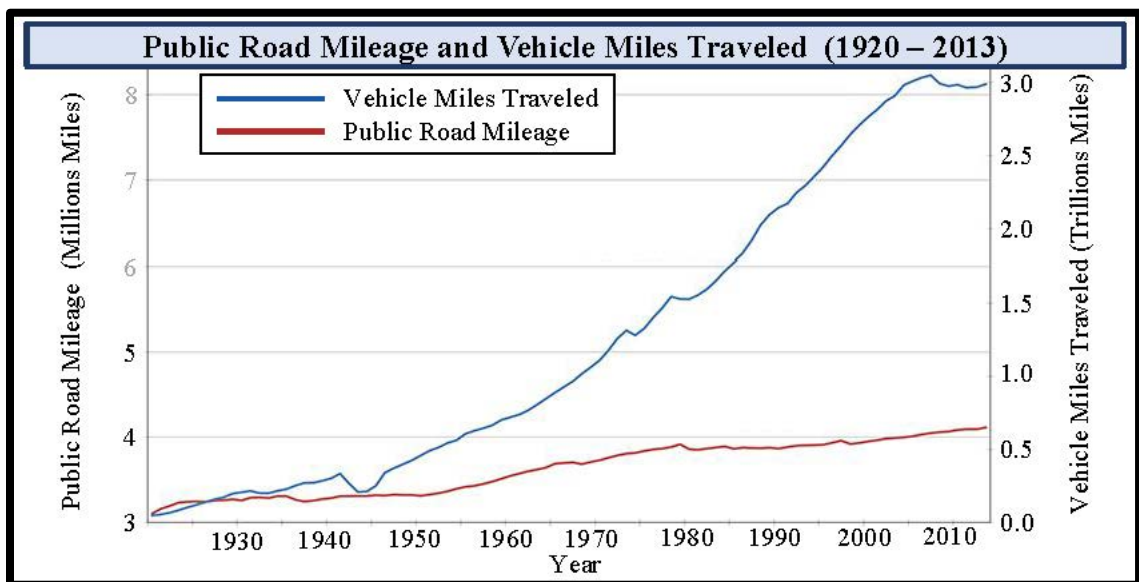


Figure 1: Public Road Mileage and VMT (1920 – 2013) (Adapted from USDOT, 2013)

Government agencies have asserted a goal of eliminating roadway fatalities. The Iowa Department of Transportation, following the lead set by the Federal Highway Administration (McGee & Sawyer, 2011), has adopted an initiative of its own, “Toward Zero Deaths: A Goal We Can Live With.” This plan, as outlined in the 2013 Iowa Strategic Highway Safety Plan (IaDOT, 2013, p. 1), stated a goal of reducing the number of fatalities 15% by 2020 (or conversely, accepting an ongoing fatality rate in Iowa of over 300 fatalities per year).

Governmental safety initiatives often start by targeting the “Four E’s,” improving roadway engineering, increasing enforcement, expanding emergency medical services, and reviewing driver education programs (McGee & Sawyer, 2011, p. 2). While these four focal areas are under the direct control of regulatory agencies, eliminating fatalities through these programs alone is far too costly (Elvik, 1999). Instead, eliminating traffic fatalities is increasingly the responsibility of the “Fifth E”: everyone (IaDOT, 2013, p. 1). This is especially pertinent, given that over 90% of all collisions are the result of driver error (USDOT, 2015a). We must emphasize the role that every individual plays in maintaining a safe automotive environment; this requires more than just education, but rather demands a cultural shift embracing safer drivers (Lerner, Singer, & Jenness, 2010; Ward, Linkenbach, Keller, & Otto, 2010). Encouraging a movement toward a safety culture has several benefits over traditional direct interventions. Peer attitudes and social norms have a strong influence on behavioral outcomes in hazardous environments (Fogarty & Shaw, 2010). Additionally, as Goetzke and Weinberger (2012) suggest, a well-organized cultural movement might enjoy a social-multiplier effect, where peer

influences diffuse across an ever-wider audience. The goal, then, of an intervention targeting safety culture is to provide a campaign that transforms individual attitudes and perceptions, and fosters widespread adoption (Ward et al., 2010). Designing such an intervention will first rely on understanding the fundamental perceptions of the automotive environment, and in particular, the individual's affective perception of risk (Charlton, Starkey, Perrone, & Isler, 2014; Ewing & Dumbaugh, 2009; Rundmo & Nordfjærn, 2017). It is also necessary that we understand not just the affective perception of risk, but its relationship to the empirical measures of crash risk as well. To guide the exploration of this relationship, the following questions and objectives were outlined:

Research Questions

- Does the individual affective perception of risk at roadway junctions demonstrate concordance with the empirical assessment of crash risks?
- Does the affective perception of risk at roadway junctions vary with regard to demographic variables?
- Does the affective perception of risk at roadway junctions exhibit a spatial pattern, and if so, which roadway attributes best predict perceptions of increased risk?

Objectives of Study

- Develop a rank-order list of risky roadway junctions in Cedar Falls, Iowa, based on empirical crash report data and well-regarded methods.
- Collect individual affective perceptions of risk at a subset of roadway junctions using a digital survey distribution, featuring junctions identified as high-risk by rank-order listing.
- Assess the aggregate results of the affective perceptions of risk at roadway junctions for concordance with respect to the empirical rank-ordering.

- Address the primary question: does the individual affective perception of risk at roadway junctions demonstrate concordance with empirical assessment of crash risks?
- Provide the null hypothesis: that individual affective risk perceptions have no relation to actual risk exposure.
 - If true, then promoting an increased safety culture could be as simple as presenting a more visible representation of actual roadway junction risk and severity of consequences.
 - If false (implying drivers are cognizant of their risk exposure), then increasing the safety culture relies on decreasing the acceptance of dangerous driving behaviors, possibly by emphasizing driver education and increased enforcement initiatives.

Summary Review

Drivers' affective perception of risk guides their decision making in the automotive environment. Drivers often underestimate their risk, and overestimate their abilities, but it is not clear how these errors are manifested, especially when considering the spatially heterogeneous distribution of crash risk in the automotive environment. Currently, the automotive environment poses a significant risk of injury or death to all participants (drivers and non-drivers alike). Understanding drivers' perception of risk in this environment could help improve driver education, law enforcement initiatives, and the design of infrastructure that encourages safer driving. These steps are critical in fostering a safety culture that seeks to eliminate traffic fatalities. A more thorough review of these ideas is presented in the next chapter.

CHAPTER II

LITERATURE REVIEW

Promoting public safety for all users in the automotive environment relies on a thorough understanding of the risks inherent to the system, and by extension, the individual's ability to perceive and assess these risks. This review begins by outlining the geographic perspective, and then describes the history of risk perception studies, and most specifically, the interest in the risk perception of drivers. Last, there is a discussion of methods available to empirically model crash risk, and to survey individual perceptions of drivers. This review provides justification for the present study and context for the methods used.

The Geographic Perspective

The psychological elements of this study are, perhaps, the most readily apparent, but, it was a geographic perspective which led to this line of inquiry. This interdisciplinary approach may require clarification for some. Therefore, it is beneficial to begin by anchoring this study to its geographical tradition, while acknowledging the inherently interdisciplinary nature of the problem.

The link between the geographical and psychological disciplines can be traced back to the "Quantitative Revolution" (Golledge, 2002, p. 3), which encompassed the development of a behavioral specialization in geography and a growing interest in the individual decision-making process (Cox & Golledge, 1969; Johnston, 1981, p. 28).

Robert Beck, in 1967, argued that neither geography nor psychology alone could answer questions about human-environment relationships (Beck, 1967; Golledge, 2002).

Restated, an individual's perception of their environment shapes their decision-making process, and in turn, heavily influences behavioral outcomes (Downs & Stea, 1974; Golledge & Stimson, 1997; Jakle, Brunn, & Roseman, 1976; Kitchin & Blades, 2002).

Behavioral research in geography has since become a formalized and methodological emphasis area (Aitken & Valentine, 2014). Within this emphasis, there is also a specific focus on micro-scale environments and related perceptions (Golledge & Stimson, 1997, p. 9). Further guiding this exploration is the identification of key psychological variables underpinning environmental perception, such as our affective perceptions (Golledge & Stimson, 1997, p. 26; Johnston, 1981, p. 135).

Finally, although underrepresented in geographic literature, there is the link between environmental perception and the evaluation of risk (Golledge & Stimson, 1997). These concepts, rooted in geographic tradition and borrowing from psychology, guided the perspective and language of the review, methods, and analysis.

Foundations in Risk Perception

Risk, in its most basic definition, is any exposure to potential danger, loss, or injury (Risk, 2010). Practical usage of the term in research has, unfortunately, been inconsistent. There is a clear contention that risk should only be used to describe known and objective probabilities (Johnston, 1981). However, risk has been widely used to reference the subjective perception of these probabilities (Fischhoff, Watson, & Hope,

1984; Gill, 2004; Rowe, 1975; Vlek & Stallen, 1980). The term has also been used more generally (though arguably incorrectly) to reference the hazards, outcomes, and consequences themselves, all while ignoring the aspect of probability altogether (Slovic, 1999). This research uses the definition of risk offered by Golledge and Stimson (1997), in which the use of risk may refer to both the objective and subjective probabilities of loss or injury. In the context of the automotive environment, risk refers to the probability of experiencing a reportable collision; this definition should provide the greatest clarity for comparing the subjective perception of crash risks to the empirical crash data records.

Investigation in risk perception is a growing discipline. Among the earliest of seminal works is that of Chauncey Starr in 1969. His research concluded that voluntary risks, such as those taken in automotive travel, are perceived to be far more acceptable than involuntary risks, or those risks derived from decision-making at institutional or governmental scales. This early work confirmed the role of subjective perceptions in risk analysis, and was partly responsible for the interdisciplinary Society of Risk Analysis and its associated journal (Deisler & Schwing, 2000).

Research in risk perception has increasingly focused on subjective risk assessments at the individual level. Key factors in subjective risk perceptions were expanded to include the illusion of control, familiarity, knowledge, and immediacy, in addition to Starr's voluntariness (Fischhoff, Slovic, Lichtenstein, Read, & Combs, 1978; Rowe, 1975; Vlek & Stallen, 1980). The role of individual psychology became inseparable from risk analysis, thus prompting development of the "psychometric paradigm" (Slovic, 1992).

The psychometric paradigm guided subjective risk perception research into the current millennium. Studies focused primarily on addressing and attributing variations in subjective risk perceptions to cultural, demographic, and experiential traits. Boholm (1998) provides an exhaustive review, concluding that clear distinctions in risk perception exist among specific sample groups. Typically, women tend to be more sensitive to risk, and more risk averse than men when controlling for other sociodemographic traits. In contrast, individuals having more extensive educational backgrounds or holding a higher socioeconomic status tend to be less sensitive, and less averse, to risk-taking behaviors.

The effects of nationality and culture on risk perceptions, if any, are not well understood. Cross-national and cross-cultural comparisons of study results are difficult due to inconsistent survey content, inconsistent control of demographic and experiential variables, and significant temporal gaps between studies (Boholm, 1998). Further, efforts to identify sociocultural groups and to correlate their shared biases in risk perceptions have yielded inconclusive results (Marris, Langford, & O'riordan, 1998) and harsh criticisms (Boholm, 1996; Sjöberg, 2000).

Improving our understanding of risk perception enables the development of campaigns that might promote a broader public awareness of safety concerns in the automotive environment. This awareness is needed to foster a safety culture and to reach a public consensus capable of driving political support (Lerner et al., 2010; Loewenstein et al., 2001; Pachur, Hertwig, & Steinmann, 2012; Starr & Whipple, 1980; Ward et al., 2010). This perspective requires a focus on the psychometric paradigm and the

perception of the individual, and benefits from the existing foundations of knowledge concerning demographic and experiential biases in risk perception (Boholm, 1998; Kahneman, 2011; Rundmo & Nordfjærn, 2017; Vlek & Stallen, 1981).

Affective Risk Perception

Affective perception, and its relation to cognition, has captured a prominent focus in psychology literature; it has also become increasingly integral to the study of risk perception. The individual's affective system — a complex of feelings, emotions, and intuitions — is given primacy in the formation of our perception, preceding cognition and decision-making (Kahneman, 2011; Tomkins, 1962; Zajonc, 1980). Affect, then, has an important influence on the outcomes of risk perception (Johnson & Tversky, 1983).

Individual assessments of risk permeate everyday decision-making processes. A large majority of risk decisions are relatively insignificant, thus made quickly and subconsciously. This does not eliminate the process of cognitive analysis in risk assessment, but it does suggest that affect is the predominant means for individual evaluations of risk (Finucane, Alhakami, Slovic, & Johnson, 2000; Keller, Siegrist, Gutscher, 2006; Pachur et al., 2012; Slovic, Finucane, Peters, & MacGregor, 2004; Slovic & Peters, 2006). It becomes imperative, then, to understand how an individual makes affective judgements.

Affective perception is subjective and innate, dependent on what an individual remembers. The recollection of direct and indirect experience, communication, and education — the “availability heuristic” — is assumed to guide our affective perception

of risky scenarios (Boholm, 1998; Golledge & Stimson, 1997; Kahneman, 2011; Keller et al., 2006; Linden, 2014; Reason, 1990; Tversky & Kahneman, 1973). Furthermore, there is a striking divergence between this affective perception of risk, and more thoughtful, cognitive analyses of risk (Loewenstein et al., 2001). Hence, decision-making and the behavioral response resulting from affective perceptions are expected to vary significantly from responses driven by cognitive thought. This suggests that there are specific conditions under which an individual forgoes the cognitive approach in favor of purely affective responses.

The reliance on affective perception, rather than cognitive assessment, results from external limitations. One limitation is a lack of knowledge of potential risks (Kuklinski, Metlay, & Kay, 1982). More pervasive limitations, however, are imposed by time and by cognitive load. When pressured for time, an individual forgoes the complex consideration of probabilities, alternatives, outcomes, and consequences; this provokes a reliance on the affective system of perception for guiding decision-making (Finucane et al., 2000; Slovic et al., 2004; Slovic & Peters, 2006). Similarly, cognitive overload (e.g., from holding an interactive conversation) increases the latency of driver reactions, and further stresses the decision-making process (Brookhuis & De Waard, 2010; Lambale, Kauranen, Laakso, & Summala, 1999). Such overloading is expected to arise quickly in driving situations (De Waard & Brookhuis, 1991). This understanding provides rationale for studying individual affective perceptions of risk in the fast-paced and highly dynamic automotive environment.

Automotive Risk, Driver Perception and Behavior

Understanding affective risk perception in the automotive environment requires a discussion of automotive risk and driver behavior. Foremost, it is key to acknowledge that the process of risk perception is independent from measured reaction times (Currie, 1969). This is, in part, due to behavioral responses in driving scenarios occurring before the actual identification of a risk. Drivers who avoid crashes do so by responding well before the appearance of a risk; this is likely a result of past experiences prompting an affective perception of potential risk (Ba, Zhang, Chan, Zhang, & Cheng, 2016). Experience, knowledge, and awareness of potential risks may improve driver response, but the improper perception of risk might just as well stimulate reactions that aggravate the development of risk (Currie, 1969). Successfully navigating the automotive environment requires extensive practice and experience, which serve to improve the affective response to risk stimuli (Deery, 2000; DeJoy, 1989; Groeger & Brown, 1989).

Drivers typically underestimate their risk exposure. The minor severities involved in most automotive collisions (often limited to property damage), coupled with the chronic and persistent nature of the risk contributes to the underestimation of risk (Rundmo, Nordfjærn, Iversen, Oltedal, & Jørgensen, 2011; Slovic, 1999). In addition to the familiarity of traffic risks, the underestimation of risk is also a byproduct of both the voluntariness of the activity and the perceived controllability of the risk scenarios (DeJoy, 1989; Fischhoff et al., 1978; Friedland, Keinan, & Regev, 1992; McKenna, 1993; Rowe, 1975; Starr, 1969; Vlek & Stallen, 1980; Wohleber & Matthews, 2016).

Coupled with the underestimation of empirical risk, drivers also overestimate their own ability to manage and mitigate automotive risks. Primarily, drivers overestimate their driving abilities relative to their driving peers (DeJoy, 1989; Glendon, Dorn, Davies, Matthews, & Taylor, 1996; Gregersen, 1996; Harré, Foster, & O'Neill, 2005; McCormick, Walkey, & Green, 1986; Svenson, 1981; Wohleber & Matthews, 2016). Drivers also overestimate their ability to manage driving tasks while impaired or tired (Wohleber & Matthews, 2016), and overestimate the abilities of their vehicles (Svenson & Eriksson, 2017). Not only do drivers overestimate their driving skill, but they further compound these risk factors by engaging in secondary tasks, such as talking or texting on cell phones, eating, or applying makeup while driving (Li, Gkritza, & Albrecht, 2014; Vanlaar & Yannis, 2006; Wohleber & Matthews, 2016). The overestimation of driving abilities is particularly prevalent amongst young and inexperienced drivers (Crundall et al., 2012; Deery, 2000; DeJoy, 1989; Finn & Bragg, 1986; Glendon et al., 1996; Gregersen, 1996).

The concurrent underestimation of risk and overestimation of ability contributes to risk-taking attitudes and behaviors (Deery, 2000; DeJoy, 1989; Gehlert, Hagemester, & Özkan, 2014; Ulleberg, 2001; Wilde, 2001). Furthermore, this perspective implies that increasing automotive safety through technological or engineered solutions would only serve to increase the risk-taking behavior of drivers (Charlton et al., 2014; Peltzman, 1975; Wilde, 2001). It is argued, then, that the widespread underestimation of risk and overestimation of abilities by drivers inevitably produces an unacceptably high crash, injury, and fatality rate in automotive environments. Addressing these attitudes requires

the promotion of a safer driving culture that acknowledges and embraces a clear understanding of crash risk (Falk & Montgomery, 2007; Lerner et al., 2010; McNeely, & Gifford, 2007; Ward et al., 2010). Such promotion relies on an understanding of current affective perceptions of risk, specifically at roadway junctions with exceptionally high crash risks.

Empirical Crash Risk Analysis

Evaluating the subjective perceptions of risk in the automotive environment is reliant on the objective assessment of individual crash risks. There are numerous procedures for conducting this empirical assessment, each with a unique set of strengths and weaknesses (Lord & Mannering, 2010; Montella, 2010). Some methods restrict analysis to crash frequency, while others attempt to include weighted measures of crash severity and crash rates (Savolainen, Mannering, Lord, & Quddus, 2011; Tarko & Kanodia, 2004). There is also a distinction between the identification of dangerous sites and the additional efforts required to extend this analysis to sites having potential for improvement (Hauer, 1996; Jonathan, Wu, & Donnell, 2016). Crash risk is spatially heterogeneous, although crash frequencies are generally significantly higher at road junctions (Evans, 2004, p. 351; Vanderbilt, 2008, p. 178). Therefore, this study will emphasize the identification of dangerous roadway junctions, relying on an assumption that those sites with a history of high crash rates represent a proneness for the future risk of automotive crashes (McGuigan, 1987, pp. 61–62).

The interest in crash risk to the individual road user implies a preference for the use of crash rate, or the number of crashes normalized for average traffic flow (Hauer, 1996; Montella, 2010). Calculating the crash rate requires the designation of analysis sites, including a summary count of crash occurrences and traffic flow data for each site (Hallmark, Basavaraju, & Pawlovich, 2002; Huang et al., 2016; Pawlovich, 2007). Despite being straightforward, this method is reliant on an assumption of accurate traffic flow data, and furthermore may bias the rank-list towards roadway sites having relatively few crashes coupled with low traffic volumes (Montella, 2010; Zegeer & Deen, 1977).

Modifications of the crash rate analysis can minimize the exaggeration of roadway sites with low traffic volumes. One suggestion is to establish a minimum threshold of crash frequency for inclusion of a particular site before establishing a rank-order listing by crash rate; this combination of frequency and rate methods accounts for the deficiencies of either method taken by itself (Hauer, 1996; Pawlovich, 2007; Zegeer & Deen, 1977). This method provides a meaningful assessment of crash rate, however, fails to address concerns of crash severity.

Crash severity, generally measured by property damages and injury outcomes, also warrants consideration as a relevant risk factor for road users. As with frequency analysis, there are several relevant methods (Pawlovich, 2007; Savolainen et al., 2011). The equivalent property-damage-only (EPDO) method is relatively straightforward, and therefore commonly used (Hauer, 1996; Zegeer & Deen, 1977). The procedure eliminates the additional categorization of crash severity, instead transforming injuries and fatalities to an appropriately weighted measure of property damage. The weighting

strategy used, however, introduces an aspect of subjectivity to the results (Pawlovich, 2007). Nonetheless, because of the spatial differentiation between the frequency and severity of crashes (Dezman et al., 2016), it seems prudent to account for both as factors of risk. The resulting EPDO index can also be normalized for traffic flow to produce an EPDO rate, which then reflects the risk faced by individual users in the automotive environment (Hallmark et al., 2002; Hauer, 1996; Montella, 2010; Pawlovich, 2007; Zegeer & Deen, 1977).

There are additional methods that provide an analysis of risk probabilities beyond frequency, severity, and rate. Such methods increase the complexity of the calculations, introduce additional subjectivity, and often require intensive data collection and management. The simplest of these methods incorporates a statistical test of significance to compare crash frequencies and rates against a predetermined critical value using a Poisson distribution; sites are then ranked according to a ratio of each site's test value and the critical value (Hauer, 1996; Lord & Mannering, 2010; Pawlovich, 2007; Zegeer & Deen, 1977). This method requires developing a categorization of sites, and does not typically integrate measures of severity. Popular extensions of this method make use of Negative Binomial distributions, and the application of Bayesian statistics (Cheng & Washington, 2005; Lord & Mannering, 2010; Montella, 2010; Savolainen et al., 2011). Although such models are informative, in many cases simple rankings or confidence intervals are sufficient (Cheng & Washington, 2005).

A broad range of methods are available for analyzing crash data and, by extension, identifying sites with exceptionally high levels of crash risk. Pursuing an

analysis of the individual perception of risk, this research aims to identify roadway junctions posing high levels of crash risk to the individual road user. This aim supports the utilization of a method that reflects crash rate (Hauer, 1996; Montella, 2010), but should also feature a measure of severity. These objectives are distinctly captured by a method developing rank-order lists based on either a crash rate, a severity rate, or an EPDO rate method.

Measuring the Perception of Risk

Understanding risk as it is perceived by individuals relies on their participation. The current understanding of risk perception developed from studies showcasing an extensive variety of research designs. This variety, while potentially problematic, might simply reflect the exploratory nature of burgeoning research attempting to map risk perceptions (Downs & Stea, 1974, pp. 6–7). The unifying thread underlying this research is the application of various survey methods.

Arguably, the most popular survey method is the questionnaire. The questionnaire was foundational to, and has remained predominant in, risk perception research (*See* Boholm, 1998; Armsby, Boyle, & Wright, 1989; Deery, 2000). Although text-driven questionnaires might outwardly appear simple, the design and distribution of any survey remains a complex procedure warranting proper diligence (Dillman, Smyth, & Christian, 2014; Fowler, 1995; Iarossi, 2006; Saris & Gallhofer, 2007). One facet of this complexity is the distinction between stated and revealed preference data, which has strong implications for risk perception surveys (Fischhoff, Slovic, & Lichtenstein, 1979).

The use of a survey questionnaire to capture respondents' perceptions of roadway junctions produces a type of stated response, rather than revealed, data.

Respondents can also be asked to state their own attitudes towards risk-taking and sensation-seeking. Variations in respondents' propensity for sensation-seeking could influence their risk perception. Early versions of a Sensation Seeking Scale construct were comprised of more than 40 items (Heino, van der Molen, & Wilde, 1996; Horvath & Zuckerman, 1993; Zuckerman, Kolin, Price, & Zoob, 1964). More recently, an abbreviated version of the construct, the Brief Sensation Seeking Scale, has exhibited significant reliability and replicability (Arnett, 1994; Fan et al., 2014; Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002; Scott-Parker, Watson, King, & Hyde, 2013). The brevity of this scale is ideal for inclusion in this, and future, risk perception research.

There are more advanced experimental methods used to measure the perception of risk. Such methods typically record observable physical characteristics, such as galvanic skin responses, eye movements, or other measures of stress response and reaction time. These procedures typically require lengthy visual experiences, active-participant driving simulations, or actual on-road driving phases (Ba et al., 2016; Currie, 1969; Gregersen, 1996; Neale et al., 2002; Taylor, 1964). These experiments provide valuable insight for the study of risk perception; however, these methods are more expensive and cumbersome, and present their own sources of bias and error.

The use of visual-stimuli in a survey questionnaire provides a method that blends the simple text-driven questionnaire with cues from more advanced biometric designs. Imagery, situated as a visual stimulus, can be utilized to provide a meaningful and

quantifiable measure of affective perception (Yoon, 2010). This intriguing style of survey design has been used only sparingly in risk perception research (Beanland, Filtness, & Jeans, 2017; Chapman, Corner, Webster, & Markowitz, 2016; Cox, Beanland, & Filtness, 2017; Finn & Bragg, 1986; Glendon et al., 1996; Leiserowitz, 2006; Wetton et al., 2010). Such a survey warrants at least the same, if not more, diligence than a strictly text-driven questionnaire. Nonetheless, this method is particularly suited for the collection of individual affective perceptions of risk given visual stimuli of specific roadway junctions.

Summary Review

This chapter has provided a thorough review of topics central to the present research. The geographic perspective is understood to have prompted an inquiry towards the spatial distribution of risk in the automotive environment, and in turn as to how such risk is perceived by individual participants in such a setting. This inquiry is shown to be inseparable from the psychological discipline, and furthermore, situates itself within the ongoing and interdisciplinary study of risk perception.

The breadth of studies over risk perception generate several considerations pertinent to this research. This literature review suggests an expected divergence between objective measures and subjective perceptions of risk, and supports a study design which utilizes the psychometric paradigm (a quantitative methodology) to record responses to a questionnaire regarding an individual's perception of risk. Additionally, there is motivation to control for gender and demographic biases throughout the data

collection and analytical process. Lastly, the affective system, and its influence over individual risk perceptions is also considered and reviewed.

These considerations are directly extensible to the perception and resulting decision-making processes of drivers in the automotive environment. Drivers generally overestimate their own ability and also underestimate their risk exposure. This almost certainly contributes to current crash and injury rates in the automotive environment, and seems to provoke a general resistance or ignorance towards traffic safety advocacy and continued driver training.

To better understand risk perception and decision-making of active drivers, it is imperative to expand our understanding of the subject. To provide a stronger foundation for this research, the review continues with a discussion of methods for the empirical identification of crash hotspots. This discussion highlights the EPDO rate methodology for its ability to incorporate measures of crash frequency and severity in a single index. There is also a review of the methods useful for collecting the individual's affective perception of risk; further discussion outlines the distinction between popular survey methods (e.g., text-driven questionnaires) and more advanced biometric methods (using simulators and physiological sensors). The use of a visually-stimulated survey serves as a reasonable compromise for this thesis. The combination of crash hotspot indices and respondent survey enables a comparison between empirical measures of risk and the subjective perceptions of risk.

CHAPTER III

METHODS

This research was designed to compare individual perceptions of risk against an empirical assessment of risk at roadway junctions and to contribute to the understanding of risk perception and traffic safety. This chapter describes the design, data, and procedures used for this research. Procedures included an exploratory regression analysis of statewide crash data in the state of Iowa, and the development of a geographic information systems (GIS) procedure for identifying crash hotspots at various scales within the state. Following these procedures, the digital survey instrument is described, including design, the use of imagery, and the method of distribution. The chapter concludes with an overview of methods used to assess various risks associated with crash hotspots, to analyze survey response data collected from members of targeted digital communities, and the statistics used to evaluate concordance between empirical assessments of crash risk and individuals surveyed perceptions of risk (Figure 2).

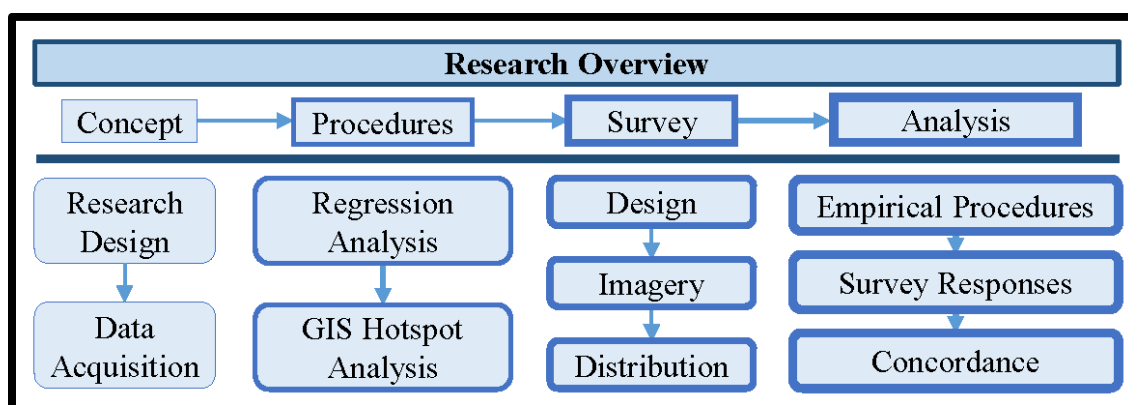


Figure 2: Research Overview

Research Design

This research utilized a mixed-methods approach to investigate risk perceptions in traffic safety. Research began with a regression analysis of the population of crash records in the state of Iowa. The statewide regression aided in defining and contextualizing the local study area within Black Hawk County. Within this county extent, a geographic information systems (GIS) procedure identified potential crash hotspots. Hotspots, and their crash histories, were used to assess and rank risk factors for these road junctions. From these rankings, a photography-driven survey instrument was designed to record individual perceptions of risk at selected intersections. Analyses assessed the leading research question: is there concordance between empirical measures of risk and the individual perceptions of risk (Figure 3)?

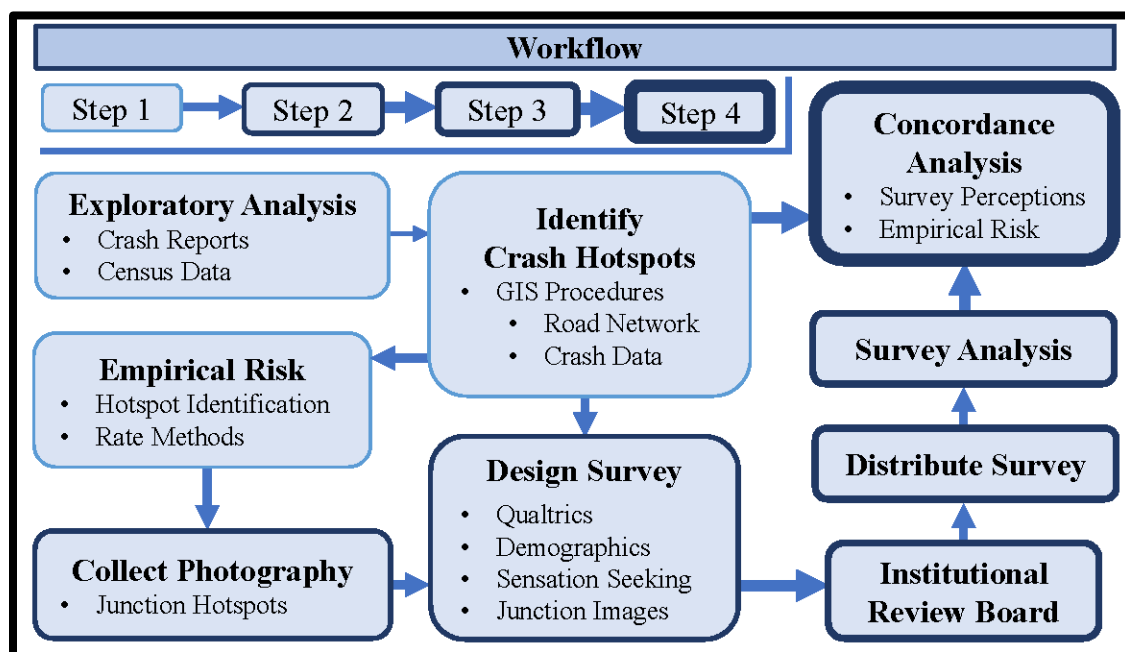


Figure 3: Workflow

Data

Data acquisition began with secondary datasets obtained from public agencies. Crash records were requested from the Iowa Department of Transportation (IaDOT). The received database included records from the year 2007 through 2016. The underlying road network data was also provided by the IaDOT. The 2015 American Community Survey (United States Census Bureau, 2016) provided demographic estimates for all Iowa counties (Table A1). These datasets were used in the empirical procedures, and provided estimates of crash risk. These data were then used to develop, distribute, and analyze a survey instrument that gathered new primary data revealing drivers' risk perceptions (Figure 4). Data was managed and analyzed with procedures in ArcGIS Suite, Microsoft Excel 2013, TIBCO Spotfire S+, and RStudio (Appendix B).

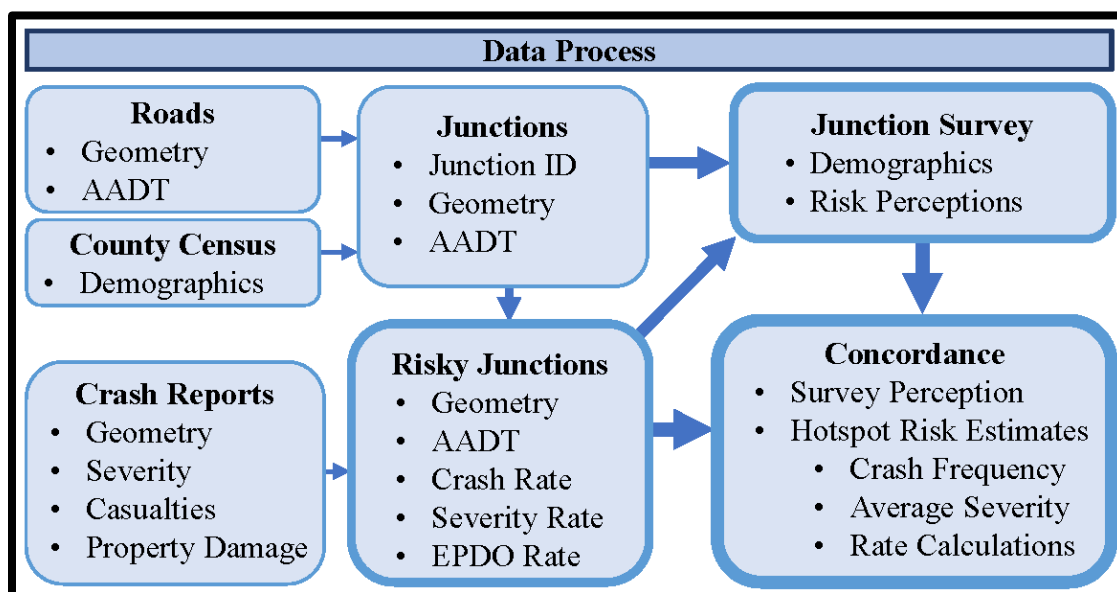


Figure 4: Project Data Flow

Exploratory Analysis of Iowa Counties

An exploratory analysis was conducted to assess the full population of crash records and to provide context for smaller scales of analysis. A regression model estimated county-wide crash counts as a function of total land area, percentage of land area in incorporated urban areas, population counts of adults 16 and over, percentage of population employed in agriculture, median household income, total length of state and national highway, and the total length of transnational interstate highway.

Backwards elimination linear regression (a process of eliminating insignificant variables from the fitted regression model) produced an accurate model ($R^2 = .9829$) with three variables: population count of driving age adults, percent of urban land area, and length of transnational interstate highways. Two additional regressions were analyzed, each adding a variable term to account for possible spatial correlations (one using a simultaneous auto-regressive term, and the other a moving-average term). The neighborhood structure considered any two counties sharing any length of border as neighbors. These regression models defined Iowa's counties and their crash histories.

This exploratory analysis revealed residual error in modeling crash rate predictions for Iowa's most highly urbanized counties. This effect was most pronounced for Polk County (and the capital city of Des Moines), but also affected Linn County (Cedar Rapids) and Johnson County (Iowa City and Coralville). Black Hawk County was influential in the regression (as measured by Cook's Distance), however was not a significant outlier.

These regressions defined potential counties suitable for a microscale crash hotspot analysis. Although urban counties exhibited residual error from the predicted model, these counties are also host to the most extensive crash records. Black Hawk County does not represent the majority of Iowa's rural counties, but it does serve as a proxy for Iowa's more heavily urbanized counties. Black Hawk County was chosen for its fit to the regression model, its representation as a highly urbanized Iowa county, its low length of transnational interstate highway, and for its locality to the research institute.

Procedure for Crash Hotspot Identification

Crash hotspots — roadway sites which present road users with an increased probability of crash occurrence and severity — were identified through an empirical procedure that joined crash reports to spatial locations. This assessment relied on the assumption that a history of high crash frequencies and severities predicts a future proneness for automotive collisions (McGuigan, 1987, pp. 61–61). The procedure created data defining crash hotspots in Black Hawk County and provided several indexes for empirically measuring risk.

The Iowa Department of Transportation's crash report data included a spatial point location in addition to a comprehensive set of attributes detailing conditions of the driver, vehicle, environment, and severity. Reports are filed by law enforcement officials either of the local jurisdiction or the Iowa State Patrol. Pertinent details for this research included the crash severity (reported categorically on a scale of 1 to 5), as well as the count of fatalities, major injuries, and property damage estimates.

ArcGIS (a geographic information system) was used to develop the dataset of crash hotspots (Figure 5). Road-line data were parsed into a planar network, and processed to create a point feature class of road junctions that included a sum of the annual average daily traffic (AADT) from each approaching road segment. A polygonal buffer with a radius of 50 meters was drawn around each road junction point. Where two or more buffers overlapped, the polygon with the highest AADT was preserved, while any overlapping buffer with a lower AADT was erased (Appendix C). Crash report point locations within remaining buffers were spatially joined to the associated junction point.

Data summarizing crash reports for each junction were calculated. This table featured each junction as a single row, and included attributes such as the count of crashes (representing crash frequency), and a sum of severity classifications, injuries, and fatalities. The Equivalent Property Damage Only value, or EPDO, was also calculated to provide a composite value of fatalities, injuries, and property damage; fatalities were accounted using the “Value of a Statistical Life,” or \$9,600,000, and each reported major injury was valued as one tenth of a statistical life, or \$960,000 (Timothy, 2016, p. 1).

The summary values (crash count, sum of severity, and EPDO) for each junction were normalized using AADT, to provide an estimate of respective rates. The use of AADT introduces a potential source of error in the calculation, due to issues inherent to traffic monitoring. Nonetheless, these rate calculations provide the best estimates of personal risk exposure for individual drivers.

The resulting list of crash hotspots and risk rates required further modification. To mitigate the inflation of junctions having relatively low traffic volumes (and thus an

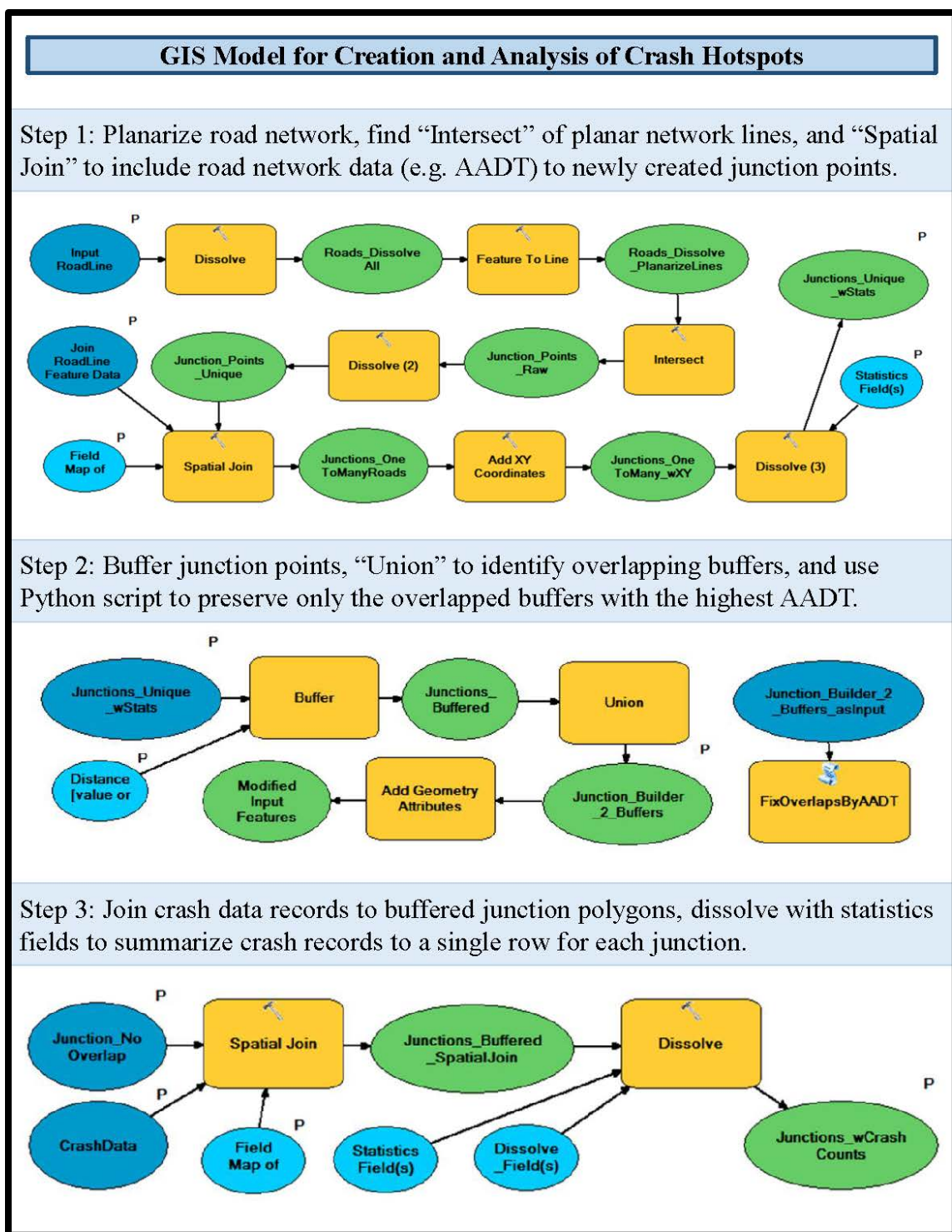


Figure 5: GIS Model for Creation and Analysis of Crash Hotspots

absurdly high risk rate), a “rate and numbers” method was used to refine the risk indices to include only intersections with at least 3 reportable collisions in the decade of data (Hauer, 1996; Pawlovich, 2007). These considerations produced a collection of hotspots representing road junctions frequently encountered during a typical daily drive, including residential connectors, commuter thoroughfares, and urban arterials.

Intersection hotspots were ranked according to the developed measures of risk. These included intersection crash frequency and average crash severity, as well as the more personal risk measures of crash rate, severity rate, and EPDO rate. These indices were replicated to ascertain the context for hotspots within the county, within the city of Cedar Falls, and of those hotspots tied exclusively to the survey design. Each risk factor provided a separate index, each a unique, yet empirical estimate of risk. These indices provided foundations for the development of a survey questionnaire featuring visual stimuli, and furthermore, provided for an analysis of concordance between empirical and perceived risks.

Survey Imagery

Several crash hotspots throughout Cedar Falls were photographed for use in the community survey. Images were recorded using a camera and motor vehicle mount, which were necessary for capturing intersection imagery while participating in active traffic conditions. Furthermore, this platform achieved economic practicality and personal availability. The process of image collection was thoroughly planned and the selection of final survey images given due care.

Imagery Collection

An original series of road intersection images were collected to suit this research. As much as possible, collection controlled for variable conditions such as the weather, season, time of day, and traffic. After processing, 38 images depicting 22 different intersections were considered for the survey instrument.

Images were captured using an Activeon CX Action Camera featuring a 5 megapixel camera sensor configured to collect a “Wide” field of view. The action camera was mounted on a 2007 Kawasaki Vulcan. Images were captured from a time lapse mode, capturing a single still photo every three seconds. This system (Appendix B) recorded more than 4,500 images totaling over 7.5 gigabytes.

Intersection photo targets were selected from the hotspot index to represent both high and low risk rankings, as well as a cross section of urban, suburban, and rural intersections. Road junctions that have been redeveloped, reconstructed, or altered in recent years create an issue in comparing current perception to historical measures of crash risk. Therefore, such sites were avoided during image collection.

All intersections photographed were selected from within Cedar Falls (a city within Black Hawk County). Collection occurred during the months of June, July, and August of 2017 between the hours of 10:00 am and 2:00 pm. Most intersections were photographed several times so as to capture an image with the least visible traffic possible. Many intersections were filmed from multiple approaching road segments.

Due to rotations of the camera on its mount, some photographs required a slight rotation to correctly align their respective horizons. This procedure was performed using

the GNU Image Manipulation Program (Appendix D). All of the images were constrained to 432 pixels by 324 pixels and stored in a JPEG file format; this was done to minimize bandwidth and increase accessibility for survey respondents.

Final Image Selection, and Considerations

The digital survey instrument featured 23 original images (Appendix E, Figure E1 and E2). The first 3 images were provided as a warm-up exercise for respondents; these images featured intersections depicting the range of intersection size and traffic densities within the study area. The experimental visual block featured the remaining twenty images. Eight intersections were each featured in 2 images; each pair of images depicted perpendicular roads approaching the same intersection (e.g., one image with a perspective facing north, the other a perspective facing west). One final intersection was featured in 4 images, which included all of the possible approaching roads for that intersection. This imagery was expected to represent the field-of-vision of a driver traveling through an intersection at speed, demanding an affective judgement of risk (Figure 6).

The camera lens captured a wide angle perspective of the hotspot intersections. This wide field of view captured peripheral details of the intersection, but also introduced potential distortions in the resulting imagery (all camera lenses impart some distortion to captured images). This lens also captured the sun in south facing imagery, which caused these images to appear overexposed, and unsuitable for the purpose, thus limiting the selection of south facing imagery in the final survey instrument.

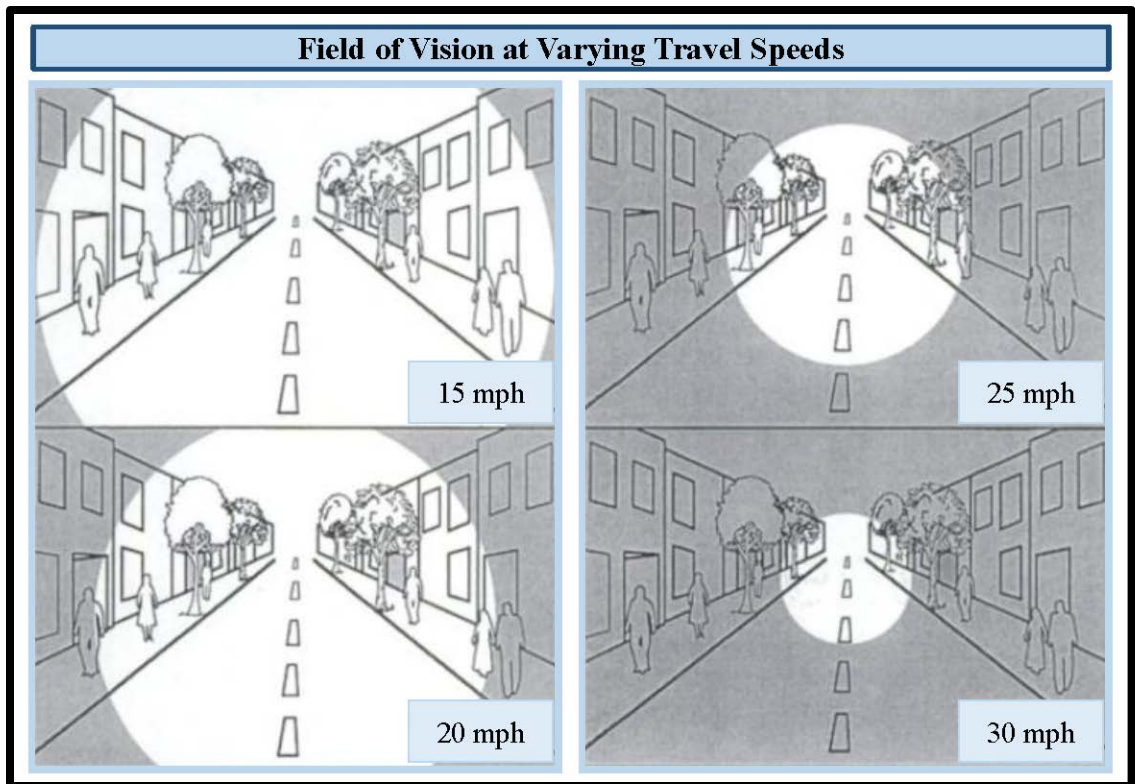


Figure 6: Changing Field of Vision at Speed (Reproduced from Nozzi, 2003)

Despite multiple attempts at imaging, some intersections were burdened with nearly endless traffic during daytime-hours. In such cases, imagery was chosen to limit the visible traffic. Images featuring potential left-turn or right-on-red traffic were not used. In all chosen survey images, any visible traffic is at a sufficient distance as not to be expected to factor into a driver's risk perception.

There were concerns over the quality and biases in selected imagery survey; concerns of visible traffic, weather conditions, and the relative sun angle were considered and controlled. Despite potential limitations, this method of image collection proved more consistent than other alternatives, such as Google's Streetview. Furthermore,

increasing the quality of imagery was expected to significantly increase equipment costs, necessitate closing of active city streets during peak hours, or both. Imagery collected from this procedure provided a key component in the development of the visual survey.

Design of the Community Survey

Crash risk is described in empirical measures, but also by the individual and subjective perception of the probability of a crash. Having developed an objective ranking of risk for various roadway junctions, it was necessary to collect a dataset of the individual perceptions of risk at those junctions. This dataset was gathered using a digital survey instrument designed and distributed using the Qualtrics survey platform. There were 36 questions total, with respondents expected to take less than 10 minutes. The survey included a demographics section, the Brief Sensation Seeking Scale (Fan et al., 2014), and an experimental block with image stimuli and risk scale responses (Figure 7).

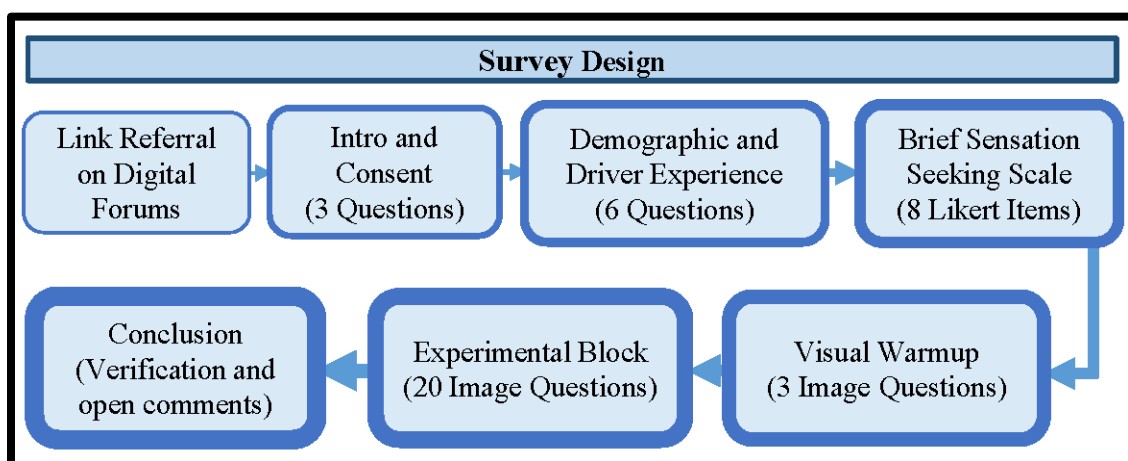


Figure 7: Survey Design

Survey Flow

The survey began with an introduction that described the purpose of the research, outlined the survey's organization, and acknowledged the use of photography some of the survey questions. Participants were asked to express their willingness to participate, to identify themselves as at least 18 years of age, and to confirm they had a valid driver's license. Respondents answering these three questions affirmatively were permitted to continue with the questionnaire (Appendix F).

The first question block consisted of six questions designed to reveal basic demographics and driver experience. Participants were asked their age and gender. They were also asked if they were a resident of the United States, for potential consideration in variations between local and international road systems. The last three questions asked individuals at what age they received their driver's license, how many miles they drove in a typical year, and to rate their driving ability.

The second question block was constructed using eight items taken from the Brief Sensation Seeking Scale (BSSS). The BSSS was designed to assess individual attitudes toward risk and thrill-seeking, and the individual's willingness to engage in risky activities (Arnett, 1994; Fan et al., 2014; Heino et al., 1996; Horvath & Zuckerman, 1993; Hoyle et al., 2002; Scott-Parker et al., 2013; Zuckerman, 1971; Zuckerman et al., 1964). The use of this scale enabled comparisons between this research and past publications, and provided additional context for risk perception responses recorded from the image-based survey questions.

The third question block introduced the visual stimuli. A brief paragraph described the presentation of photographs and the risk response scale. The response scale featured six selectable stops with one label on each end, ranging from “Far below average” to “Far above average”; this represented an ordinal continuum of risk from low to high (Gill, 2004). The choice of six stops was intentional, to avoid potential central tendency bias. Respondents were asked to provide an estimation of risk and to respond as quickly as possible (intended to capture a more affective risk response). Respondents were also informed that the photography was not intended to be misleading.

Respondents were presented with a total of 23 image-based questions. Each question featured a single image along with the risk response scale centrally-aligned below the image; each survey featured the same 23 road-junction images. This imagery presented the perspective of a driver approaching to stop at the junction just prior to the legally designated stop-line. The sequencing of the first three image questions was the same for all surveys, providing a warm-up exercise for respondents, and a measure of control for later analysis. The last twenty images were then presented in a random sequence using a built-in feature of the Qualtrics platform.

The survey concluded with two questions. One question asked participants to type in their birth year, which coupled with the age question from the demographics block, provided another means of verifying respondent integrity and the reliability of their responses. A second question invited participants to provide additional comments, suggestions, or feedback. The survey was intentionally as short as possible, to encourage a higher response rate and reduce respondent fatigue.

Digital Development Process

The survey instrument was designed in a digital format within the framework of the Qualtrics survey software. This software is well documented (Snow, 2011). Nonetheless, it is valuable to report on the capabilities of this platform for future replication. These capabilities include modern accessibility, survey flow controls, advanced customization, as well as intuitive and feature-rich interfaces for tasks such as the integration of imagery.

The Qualtrics web-based interface was readily accessible from any computer workstation with internet access. This interface was responsive using a relatively weak, but highly portable ChromeOS netbook (Appendix B). Furthermore, the interface included many user-friendly, point-and-click, and drag-and-drop style elements for designing the survey instrument.

A key aspect of the Qualtrics design experience was its control over survey flow. These control tools enabled easy reordering of large blocks of the survey instrument. Advanced flow control tools provided advanced logic tree functionalities, such as basic if, and, or statements, multiple conditional statements, nested functions, and boolean display logic. This level of control over the survey order and display can be used to tailor the presentation of survey blocks to respondents based on their answers to earlier questions. In this research, these controls were used to present visual cognition questions in a randomized order, and to prematurely end the survey for respondents who failed to provide their consent, were under age 18, or did not have a driving license.

Qualtrics also provides fine control over the survey's appearance, including details of the question prompt and the question response controls. Formatting for this survey was primarily left to default text and question settings, chosen from the interface. Images were integrated through the Qualtrics interface. The interface include a robust photo album feature, and point-and-click user controls for placing and controlling an image's pixel display size, alignment, and mouse-over text; these customizations require no prior coding experience. The interface generates the underlying HTML coding, enabling an advanced user to provide additional markup coding to the image, question block, and page elements. In this research, these tools were used to align and center the text-prompt, image, and risk-estimation scales for image-based questions.

Distribution of the Visual Survey

The survey was digitally distributed through postings of unique and traceable hyperlinks created within the Qualtrics interface. A new research account was created for each specific community targeted, and from this account each link was posted only one time to the user community. These links functioned the same as a Qualtrics anonymous, multiple-complete link, with the exception that it provided information as to the originating community of each respondent. This additional demographic data became a fundamental element of the empirical analyses. No incentives for participation were provided, and participants were fully informed of the nature of the survey. The Institutional Review Board at the University of Northern Iowa approved the survey instrument for distribution prior to recruitment.

Trackable Links

Unique links were created in Qualtrics to track the originating community of each survey respondent. This link-tracking was achieved using features of Qualtrics and Google's Gmail. In Qualtrics, the survey options were configured for "Open Access" (enabling multiple-completes per single generated link), and to "Prevent Ballot Box Stuffing" (allowing only one entry per physical hardware device). In the Qualtrics Contact Manager, several new email contacts were created, one for each unique survey link; each contact was created using the email address of the researcher along with the addition of a unique filter term. (Adding "+Link1" in a Gmail address does not change the intended recipient, though this tag is useful for tracking; e.g., investigator+Link1@gmail.com.) This unique term is then embedded in every survey response, retrievable by creating a new Qualtrics report variable using the "Recipient Email" contact field. This tracking provided an additional source of generalized demographic data, and a trust mechanism to potentially filter abusive and exploitative user groups, or "troll entities" (Chiregi & Navimipour, 2016; Herring, Job-Sluder, Scheckler, & Barab, 2002).

Survey links were emailed to the investigator. Each email contained a unique link as described above, and was configured to allow multiple completes (an advanced option within the Qualtrics e-mail dialogs). The links were received by the investigator and posted, along with a recruitment statement, to the respective target audience group. Distribution began on Friday the 13th of October 2017 at approximately 9:00 am. Survey responses were finalized and recorded on Tuesday, November 7th of 2017.

Target Communities

Survey links were posted to several subreddits on the Reddit website, as well as other special interest discussion forums, and to the investigator’s personal Facebook page (Table 1). Although many sites maintain a count of the number of registered users, these numbers do not accurately portray the size of the currently active user base. One anonymous research account was able to post links to several unique subreddits, while the other web forums each required a separate new user registration to post.

Reddit.com provided an opportunity to reach multiple target communities and a large number of respondents through a single new user account. Reddit enables users to post text or hyperlinks, which then become a stand-alone web page allowing other users to comment. Although Reddit features an “All” page that shows content from any topic,

Table 1:
Target Communities

Target Communities and User Registry			
Reddit: Subreddits		Other Forums	
AskAcademia	4,909	ADV Rider	336,940
Bicycling	218,513	Bimmer Forums	711,787
Cars	432,804	Bike Forums	386,634
Flying	54,978	Edmunds	<i>No data</i>
Geography	30,433	Facebook	<i>Over 2 billion</i>
GradSchool	31,251	Grad Café	227,188
Motoreycles	351,929	Mountain Bike Review	431,973
Truckers	4,909	Nissan Infinity Club	252,405
SampleSize	54,407	*Registry data recorded 11/13/2017 12:00PM	
UrbanPlanning	35,465		
UrbanStudies	3,926		

the majority of users are expected to self-select affiliations within smaller topical hierarchies known as subreddits; the self-selected affiliations of users within subreddits serves to divide the broader Reddit audience into more specialized communities with potentially unique demographic traits.

There are limited demographic data available to describe Reddit's millions of users. Overall, Reddit's demographic skews toward younger Caucasian males (Barthel, Stocking, Holcomb, & Mitchell, 2016). However, broad generalizations do not necessarily portray the demographics of the niche communities within subreddits. Shatz (2017) provides a thorough review of using Reddit for targeted survey recruitment. This research targeted communities of bicyclists, enthusiast and professional drivers, motorcyclists, pilots, and academic users through specific subreddits: AskAcademia, Bicycling, Cars, Flying, Geography, GradSchool, Motorcycles, Truckers, SampleSize, UrbanPlanning, and UrbanStudies.

Survey links were also distributed to highly specific special interest forum and discussion web sites. These sites typically retain a regular, though limited, readership with a vested interest in the discussion topic. As with Reddit, there are limited data available for characterizing each community. Target web sites were chosen for their unique perspectives of the automotive environment. These forum included communities of bicyclists, drivers, motorcyclists, and academic users. The target websites included ADVRider.com, BimmerForums.com, BikeForums.net, Edmunds.com, Facebook.com, TheGradCafe.com, MTBR.com, and NICOClub.com.

Analysis of Data

Despite the brevity of the survey instrument, the response data necessitated several analyses. These analyses began with an investigation of the survey method, and the demographics of respondents. An analysis of the Brief Sensation Seeking Scale provided additional context for respondent demographics and their respective communities. Lastly, correlations and case studies were used to assess the concordance between empirical measures of risk and the subjective perceptions of risk.

The visual design and digital distribution aspects of the survey instrument were both regarded as experimental methods, prompting an analysis of the success and limitations of this survey methodology. First, a quantitative analysis was used to assess the total number of responses, the survey completion rate, and the observed respondent loss throughout the survey. Second, qualitative analysis was used to summarize the general reception of the survey amongst various communities.

An analysis of the respondent demographics reinforced the findings from the analysis of the survey method, and provided context for comparing respondent's perceptions of risk to empirical measures of risk. Self-reported demographic details were analyzed through comparisons of respondent's communities, driving experience, gender, and residency. Summary statistics were reviewed and visualized for each classification of the total respondent pool.

The Brief Sensation Seeking Scale (BSSS) was also considered as one aspect of the respondent's demographic data. Correlations and variable inflation factors were used to test potential multicollinearity amongst the eight Likert items of the BSSS. Additional

Pearson's product-moment correlation coefficients were calculated for each of the BSSS items and respondent's self-reported demographic details. Generalized linear models and cellular reference models assessed the predictive power of the BSSS and further distinguished differences amongst respondent's community affiliations.

The final analyses were designed to answer the leading research question regarding driver's perception of risk and potential concordance between these perceptions and the actual risks posed by the automotive environment. First, Pearson's correlations were used to assess concordance between drivers' perception of risk and five distinctive measures of risk propensity (crash rate, severity rate, equivalent-property-damage-only rate, crash frequency, and average crash severity). These correlation tests were repeated for the perceptions of risk within respondent communities, and for varying degrees of the BSSS. Second, the variance between risk perception for each image-pair was examined (each intersection in the survey was shown in two images, each a different approaching road segment). Finally, select intersections were reviewed as case studies, granting deeper insight into the way in which drivers form their perception of risk.

Summary of Methods

This research was dependent on multiple experimental methods. Initially, crash records and road-line network data were requested from the Iowa Department of Transportation. These data were analyzed using a linear regression model, and further refined using a geographic information system to define crash hotspots, their respective crash histories, and to estimate their crash risk.

These initial analyses shaped the design and development of a digitally-distributed, visual-stimulated survey. This survey included traditional demographic questions, elements from the Brief Sensation Seeking Scale, as well as questions in response to visual imagery. These imagery questions were designed to record respondent's risk perceptions of selected crash hotspots.

A methodological analysis was completed to assess the potential success and limitations of the survey methods. This analysis included a qualitative report on the reception of the survey by various communities. A quantitative analysis assessed the completion rate and demographics from the survey distribution.

The survey provided new primary data describing respondents, their communities, and their risk perceptions. Data were analyzed with mixed-methods approaches utilizing correlations, linear modelling, and intersection case studies. The culmination of these analyses is an assessment of the concordance between empirical measures of personal risk exposure and the subjective perception of automotive risk.

CHAPTER IV

RESULTS

This chapter presents a comprehensive analysis of data collected and generated during this research. The review will begin with the results from the exploratory regression models and the crash hotspot analysis. Following these empirical procedures, the review will outline the insights gained from the survey design and distribution, including an analysis of survey respondents, their self-reported driving experience and ability, and their responses to the Brief Sensation Seeking Scale. The chapter will conclude with comparisons between the empirical measures of risk and subjective perceptions of risk in the automotive environment.

Exploratory Regression Analysis

A linear regression model assessed the population of crash records in the state of Iowa. Crash records were first aggregated by county to create 99 unique records. Using several attributes of these counties, the model was refined using a stepwise backwards elimination regression method. The resulting model accounted for the driving-age population of each county, the percentage of urbanized land area, and the length of transnational highways with an R^2 of .98 and with 95 degrees of freedom (Table 2). These findings helped to define the extent for the microscale crash hotspot analysis.

The most significant factor in the regression analysis was the population of residents over age sixteen. Results indicated that for every additional one thousand

Table 2:
Results of Exploratory Regression Analysis

Backwards Elimination Linear Regression Results Chart				
Multiple / Adjusted R-Square = 0.9834 / 0.9829				
Variable	Unit	Slope	P-Value	Significance
AreaPerc.MSA	Percent	327.5467	.0003	Very Strong
-- Each percent increase in urban area predicts an increase of over 300 crashes per decade.				
Pop.16Up	Population	.2048	.0000	Very Strong
-- Every additional 1,000 driving-age adults predicts an increase of 204 crashes per decade.				
Length.TNHwy	Meters	.0299	.0000	Very Strong
-- Every additional kilometer of highway predicts an increase of 29 crashes per decade.				

residents there was an expected increase of 204 crashes per decade. This finding was unsurprising, and represents a baseline for crash propensity among driving Iowans.

The second most significant factor in the regression analysis was the percentage of urban land area. For each percentage increase in urban land area, the model predicted an increase of over 300 crashes per decade. To better understand this result, the average land area of an Iowa county is 568 square miles, therefore a one percent increase in urban land area is approximately five square miles.

The third significant factor in the analysis was the length of transnational highway in each county. Each additional mile of highway predicted an increase of almost 30 crashes per decade. The resulting increase in crashes is expected, given the large volume of traffic these roads typically endure. It should be noted however, that a significant proportion of this traffic would be expected to come from non-resident drivers, thus skewing crash counts in counties with long lengths of transnational highways.

Several measures were used to assess the rigor of the regression model. A normal probability plot was utilized to identify significant outliers, and Cook's Distance was used to identify strongly influential points. Two counties — Polk and Linn — were both outliers and influential points, suggesting they exerted a strong influence over the predicted coefficients of the model's variable factors.

Two revisions of the linear regression model were also tested to address potential spatial spillover effects. One revision included the addition of a spatial autoregressive factor, the other revision utilized a moving average factor. Neither of these two spatial regressions resulted in notable deviations from the initial linear regression.

The most striking revelation from the regression analysis was the visible distinction between urban and rural counties (Figure 8). Iowa's rural and agrarian counties fit the model exceptionally well. In contrast, many of Iowa's more urbanized counties exhibited large residual errors. The arrangement of this error was inconsistent; some urban counties experienced fewer reported crashes than predicted, and others suffered more crashes than predicted. Polk county and the city of Des Moines suffered a significantly higher number of crashes than predicted; Wood, Webster, and Dubuque counties (Sioux City, Fort Dodge, and Dubuque cities respectively) also had higher numbers of actual crashes than predicted. Linn, Johnson, and Dallas counties (the cities of Cedar Rapids, Iowa City/Coralville, and Des Moines' suburbs respectively) fared better, having fewer crash reports than predicted. Less significantly, but still with fewer crashes than predicted, were the counties of Black Hawk, Story, and Muscatine (respectively hosting the cities of Waterloo/Cedar Falls, Ames, and Muscatine).

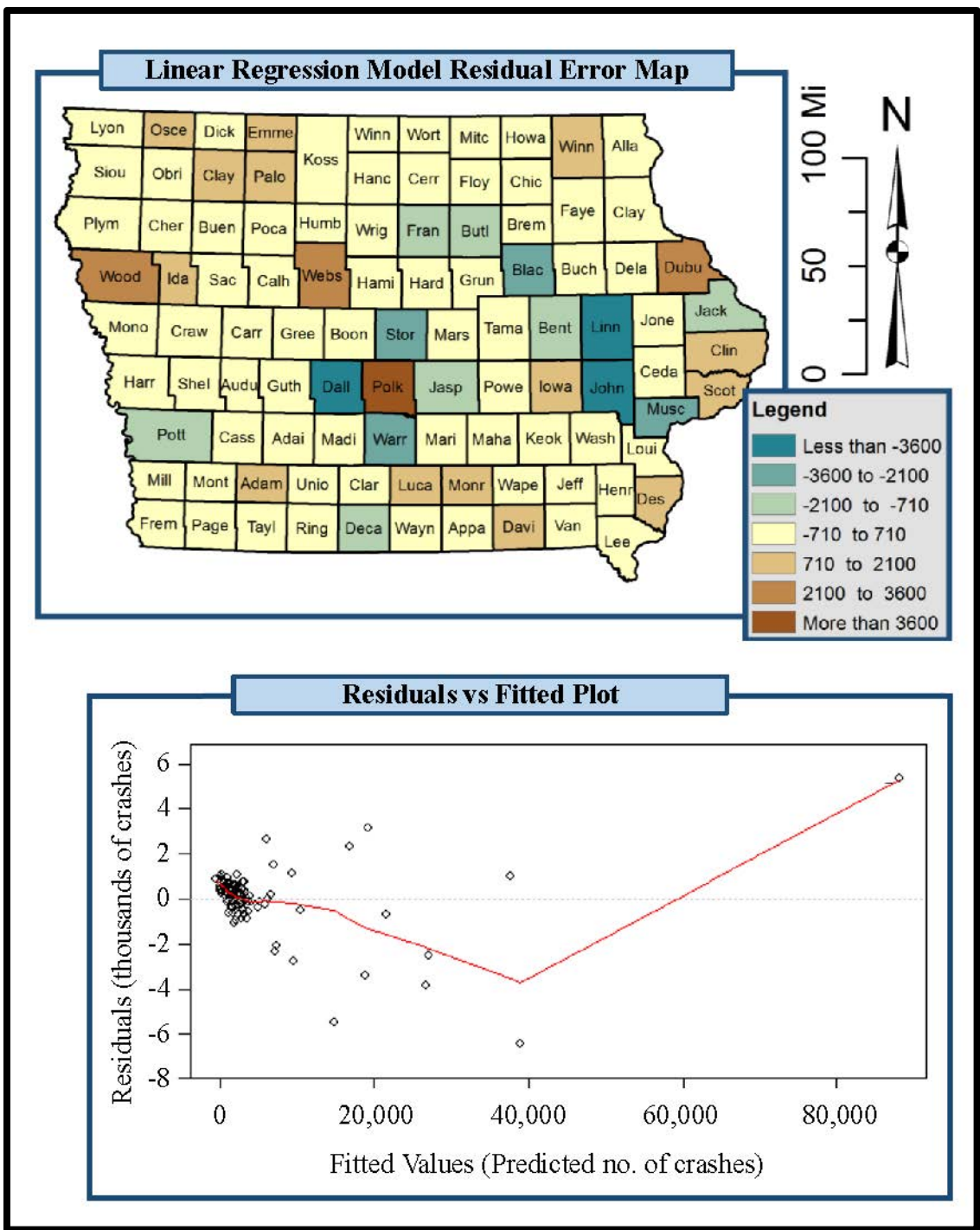


Figure 8: Map of Residual Error. Derived from a regression model accounting for driving population, urban land area, and highway mileage.

The distinction between urban and rural counties was considered in defining the extent for the microscale crash hotspot analysis. Urban environments are host to the greatest frequencies of automotive crashes, which rationalizes a focus on one of Iowa's more urbanized counties. Of Iowa's limited number of urban counties, Black Hawk County is neither a significant outlier, nor host to any significant length of transnational highway. These two points suggest that the crash history of Black Hawk County is representative of a typical urban setting in Iowa and is not biased by large volumes of non-resident through-traffic traveling on national highways.

Crash Hotspot Analysis

The hotspot analysis was performed to develop an objective estimation of risk at specific roadway sites using crash records within Black Hawk County. Several key observations were made as a result of the design and implementation of the geographic information systems procedure. First, the hotspot procedure reinforced the findings of the exploratory analysis and confirmed the need to distinguish urban from rural crash hotspots. Second, development of the hotspot analysis revealed a series of subjective decisions underlying these types of analyses (and calls into question the reporting of such subjectivities across all studies of this nature). Third, the hotspot analysis suggested significant limitations in constraining the estimation of risk to a single index and supported the idea that risk estimations should be reported in multiple measures.

There was a notable distinction between the frequencies, rates, and severities of urban and rural crash frequencies. Early iterations of the hotspot procedure produced

indices of crash risk for intersection sites county-wide. These preliminary risk indices were widely dispersed across several communities and spread across urban and rural land areas. There was a noticeable preponderance of high crash rate sites falling within the urban boundary. When accounting for severity (especially through the equivalent property-damage-only, or EPDO rate index), however, crash hotspots shifted toward the rural periphery (Figure 9).

This dispersion and segmentation of risk typologies across the county extent encouraged a refinement in the hotspot procedure. The procedures, and risk indices, were reiterated and constrained to the extent of the urban boundary of Cedar Falls. This extent provided a more useful spatial distribution of study sites. The urban-focused risk index was more evenly dispersed across varying configurations of urban intersections, best reflected the risk faced by a majority of daily driving commuters, and defined a cross-section of intersections within a singular community (Figure 10).

The demarcation of hotspot sites necessitated decisions that introduced subjectivity in the risk indices. The most critical decision was the definition of buffer radii; crashes occurring within these radii are assumed to bear a connection to the features of the hotspot site. The demarcation procedure also revealed the complexity of many intersections, especially where several junctions converge in close proximity (such as at frontage roads, or intersection complexes at freeway entrance and exit ramps); in such cases, hotspot buffers often overlapped. A script was used to modify the initial buffers such that crashes falling in overlapping buffers were assigned to a single intersection having the highest average annual daily traffic (Appendix C).

Mapping Crash Risk in Black Hawk County

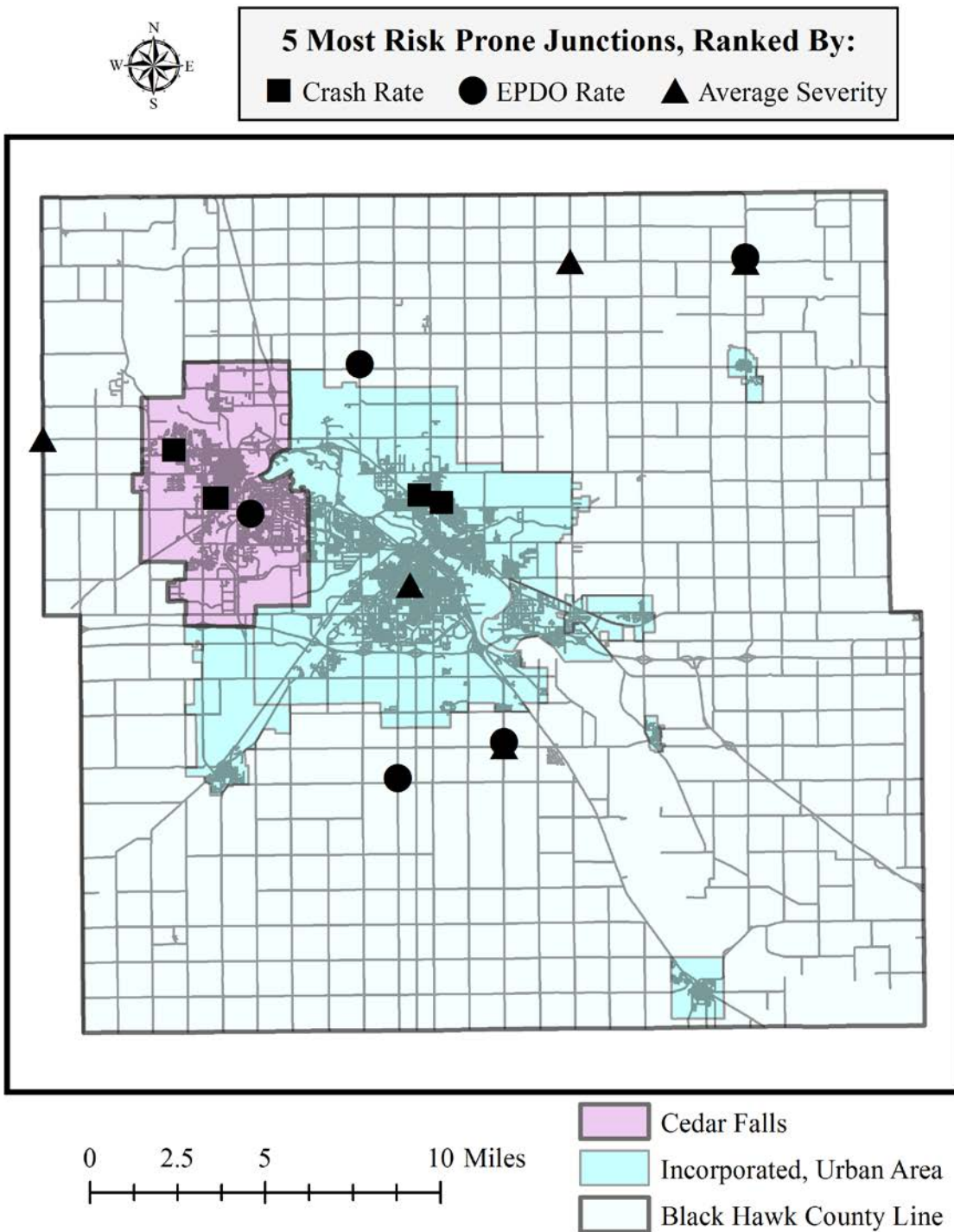


Figure 9: Map of High-Risk Intersections County Wide

Mapping Crash Risk in the City of Cedar Falls

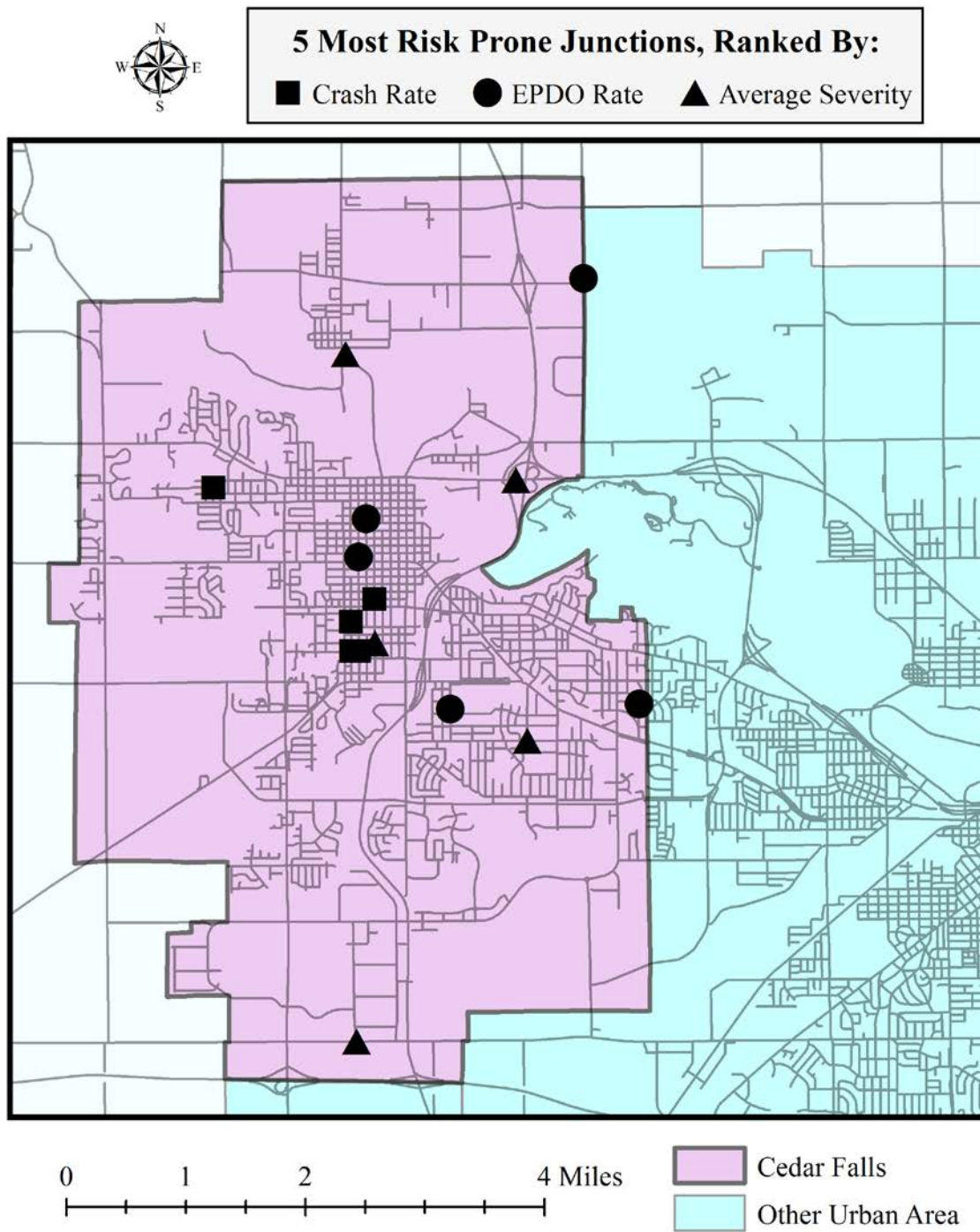


Figure 10: Map of High-Risk Intersections City Wide

Subjectivity was also a fundamental aspect of developing the empirical risk estimations. Risk can be described as the frequency of a hazard, the severity of a hazard, or by some weighting of the two (and potentially other factors, e.g., property damage and societal costs). Risk can also be considered from the sweeping public view, using absolute factors of frequency and severity. The alternative to this view is to adopt a personal and individual perspective that considers these risk factors relative to traffic volumes (derived from risk-rate calculations using reported annual average daily traffic estimates). Although many organizations publish procedures for calculating a single weighted index, this estimation of risk was regarded as impossibly precise. To increase accuracy, this research has considered several indices reliant on measures of crash rate and crash severities, and also provided a detailed description of the construction of the weighted EPDO rate index.

Survey Distribution

Despite the growing history of digital research, such methods are being continually improved and refined. In particular, the use of a digital survey presents novel opportunities for researchers to distribute their surveys to increasingly targeted communities (Shatz, 2017). With this in mind, the survey responses are first considered in aggregate, including the total response count and overall completion rate and completion times. A more thorough review includes specific response data for each trackable survey link distributed, and a qualitative description of various communities' reception and public commentary.

Response Count and Completion Rate

The survey link was clicked by 433 respondents, though only 300 respondents completed all of the questions in the survey (Figure 11). This yielded a completion rate of 69.3%. The respondent losses can be identified throughout the survey's flow. Six survey respondents never answered the first question, and 13 more did not complete the demographic questions. Twenty-one respondents were lost before the Brief Sensation Seeking Scale, and 22 more were lost at the visual warmup images. Fifty-four respondents were lost during the experimental visual block, and 17 more, otherwise complete responses were eliminated for not answering the final verification question.

Completion time was similar for each of the various survey distributions. Most complete responses were well under 10 minutes. This suggests that respondents did not spend much time analyzing photographs; instead, respondents provided their first impressions and affective perceptions of risk for pictured junctions. Beyond removal of incomplete responses and verification of the respondent's age, data cleansing procedures were intentionally minimal to avoid concerns of researcher-bias and data manipulation.

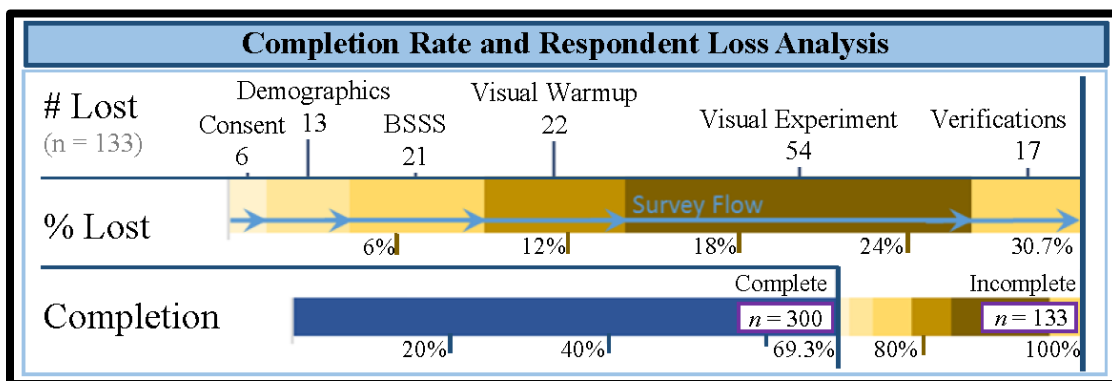


Figure 11: Survey Completion Rate Analysis

Survey Reception

Different reactions to the survey invitation were observed in communities before response data were analyzed. (Respondent comments are presented anonymously in Appendix G.) Reactions varied between different targeted forums, and between the niche subreddit communities. In many cases, the survey invitation was rebuked, and research accounts banned by forum moderators. This was true of large automotive and bicycling communities, resulting in a loss of respondents and biases in the community demographics. These biases were an unfortunate effect of heavy-handed moderators, and did not represent a lack of interest by individual community members. In total, 60% of respondents originated from various subreddit communities, with other respondents originating from the other disparate web forum communities.

Motorcyclists were the most receptive audiences. This group included users of the motorcycles subreddit community and the ADVRider community. These groups accounted for two-thirds of survey respondents and sparked respectful, though critical, discussion of the survey methods (especially concerning the experimental visual cognition elements). Despite their reservations for the experiment, these communities were overwhelmingly participatory.

A much smaller, but significantly more vocal, respondent group was recruited from the flying subreddit (a community primarily comprised of active student pilots, Private Pilot's License holders, and professional and military pilots). Their initial comments were disparaging. Early commentators regarded the survey as farce, which likely reduced further respondent participation. Other commentators asserted the presence

of errors in the display of questions, however, review of the survey could not confirm these errors (nor were they noticed by any other respondents). One commentator implied the survey had been removed or deleted, despite the survey link and community post being active for more than 30 days afterward. Despite evidence of readership, the estimated response rate from the pilot community was underwhelming.

Several bicycling communities were approached, but only one community's moderators allowed posting of the survey link. The link was posted to the forums at MTBR.com, or the Mountain Bike Review. It could be argued that mountain bike riders take more risks than the general populace (considering the "extreme" aspects of the sport). However, these riders may be more specifically choosing soft-trails as a means of reducing their exposure to risk by separating themselves from automotive traffic.

Many other communities were also invited to participate, but did not produce as large of a respondent pool. These communities included niche make and model specific car forums, discipline-specific academic subreddits, and professional truck driving communities. Despite these forums retaining a large number of registered users, the actual number of active users within these communities appeared to be much smaller. Nonetheless, most of these communities were receptive to the survey, and provided a broader demographic for analysis.

Communities were aggregated by common associations to create larger clusters of respondents (Table 3). Classifications were described as academics, bicyclists, driving enthusiasts, motorcyclists, and professional operators. One last classification was derived from a survey link disseminated through social media. This link was posted to Facebook,

and given to friends and family. Despite encouragement to distribute this link widely, this social media distribution provided an underwhelming response. With no specific community affiliations, these respondents were classified as a general audience, although potentially biased by a predisposition to the research subject matter.

Table 3:
Details for Individual Survey Distribution Links

Survey Distribution, Reception, and Response				
Community	Specific Webpage	Started	Finished	Posted
Motorcyclist	ADV Rider	83	59	10/18/17 7:40
Driving Enthusiast	Bimmer Forums	3	1	10/23/17 13:40
Academic	Grad Café Forums	1	0	10/13/17 9:18
Bicyclist	Mountain Bike Review	42	30	10/18/17 12:50
Driving Enthusiast	Nissan-Infinity Club	13	12	10/23/17 13:30
Academic	Reddit r/GradSchool	9	8	10/12/17 9:22
Academic	Reddit r/UrbanPlanning	7	6	10/17/17 8:39
Academic	Reddit r/UrbanStudies	8	5	10/17/17 8:57
Academic	Reddit r/Geography	10	4	10/17/17 9:15
General	Reddit r/SampleSize	4	3	10/12/17 11:26
Motorcyclist	Reddit r/Motorcycles	203	136	10/13/17 9:05
Professional	Reddit r/Flying	17	8	10/13/17 8:57
Professional	Reddit r/Truckers	15	12	10/17/17 11:00
General	Various: Social Medias	18	16	10/23/17 13:00
Total:		433	300	Closed 11/7/2017
Bicyclist	Bike Forums	Link-Post Blocked by Moderators		n/a
Academic	Reddit r/AskAcademia			10/12/17 9:30
Driving Enthusiast	Reddit r/Cars			10/13/17 8:45
Bicyclist	Reddit r/Bicycling			10/13/17 9:15

Respondent Analysis

Demographic data from the 300 completed responses were analyzed (Table A2). This data included three primary elements. Respondents were asked to provide some descriptive data about themselves, to complete eight questions comprising the Brief Sensation Seeking Scale, and were classified according to the community where they discovered the survey link. These data were analyzed to acknowledge potential biases in the demographics of the survey respondents, to understand differences in the respondent communities, and to provide context to the reported perceptions of risk.

Descriptive Demographic Data

Respondents were asked to self-report their age, gender, United States residency status, and to self-rate their driving experience and driving ability. Respondents were also classified according to their community affiliations (determined through the trackable links procedure). Exploration of this data provided context for interpreting the individual perceptions of risk (Figure 12 and 13).

There was an apparent skew towards a younger audience among the 300 completed responses. This was expected given the nature of the digital distribution, and the underlying demographic of the Reddit communities. Despite this skew, there was a reasonable representation of all ages, from those just 18 to those over age 65.

A gender bias was the most apparent, and most damaging to the survey results. Nine out of 10 respondents ($n = 270$) identified as male, while only 29 respondents identified as female, and 1 respondent identified as other. Females were similarly

distributed across ages, and shared similar risk perceptions as male counterparts.

Females also expressed similar self-rated driving abilities as compared to their male counterparts, although most females reported driving fewer miles per year.

Survey respondents included both United States residents and international respondents. Although there were concerns about non-U.S. drivers' responses, their risk perceptions were similar to their U.S. counterparts. Non-U.S. drivers were, however, less likely to drive more than 20,000 miles per year compared to U.S. residents.

Respondent demographics were also considered according to their driving experience (measured by proxy as a respondent's miles driven per year). Most notably, the highest mileage drivers also tended towards being the oldest. Furthermore, although risk responses were relatively consistent across all demographics, additional driving experience expanded the range of risk responses — higher mileage drivers exhibited both the highest and lowest overall risk perceptions.

A final examination of available demographic attributes considered respondents' communities. This demographic classification produced distinctive differences. Age varied across the communities; on average, motorcyclists represented the youngest respondents, while professional operators and driving enthusiasts represented the oldest respondents. Overall, averaged risk perceptions were consistent across communities, however, self-rated driving ability varied somewhat significantly. Professional operators and driving enthusiasts consistently rated themselves among the most capable of drivers, while academics rated themselves the closest to having average abilities (however, even academic respondents exhibited the Above-Average Effect).

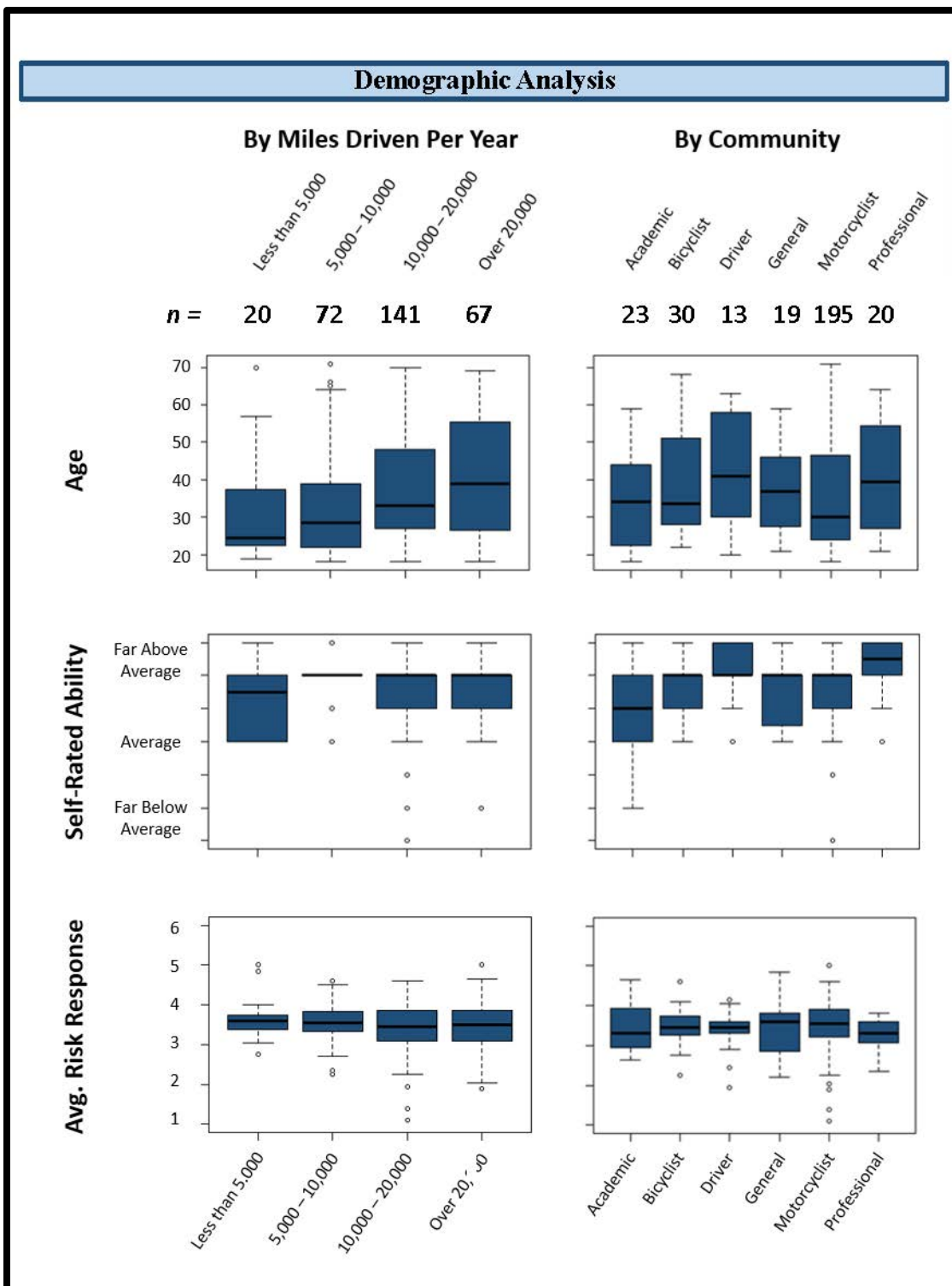


Figure 12: Demographic Analysis by Community and Driver Experience

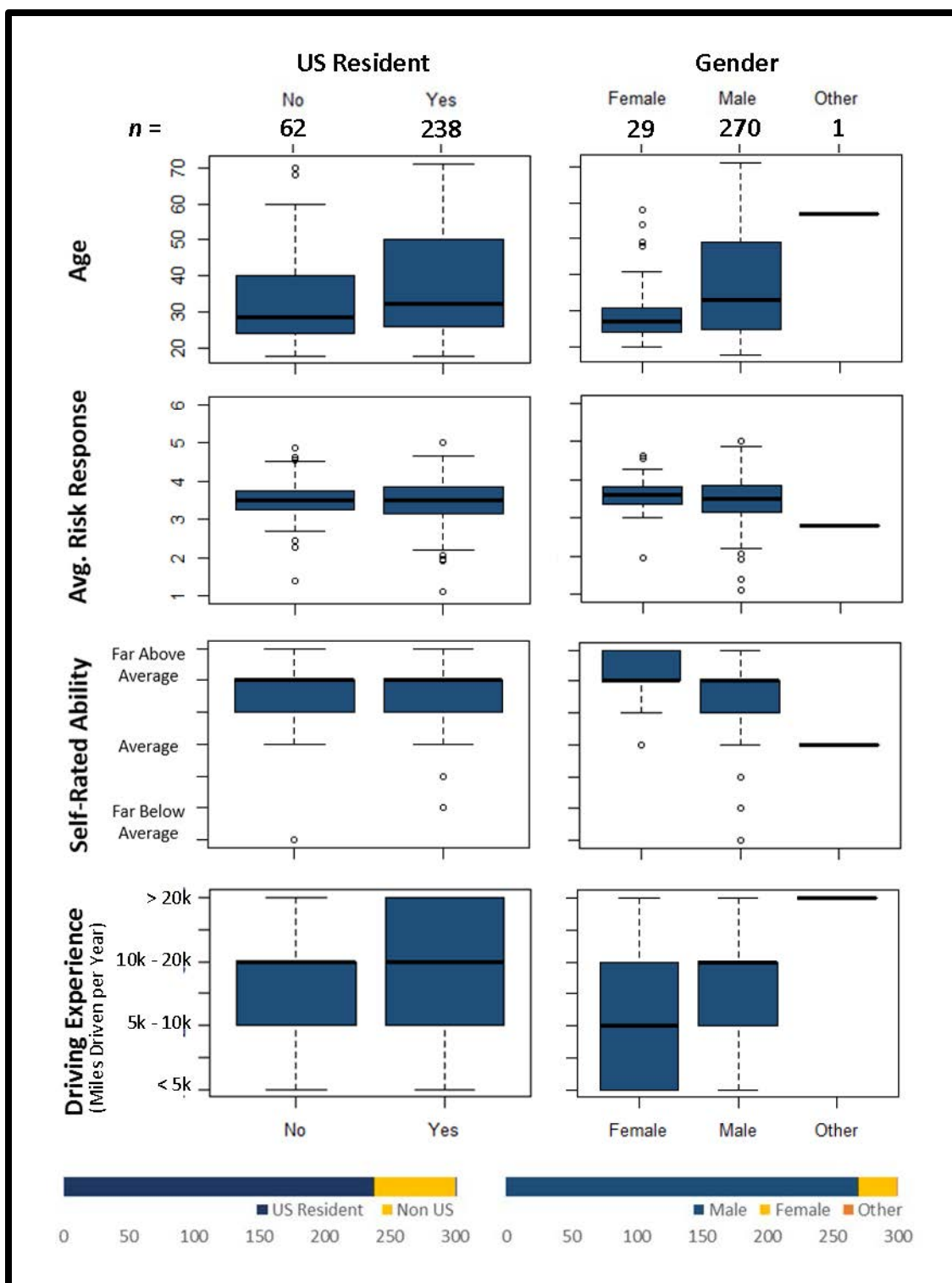


Figure 13: Demographic Analysis by Residency and Gender

Brief Sensation Seeking Scale

The Brief Sensation Seeking Scale (BSSS) was intended to provide insight into respondent's attitudes and perceptions of risk. The scale was composed of eight Likert scale items, which were treated both independently and as a summative composite score. The scale was first analyzed for multicollinearity. Afterwards, respondent's descriptive demographic data was analyzed for correlations with individual response items of the BSSS (Table 4). A final analysis utilized the BSSS scale and its individual items to explore distinctions between respondent communities.

The BSSS scale items did exhibit moderate correlations amongst themselves (Appendix H). Many of these inter-item correlations were statistically significant, but did not appear to cause a multicollinearity issue (the maximum correlation was between scale Items 4 and 8, with an effect size of 0.487). A variable inflation factor test found the highest inflation factor was 1.7 for Item 8; meanwhile, Cronbach's α was .71.

Age was correlated with BSSS Item 1. Older respondents were less likely to express an interest in exploring strange places. Additionally, older respondents expressed a lower overall sensation seeking score; although this finding was not supported with statistical significance, it is consistent with earlier studies (Fan et al., 2014).

Driver experience was correlated with BSSS Items 1 and 2. Respondents who drove more miles per year expressed less interest in exploring new places, and, more significantly, reported being less restless when spending time at home. Respondent's driving experience was also associated with lower overall BSSS scores, although not with any testable statistical significance.

Table 4:
Correlations between Items of the Brief Sensation Seeking Scale and demographics.

Correlations between Individual Items of the Brief Sensation Seeking Scale and Demographic Response Data					
BSSS Statement	Item #	Driver Experience	Driver Ability	Risk Perception	Age
I would like to explore strange places	1	-.10 ^x	-.09	.08	-.13*
I get restless when I spend too much time at home	2	-.15*	-.03	.02	-.09
I like to do frightening things	3	-.06	.18**	.12*	-.08
I like wild parties	4	.04	.08	-.01	.02
I would like to take off on a trip with no preplanned routes or timetables	5	-.08	.01	.05	-.01
I prefer friends who are excitingly unpredictable	6	.01	.05	.00	.06
I would like to try bungee jumping	7	-.04	.08	.00	-.07
I would love to have new and exciting experiences, even if they are illegal	8	-.02	.12*	.11 ^x	-.06
Total BSSS Composite		-.08	.10	.08	-.08
P-value: ^x < .1 * < .05 ** < .01 *** < .001					

There were significant correlations between items of the BSSS and with respondent's self-reported driving abilities and their overall risk perception. Agreement with Item 8 (seeking new experiences, even if illegal) correlated strongly with increased self-perception of driving ability, and in overall risk perception. Agreement with Item 3, "I like to do frightening things," correlated with elevated perceptions of risk and with increased perceived driving abilities (this correlation had the greatest observed effect size, and was the most significant overall). Despite their similarities, self-reported driving abilities and averaged risk perceptions were not significantly correlated (having a Pearson moment-correlation of only $-.0285$ and a p -value of 0.6223).

Items of the BSSS were also used to assess distinctions between respondent communities (Table 5). First, a generalized linear model was used to assess each scale item as a factor in predicting respondent's community affiliations; although parameters are not estimable for this model, the p value indicates which BSSS items were most significant in predicting a respondent's community (Ogorek, 2012). Second, a cellular reference model was used to compare each community of respondents against the average of all responses. This model compared each community's set of responses to BSSS Items against the full population of respondent responses. The results report on the magnitude and significance of variations in BSSS responses between communities.

Academics, driving enthusiasts, and the general audience exhibited the lowest sensation seeking scores. Academics expressed a preference for avoiding frightening things (Item 3). Drivers disagreed strongly with Items 7 and 8 (bungee jumping, and trying new activities). The general audience disagreed with Items 1, 3, 5, and 8.

Table 5:
Modeling the Brief Sensation Seeking Scale and Community Affiliations

Distinctions in Respondent Communities Found Using BSSS Items								
	P-Val (Significance of BSSS Item for predicting Community)	Average Response to BSSS Item	Academic	Bicyclist	Driver	General	Motorcyclist	Professional
			Sample Size (n =)					
			23	30	13	19	195	20
B1	.35	4.30				-0.36 ^x		-0.70 ^{***}
B2	.04 [*]	3.73		0.50 [*]				
B3	.00 ^{**}	2.99	-0.86 ^{***}			-0.67 [*]	0.19 ^x	
B4	.21	2.16						
B5	.01 ^{**}	3.87	-0.43 ^x			-0.66 [*]		
B6	.07 ^x	2.77						
B7	.98	2.80			-0.72 ^x			
B8	.09 ^x	2.78			-0.63 ^x	-0.52 ^x		
Sum	.05 ^x	25.40	-1.83	0.33	-2.78 ^x	-2.93 [*]	0.68	-0.45
P-value:			^x < .1	[*] < .05	^{**} < .01	^{***} < .001		

Bicyclists, as a community, expressed a unique agreement with BSSS Item 2.

This community strongly agreed that they would become restless if spending too much time at home. Bicyclists also represented the second highest summative sensation seeking scores of any community.

Professional operators, pilots and truck drivers, responded with significantly less agreement for Item 1 than the overall average for respondents. Professional operators

overwhelmingly expressed less interest in exploring new places; notably, these respondents were also amongst the highest mileage drivers of any community.

Motorcyclists expressed a unique agreement with BSSS Item 3, “I like to do frightening things.” As a community, they also expressed the highest overall sensation seeking scores. It is important to remember, too, that motorcyclists comprised the majority of respondents; therefore, despite the small effect sizes and low p values, these observed deviations from the overall average remain quite considerable.

Analysis of Objective and Subjective Risk

The leading research question asked whether there was concordance between the empirical estimations of risk and the subjective perceptions of risk. A geographic information system identified crash hotspots and produced several indices of crash proneness and severity. A visual survey instrument targeted towards digital communities collected individual perceptions of risk at a selected subset of crash hotspots. Multiple methods were used to examine potential concordance between these objective and subjective measures. Correlation tests were used to evaluate the average surveyed perceptions of risk and the various empirical measures of risk. An additional correlation test explored the variance between different perspectives of imagery from the same intersection. Finally, a selected series of survey intersections are presented as detailed case studies, completing the micro-scale analysis of the potential concordance between our perception of risk and the reality of risk in the automotive environment.

Correlations

Each survey junction included a rank-index representing crash frequency, average severity, crash rate, severity rate, and the weighted equivalent property-damage-only rate. The three rate calculations best represent an individual's personal crash risk (by normalizing the risk measure according to Annual Average Daily Traffic, or AADT). Pearson product-moment correlations were used to assess the concordance between the five objective measures of risk and the average of the perceptions of risk measured for each of the 20 survey photographs (Appendix H). Correlations using the 20 rows of data (Table A3) were analyzed for each community, for high and low sensation seekers separately, and for all respondents together. The results are shown in Table 6.

Correlations between risk perception and objective risk measures were calculated for each community of respondents. These correlations were distinctive, and statistically significant, within the different communities. Academics exhibited weak correlations across all scales. Bicyclists, motorcyclists, and professional operators' perception of risk were significantly and negatively correlated with the rate estimates of risk; implying their perception of risk was predictably reversed from the realities of personal crash risk. In contrast, driving enthusiasts and general audience respondents exhibited significant and positive correlations with risk estimates; suggesting these respondents were more accurate in their perception of personal risk exposure.

The Brief Sensation Seeking Scale (BSSS) was also used to assess objective and subjective correlations. Respondents were divided into two groups of respondents based on their composite BSSS scores; BSSS scores at or above the median were considered

Table 6:
Correlations between Objective and Subjective Risk Estimates

Correlations between Perceived Risk and Actual Risk Estimates for Twenty Surveyed Junction Photographs: for each community, low and high sensation-seekers, and overall											
		Actual Risk Indices									
		Crash Rate		Severity Rate		EPDO Rate		Average Severity		Crash Frequency	
		Cor	P-Val	Cor	P-Val	Cor	P-Val	Cor	P-Val	Cor	P-Val
Averaged Perceptions of Risk, by Group	Academic	-.14	.56	-.02	.94	-.24	.31	.01	.95	-.03	.89
	Bicyclist	-.47	.03 *	-.44	.05 x	-.62	.00**	.06	.80	.30	.20
	Driver	.39	.09 x	.46	.04 *	.19	.41	-.33	.15	-.06	.81
	General	.31	.19	.46	.04 *	.32	.18	-.01	.97	-.10	.69
	Motorcyclist	-.19	.42	-.25	.30	-.44	.05 x	-.17	.48	.20	.39
	Professional	-.41	.07 x	-.32	.17	-.45	.05 *	.18	.45	.23	.33
	Low BSSS	-.23	.32	-.20	.40	-.40	.08 x	-.03	.89	.19	.41
	High BSSS	-.09	.72	-.10	.68	-.34	.18	-.17	.46	.13	.58
	ALL	-.16	.49	-.15	.52	-.36	.11	-.10	.66	.17	.48
	P-value:		x < .1		* < .05		** < .01		*** < .001		

high sensation seekers, while scores falling below the median were considered as low sensation seekers (Fan et al., 2014). This application of the BSSS did not produce unique distinctions from the correlations for all respondents.

Considering all respondents, the individual ratings of risk did not exhibit any statistical significances. The lack of a strong correlation suggests that individuals were unable to accurately predict the level of automotive risks for photographed junctions. Despite uncertainty in the results (from small sample sizes and marginal effect sizes), correlation coefficients were negative for all estimates of personal risk rates; this could potentially indicate that survey respondents not only misperceived risks, but that they were liable to perceive higher risk-rate intersections as being safer, and that they perceived safer intersections as having higher risks.

Different Perspectives of the Same Intersection

Individual risk perceptions were further examined by comparing the perceived risk ratings of different approach images taken from the same intersections. A paired t-test did not reveal significant differences between images of the same intersections (p-value of .40). There were, however, three intersections which exhibited larger variability.

In each case featuring high variability between perceptions of perpendicular perspectives, the featured intersection was a low traffic residential connector without any road paint markings (Figure 14). Each of these intersections also included one image with a stop sign, and a second image that had no signal control (thus continuous thru-traffic) in the other direction. The presence of a stop sign encouraged respondents to

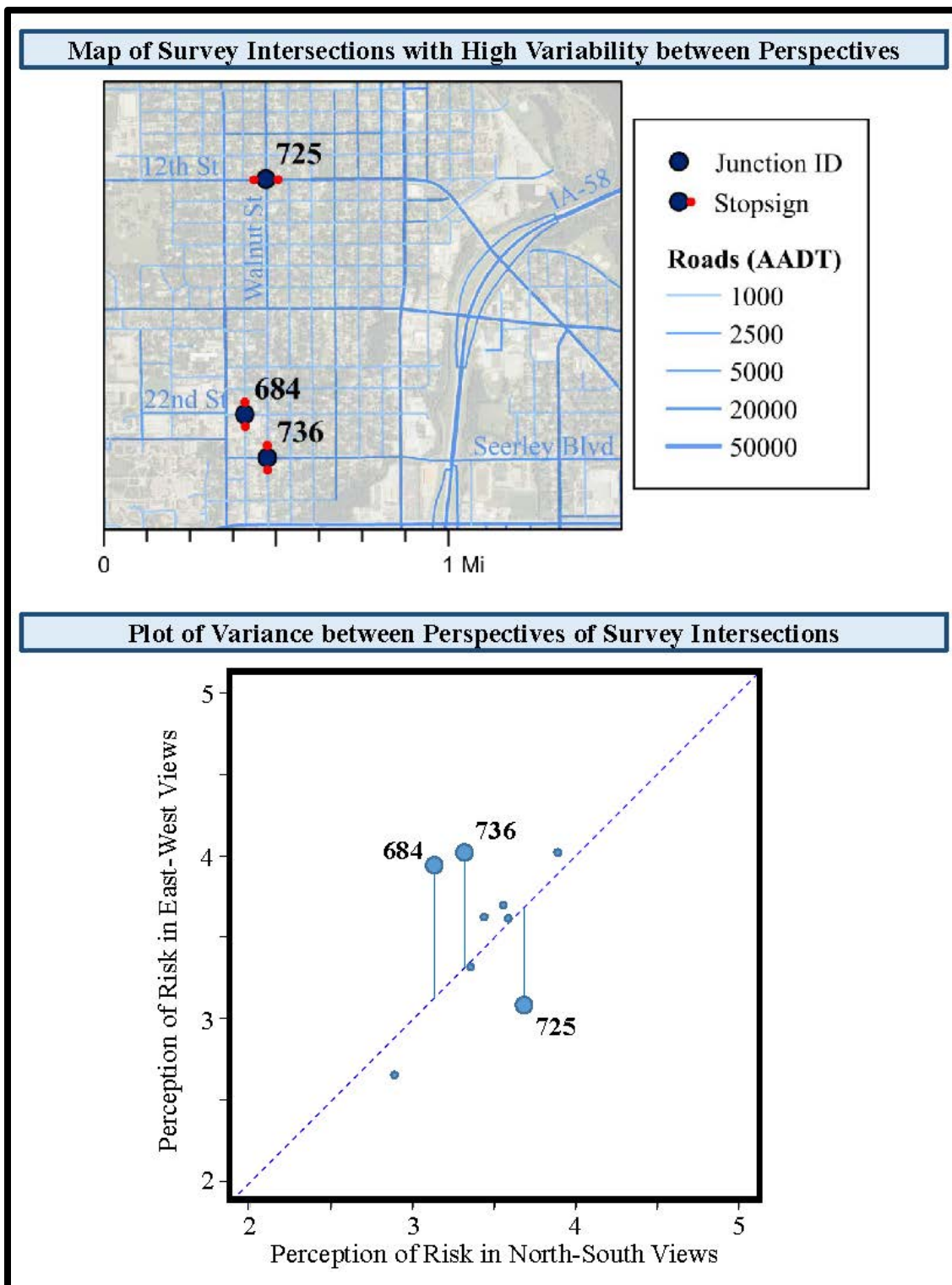


Figure 14: Map and Plot of Variance in Perception between Views of the Same Site

decrease their risk estimate (thus increasing their perceived safety); conversely, the lack of a stop sign in the image caused an increase in respondent's risk estimates, and decreased their perception of safety for the same intersections. This result confirms that drivers do account for road geometrics in their perception of risk.

Select Intersection Case Studies

Four case study examples were selected to demonstrate the distinctions between crash frequency and crash rate, as well as between perceived and actual measures of risk. The intersections are numbered using a unique index initially assigned to all junctions in Black Hawk County. The four intersections are all located within 3 miles of each other, and within 2 miles of the University of Northern Iowa. This sample is a cross-section of the daily activity spaces of many Cedar Falls residents (Figure 15).

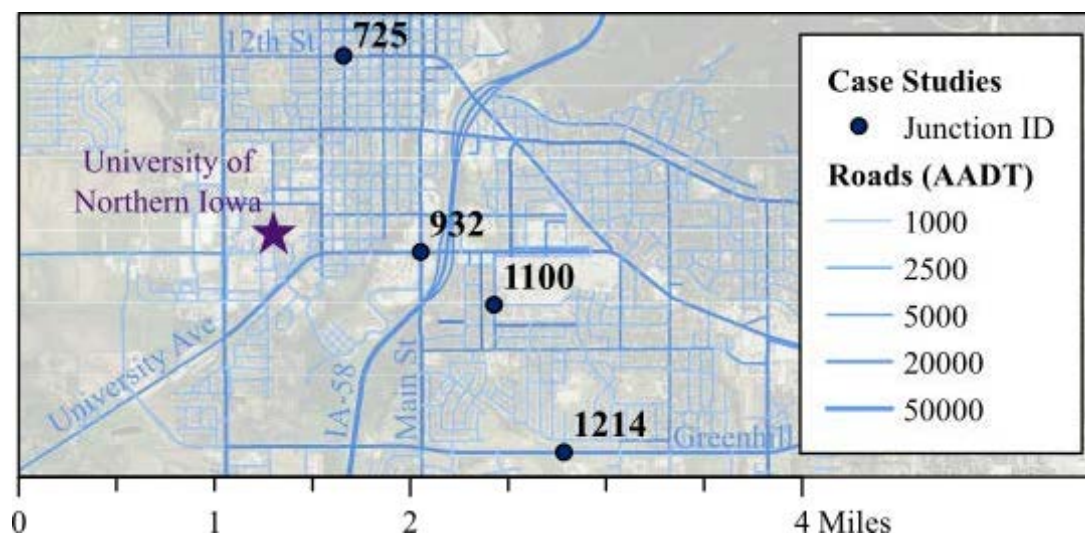


Figure 15: Map of Case Study Intersections



Figure 16: Junction 1100 Survey Photography (Left: West, Right: North)

Junction 1100. In both images (Figure 16), Junction 1100 (the intersection of Boulder and Maple Drives) was rated by respondents as posing well below average risk. In reality, this intersection was a notable crash hotspot in Cedar Falls. Locals use this residential connector as a backway to the popular College Square Shopping Mall, and speeding is a common observation along the route. The junction sees 2800 cars per day, has hosted 8 crashes, 1 fatality, and 2 reported injuries over the past decade. Despite its low perceived risk, Junction 1100 holds the top spot on the EPDO rate index (Table 7).

Table 7:

Junction 1100 Crash Data, Risk Indices, and Surveyed Perception

JID: 1100		Boulder and Maple Drive		42.509151, -92.438468		
Crash Report Data		Empirical Risk Indices		Surveyed Perception of Risk		
AADT	2843	Crash Rate	4.125		North	West
Crash Count	8	Severity Rate	4.750		Risk	2.89 2.64
Severity	14	EPDO Rate	6.000		Std. Dev.	1.28 1.18
Fatal	1	Crash Frequency	1.000		<i>(expected average)</i> 3.50	
Injured	2	Average Severity	5.375		<i>(survey total average)</i> 3.49	



Figure 17: Junction 0725 Survey Photography (Left: West, Right: North)

Junction 0725. The west-bound approach to Junction 0725 (the intersection of Walnut and 12th Streets) was perceived as posing below average risk, though the north bound approach (without the stop sign) was perceived as having average risk potential (Figure 17). These perceptions were lower than the actual crash risk. The intersection experiences over 8,000 cars per day, but with 59 reported crashes in the last decade, still ranks high on the crash rate index. With 1 reported fatality and 19 reported injuries, this risk should rightfully be considered in terms of its severity as well as frequency (Table 8).

Table 8:

Junction 0725 Crash Data, Risk Indices, and Surveyed Perception

JID: 0725		Walnut and 12th Street		42.527632, -92.453398		
Crash Report Data		Empirical Risk Indices		Surveyed Perception of Risk		
AADT	8550	Crash Rate	5.375		North	West
Crash Count	59	Severity Rate	5.375		Risk	3.66 3.11
Severity	80	EPDO Rate	5.375		Std. Dev.	1.29 1.19
Fatal	1	Crash Frequency	5.375		(<i>expected average</i>)	3.50
Injured	19	Average Severity	3.500		(<i>survey total average</i>)	3.49



Figure 18: Junction 1214 Survey Photography (Left: West, Right: North)

Junction 1214. Both images (Figure 18) from Junction 1214 (Greenhill Road and Orchard Hill Drive) were rated as well above average risk; this was despite the images showcasing wide lanes, clear sight lines, and open grass safety buffers. The intersection experiences 8,000 cars per day, but only incurred 10 reported crashes in the last decade, meaning this intersection was not particularly crash prone. However, it does rank high on the severity index, possibly owing to high speeds when relatively infrequent crashes do occur. The above average perception of risk at this intersection was surprising (Table 9).

Table 9:

Junction 1214 Crash Data, Risk Indices, and Surveyed Perception

JID: 1214		Greenhill and Orchard Hill		42.498187, -92.431605		
Crash Report Data		Empirical Risk Indices		Surveyed Perception of Risk		
AADT	8100	Crash Rate	1.625		North	West
Crash Count	10	Severity Rate	3.500		Risk	3.89 4.01
Severity	21	EPDO Rate	2.875		Std. Dev.	1.20 1.31
Fatal	0	Crash Frequency	1.625		(expected average)	3.50
Injured	15	Average Severity	6.000		(survey total average)	3.49



Figure 19: Junction 0932 Survey Photography (Left: West, Right: North)

Junction 0932. These two images (Figure 19) were perceived as having slightly above average risk, which aligned well the risk-rate indices. The high volume of traffic at this intersection (Main Street and University Avenue) is mitigated by robust traffic signals, center lane dividers, road paint, and designated turn lanes. Nearly 50,000 cars pass through this intersection every day, offsetting the 87 reported crashes (no fatalities, however). Although the intersection is among the most frequent sites for crashes in the city, the actual crash rate (and measure of personal risk) was only average (Table 10).

Table 10:

Junction 0932 Crash Data, Risk Indices, and Surveyed Perception

JID: 0932		Main and University		42.513115, -92.445814		
Crash Report Data		Empirical Risk Indices		Surveyed Perception of Risk		
AADT	49500	Crash Rate	3.500		North	West
Crash Count	87	Severity Rate	2.875		Risk	3.56 3.70
Severity	121	EPDO Rate	3.500		Std. Dev.	1.13 1.12
Fatal	0	Crash Frequency	6.000		(<i>expected average</i>)	3.50
Injured	34	Average Severity	4.750		(<i>survey total average</i>)	3.49

Summary of Results

This chapter described the results from an exploratory regression analysis and the identification of crash hotspots, as well as the development, distribution, and responses to the visually stimulated digital survey. These results reproduced and expanded on results from existing literature, verified the efficaciousness of the methods, and provided for further discussions of geography, psychology, and, above all, traffic safety.

A regression analysis verified the existence of a striking division between rural and urban crash patterns, and recognized Black Hawk County and the city of Cedar Falls as a suitable study area representative of state-wide crash data. Within this study extent, a crash hotspot analysis revealed significant variability in the frequency, severity, and adjusted rates of crashes at intersection hotspots. The analysis of the crash hotspots provided data for later analyses, and aided with the development and distribution of the visual survey instrument.

Despite being blocked by many larger communities, the targeted digital distribution methods were viable. Three hundred participants were recruited from various special-interest communities. Clear distinctions between digital communities were observed in the responses to demographic and sensation-seeking questions. For instance, academic respondents were the most restrained in self-reporting their driving abilities (though they still reported themselves consistently as being above average). Motorcyclists overwhelmingly agreed that “[they] like to do frightening things.” Despite their differences, respondents’ average risk perceptions were similar for all communities.

The results from the empirical crash hotspot analysis and from the digital survey distribution were comparatively analyzed to assess concordance between the objective and subjective measures of risk. The most significant correlations suggested a negative relationship between the perception of risk and actual risk rates for bicyclists, motorcyclists, and professional operators. Drivers and general community members achieved positive correlations between their perception of risk and the actual risk rate. Correlations utilizing the full respondent pool were insignificant, although the correlation coefficients were consistently negative for all rate-based risk indices.

No significant variations were found when comparing perceptions from two different images of the same intersection. A closer examination of the sample intersections revealed that the presence of a stop-sign within the image decreased a respondent's perception of risk, while the lack of a stop-sign at the same intersection increased the perception of risk. This result does, however, demonstrate that drivers' perception of risk does vary based on road geometrics.

The results from this research reveal the complexities of analyzing crash data, the challenges of reaching survey participants, and the reality of negative results. Although these results were not conclusive, the findings nonetheless fail to reject the null hypothesis: that our individual perceptions of risk are unlikely to bear concordance with our actual personal risk exposure as participants in the automotive environment.

CHAPTER V

DISCUSSION

The methods and results of this research stem from deliberate consideration of past literature, current constraints and objectives, as well as future replicability and reliability. This chapter will discuss in detail the compromises made during this research, the necessary subjectivities encountered throughout the procedures, and provide interpretations of the most interesting results.

Exploratory Regression Analysis

The design of this research was heavily dependent on the scale of the various analyses. It was critical to both understand and acknowledge the entire history of crash reports while also limiting the extent of analysis. Initial explorations of these data used an areal linear regression to assess the statewide data at individual county scales. The key findings were the distinction between urbanized and rural counties and associated crash trends, and the expected increase in crash counts resulting from additional miles of transnational highways. Performing the regression analysis demonstrated the potential, and limitations of this type of procedure.

The regression equation included three factors: driving age population, percent of urban land area, and length of transnational highway. Increasing any of these three factors coincided with increases in predicted crash counts. Given increased lengths of highway, we should expect an increase in traffic, some of which would be non-resident

thru traffic. This increase in traffic implies an increase in the number of crashes. Future research must consider this effect when interpreting areal analyses of crash data.

A more surprising observation was the residual error in Polk County. The capital county is Iowa's leader in population, urban area, and transnational highways. The county also boasts a significant lead in crash reports. This may seem unsurprising at first, but even with factoring for its lead in the model variables, Polk County, and the city of Des Moines, suffered 6,000 more crashes than the model results predicted. This underestimation of crashes might be because of heteroscedasticity, or perhaps the high number of actual crashes is due to the "intersection" of two national highways (I-80 and I-35); due to their configuration, the two interstates actually cross twice in the county!

Aside from Polk County, many of Iowa's other urbanized counties had lower numbers of crashes than predicted by the model. This, combined with the fact that urban collisions are generally less severe (Eiksund, 2009), suggests that despite the added stress from visual clutter and additional traffic, urban driving appears safer than driving in the rural countryside. Perhaps, rural populations take more driving risks compared with urban drivers (Cox et al., 2017; Eiksund, 2009; Rakauskas, Ward, Gerberich, 2009). Rural risk may be further exacerbated by cognitive underload, a circumstance borne from boredom and fatigue (Brookhuis & de Waard, 2010). These findings support risk homeostasis theory, suggesting that drivers could adopt safer driving behaviors in the city as compensation for the inherent complexity of the urban environment. Nonetheless, urban areas continue to have the highest absolute number of crashes, with an uncertain potential for serious injury and death.

Replication of the areal regression at finer scales could provide further explanation of the urban-rural divide in Iowa's crash history. Unfortunately, census and administrative datasets are more difficult to analyze at these smaller scales. Census tract units rarely align with urban administrative boundaries, and even when such data is easily joined, there are questions about the margin of error in the American Community Survey, at finer scales (Neidert, 2017). As performed, the areal regression analysis successfully summarized a macroscale view of the Iowa crash report data, however the designation of crash hotspot sites required the design of a microscale analysis.

Crash Hotspot Analysis GIS Procedure

There are many methods available for crash hotspot analysis. Each potential model includes necessary subjectivity that permeate the geographic information system (GIS) methods, and influence the empirical derivation of risk estimates. Nuances in these subjectivities may have broad effects on the results. Therefore, the interpretation of hotspot demarcation and empirical risk estimates warrants a thorough discussion.

Hotspot Demarcation

The hotspot analysis was developed to provide a static representation of risk heterogeneity throughout the road network space. The Iowa Department of Transportation (IaDOT) maintains a statewide Safety Improvement Candidate Location (SICL) list. This list reinforced the findings of the exploratory regression analysis, with many of the SICL hotspots falling within an urbanized city. The list also provided a

template for the hotspot procedures in this research; the method was used to assess intersections based on the history of crashes occurring within a specified radius.

The SICL procedure was adapted to fit the county and city scales used in this research. The procedure was chosen for its simplicity and appropriateness to the analysis. The method was outlined using ArcGIS's ModelBuilder to enhance its replicability; the model derived planar nodes from road line-network data at any scale, and aggregated crash records within a parameterized radius from the derived nodes.

Several alternative models were considered. One included aggregating crash reports to intersections based on nearest Euclidean distances, and another similar model would have utilized Voronoi algorithms. These models would eliminate the concerns of overlapping buffer radii resulting from the SICL method and would better describe the scenario of two similarly busy intersections in nearby space, but would also reduce the weighting given to a busy primary road junction flanked by two adjacent frontage-intersections. The most precise methodological alternative would include manually geocoding crash report data using written reports; however, this would also entail much higher sensitivity in data acquisition, data handling, and potential distribution.

After implementing the SICL method, subjectivities in the parameters of the GIS model were found. The model was most sensitive to the selection of a buffer radius for crash report aggregation; there is no alternative to this decision, except use of a different model. The designation of intersection nodes in road line data is also subjective; this procedure can be accomplished either geometrically, or through the Network Analyst ArcGIS extension. Network Analyst includes intersections and single line-ends as nodes,

whereas the standard Intersect geometric tool only returns intersections of two or more lines as a node. Both required dissolving and planarizing the IaDOT road network data. For simplicity and replicability, only standard geometric tools were used in the model.

Accuracy of the road and traffic data introduced additional limitations affecting the model. Principally, the lack of a Z-coordinate prevents full automation of the model procedure. Without the Z-coordinate there is a significant loss of accuracy occurring at grade-separated road crossings, such as inner-city elevated freeways. Fortunately, there were a limited number of such crossings in Cedar Falls, and the emphasis on individual crash rates deemphasized the role of higher traffic roads typically associated with grade-separated crossings. It is noteworthy however, that this rate calculation is reliant on the accuracy of average annual daily traffic estimates. Traffic (and thereby risk) is highly variable, not just spatially but temporally too.

Despite its limitations, the model used in this research is straightforward and robust. The model tools utilized are well-supported in the ArcGIS Desktop environment, and the procedure is expected to be replicable using open source software alternatives. The GIS model accurately anchored a decade of crash reports in a geographic context, and provided a reasonably precise history of crashes at intersections on the planarized road network in Black Hawk County.

Empirical Estimation of Risk

Transforming the history of crash records into a quantifiable measure of risk introduced additional subjectivity. Frequency of crashes, severity of crashes, and the

costs of crashes can be measured, but draw very different maps of the automotive environment. The procedures for aggregating these attributes varies between agencies and organizations. To better encompass the dynamic interpretation of risk, several indices of risk were used in this research.

The interpretation of personal risk requires consideration of traffic volume. Adjusting crash counts to account for traffic flow significantly redraws the risk hotspot map (Figure 20). This phenomenon is perhaps unsurprising, but often overlooked. (With good reason, most traffic agencies are rightfully advocating for the biggest improvements for the smallest investment; these analytical methods, such as Iowa's Safety Improvement Candidate Locations, favor hazardous intersections with traffic flows generally higher than the system average, and do little to offset individual personal risk exposure.) Less busy intersections are often host to more than a fair share of crashes, but these sites are overlooked due to low traffic volumes.

The result of the rate calculation is so dramatic that it demands the inclusion of an additional threshold – a minimum number of absolute crash counts – to make sense of the

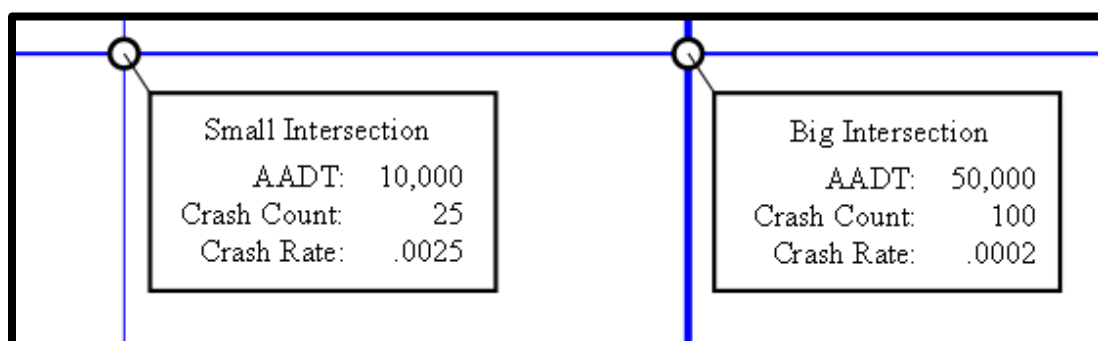


Figure 20: Rate vs Frequency. Two hypothetical intersections demonstrate the significance of the rate calculation, and its importance in understanding personal risk.

redrawn risk-by-rate map. Adopting this threshold results in a risk-by-rate map highlighting low-traffic road routes, but routes busy enough to be recognized as residential and commuter thoroughfares found on many driver's daily trips. This aligns well with the consideration that most crashes occur remarkably close to home, and potentially involve complacency on the part of the driver ("One in three," 2009).

Colloquially, people seem quick to point out busy intersections as being dangerous intersections, yet the rate calculation demonstrates that less busy intersections are equally dangerous to the individual, if not more so. Perhaps, it is that our affective perceptions are not capable of evaluating the significance of this rate calculation. Or perhaps it is an echo of the availability heuristic, where we are more likely to have experienced, even able to recall from memory, that lingering sight of wrinkled metal left after a crash at a busier intersection.

Survey Methods

Digital distribution of a survey instrument introduces unique limitations. As with many publicly distributed survey forms, the format is vulnerable to non-response biases and is also vulnerable to malicious respondents. The design of the survey was dependent on the framework provided by the Qualtrics platform. There were also significant concerns regarding the introduction of uncontrolled variables in the use of photography — the lens of the camera, in effect, becomes the editor. Despite these limitations, this survey methodology provided a means of soliciting individual perceptions of risk across a large population within given time and budget constraints.

Digital Design

The digital design of the survey instrument provided many benefits for this research. Nonetheless, all survey designs must accept certain compromises and limitations. The survey was designed to be brief to encourage a higher response rate; although the response rate is incalculable due to the distribution methods, it was posited that adding any length to the survey questionnaire would have increased the rate of lost respondents, or worse, blurred the results due to respondent fatigue. However, a longer survey instrument would have garnered additional demographic data and could have assessed a larger bank of image questions.

The survey was developed entirely within the Qualtrics Research Core survey software. This software provided a powerful platform for the development of survey questions, for organizing the layout and flow of the survey, and for incorporating the image-based questions. The software also streamlined the distribution of the instrument, provided on-the-fly analytics and visualizations, and enabled exporting the survey responses in multiple formats. The software was more than adequate for this research and surpassed expectations. Potential future research projects should strongly consider the use of Qualtrics software above other alternatives.

Use of Imagery

Embedding photography within the digital survey instrument was a simple and replicable method of assessing visual cognition and affective perception. Images were more easily and reliably transferred than video solutions, and much more cost-effective

than simulated or on-road driving exercises (safer for participants and researchers too). Imagery collection included adequate consideration for the environmental conditions, including the sky, sun, weather, and traffic. The collection procedures, as performed, are expected to be successfully replicable in future research.

There were concerns regarding the camera, mount, and vehicular platform used in this research. Although the equipment used may not have been ideal, it met the objectives of replicability. Part of this replicability includes an aspect of cost-effectiveness; the chosen camera was consumer-grade and affordable, and the vehicular platform readily available.

The raw images collected were of a higher resolution than the images distributed in the survey instrument. Image resolution was constrained to assure technical reliability and consistency across various respondent devices and internet networks. Although there was no restriction on the use of zoom features built into most common mobile devices and web browsers, several users commented that the pictures were small. On the other hand, there were only a couple comments expressing technical difficulties with the survey instrument or with the loading and display of imagery.

The use of imagery to provoke driver's affective perception of risk is still arguably experimental, although was successful in obtaining results for this research. At driving speed, drivers can only expect to assess a very narrow field-of-view (Nozzi, 2003). Furthermore, in such a high-paced environment, drivers should expect that "first impressions are usually the only impressions" (Vanderbilt, 2008, p. 26).

Distribution

The digital distribution method used in this research was chosen to solicit a wide, yet targeted audience. This included an emphasis on the distribution of links through the social link-aggregation site, Reddit.com. Despite an underlying demographic bias towards young adult males, subreddit communities represented respondent groups with unique interests and perspectives (especially in their responses to items of the Brief Sensation Seeking Scale). Even accepting these biases, the use of Reddit provided more diverse respondent demographics than the commonly used convenience sampling of college student populations in many published articles (Shatz, 2017).

Despite the lack of a response rate calculation, the completion rate was a useful analytic. Although the completion rate (69%) seemed low in comparison to traditional surveys, it was similar to the completion rate found by Shatz in 2017. Perhaps the expectation of a high completion rate is misguided for this style of distribution; respondents who click-through to the survey have no attachment to the results or the researcher, and minimal motivation to complete the questionnaire. Although the completion rate might have been improved with monetary compensation, this type of motivation might also result in erroneous, or junk, data (Shatz, 2017).

The link-tracking (tracing the respondent's originating community) revealed distinctive differences in respondent communities (including within Reddit's subreddits), and was a vital part of this research's results. The procedure for tracking links was not difficult, but also not straightforward. Future research could benefit from replicating this procedure, and Qualtrics should consider including an interface for such a basic feature.

Analysis of Survey Results

Community Distinctions

The way in which various communities responded to the survey invitation was surprising. Motorcyclist communities were receptive and participatory, while the pilot community was scathing. Meanwhile, other communities never received the survey invitation at all, due to the power and role of individual moderators.

The role of forum moderators is well understood and often appreciated. Moderators serve to protect digital communities and forums from abuse by individuals, groups, and even automated spam (Chiregi & Navimipour, 2016; Herring et al., 2002). In this research, moderators of some of the largest target communities prevented posting of the survey invitation. This was surprising, especially on Reddit, where users might mistakenly believe their 'vote' directly controls the type of content that surfaces; however, there was obvious gatekeeping occurring within certain target communities (Leavitt & Clark, 2014; McGee, 2013).

The reactions and survey responses received from the pilot community were surprising. Pilots, as a community, were expected to be open to the discussion of risk, risk management, and the severity of outcomes (McClellan, 2009). Risk perception, risk management, and human behavior are covered in detail in Chapter 2 of the Federal Aviation Administration's Pilot's Handbook of Aeronautical Knowledge – required reading for any student, private, or commercial pilot. Despite this, pilots were among the most likely respondents to leave the survey incomplete and expressed among the most exaggerated self-ratings of driver abilities. Furthermore, they were among the few

communities with statistically significant correlations between their perceived and actual risks: as their perception of risk decreased, the equivalent-property-damage-only (EPDO) and crash rate indices actually increased.

Motorcyclists were the most willing to participate in the survey, and equally willing to participate in the discussion of risk. Their community comprised the majority of the survey's respondents, and the greatest range of ages (though their demographics did skew toward a younger audience). Their averaged risk responses were similar to other communities, however, they were significantly more inclined "to like doing frightening things." Like pilots, however, their perceptions of risk were inverse to the realities of the EPDO and crash rate indices.

The Brief Sensation Seeking Scale

The Brief Sensation Seeking Scale (BSSS) did not exhibit significant relationships with the individual perceptions of risk. However, the BSSS did function as an interesting tool for examining unique distinctions between communities. Individual items of the BSSS were strongly correlated with certain communities of respondents (such as bicyclist's strong inclination to "become restless when spending too much time at home"). The BSSS also correlated with other attributes of respondent's demographic data (such as self-rated driver ability, and miles driven per year). Although the BSSS did not help address the leading questions and objectives in this research, it could be a useful tool for similar behavioral research in the future.

Above Average Effect

The Above-Average Effect has been observed in many studies; this survey research has successfully replicated those findings (McKenna, 1993; Svenson, 1981; Wohleber & Matthews, 2016). The effect was observable across all respondent communities, and for all demographics (Figure 21). This subtle, yet pernicious, overconfidence among drivers is expected to promote risk-taking driving behaviors and complacency towards adopting risk-avoidance strategies (including active defensive driving, passive driver education, and closed-course driver training). The reality is that nearly all drivers suffer this effect (even those who have been educated and informed of it); in short, we are “unskilled and unaware of it” (Kruger & Dunning, 1999; Vanderbilt, 2008, p. 61).

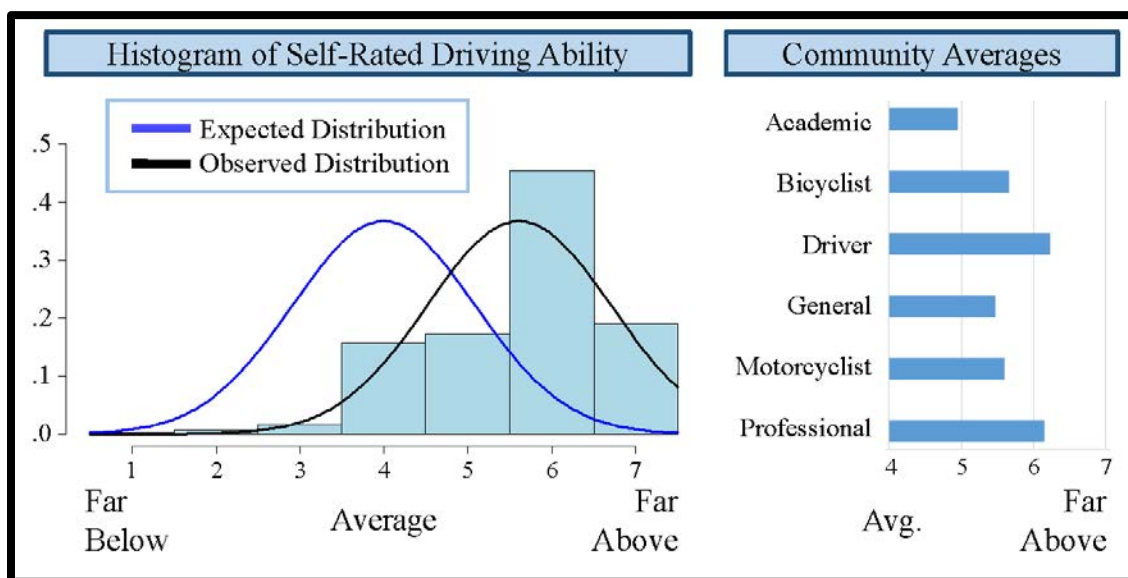


Figure 21: Visualizing Self-Rating of Driving Abilities

Perception of Risk

The perceptions of risk recorded from the survey were consistent across all demographics, including communities, ages, and genders. This consistency, however, was not indicative of respondent accuracy. Respondent's perceptions of risk were not correlated with actual estimates of risk. Furthermore, although the effect sizes were small and statistically insignificant, the correlation coefficients were negative between the perception of risk and all risk-rate estimates (suggesting that respondents might perceive safer intersections as dangerous, and dangerous as intersections as safe). This has startling ramifications for traffic safety, and risk homeostasis theory.

Let us first consider the situation if we accept risk homeostasis theory, and believe that drivers adjust their habits according to their perceived risk. The results from this research would suggest that drivers drive more safely through intersections where they are already the safest! Conversely, it would also mean that based on their incorrect perceptions of risk, that drivers are more complacent and more prone to risky behavior at intersections where they already face additional environmental risk!

These findings do not refute the idea of risk homeostasis. Drivers under added stress, such as when driving in unfamiliar places, are still likely to adjust their behavior accordingly. Drivers might also adjust their behavior to suit heavy traffic, or adverse weather. We must, however, acknowledge that risk homeostasis is not a catchall for all circumstances, and that drivers in familiar and comfortable settings are less able to accurately adjust their "target risk" (Wilde, 2001, p. 42). We can still agree with Dr. Wilde however, that reducing driver's target risk would improve traffic safety overall.

One might dismiss these findings because of the lack of statistical significance. Such a reader should review the work of Ezra Hauer, and his writing, *The Harm Done by Tests of Significance* (2004). Although there was limited testable significance between actual and perceived risks, there was consistency. Respondent's perceptions were inversely correlated for all of the risk-rate indices. Respondents were more accurate in predicting the crash frequency of an intersection; respondents rated higher frequency crash sites, and generally busier intersections, as having higher risk (these same sites generally represent the lowest levels of personal risk exposure). At the very least, this lack of significance only serves to support the argument that drivers are unable to perceive their actual risk exposure on the road.

Summary of Discussions

The discussions in this chapter have briefly reviewed and interpreted results from the regression analysis, hotspot demarcation, and survey distribution. These discussions considered the assumptions and limitations of the chosen methods, and potential implications of the survey response data. Although many of the data were statistically insignificant, the results remain relevant to understanding the perception of drivers.

The regression analysis and hotspot demarcation procedures were both aimed toward developing empirical estimates of risk. Aside from the inherent subjectivity of these procedures (e.g., choosing regression factors and scales, and delimiting hotspot radii), these processes revealed the contrast between absolute measures of crash frequency and an adjusted crash rate. Although busy intersections often host more

crashes, this does not imply that they pose the greatest levels of personal risk. Drivers should be aware of the effect of this rate calculation on their personal risk exposure.

The survey questionnaire demonstrated the viability of using targeted digital recruitment methods, as well as the use of imagery to record respondent perceptions. The survey results suggest that digital communities possess unique, underlying demographics. The Brief Sensation Seeking Scale, although not strongly associated with perceptions of risk, clearly outlined the distinctions between survey communities. This suggests that targeted digital surveys could be useful in future sociocultural survey research.

The survey results also revealed key considerations about drivers' perceptions, both of the environment, and of themselves. Respondents overwhelmingly rated their own driving ability as significantly above average (a replication of results from past research publications). Respondents' perceptions of risk were affected by characteristics of the environment; most clearly, respondents felt that stop-signs increased their safety. This finding suggests that drivers account for environmental factors when considering their exposure to risk. This accounting however, does not indicate accuracy.

The key result of this research suggests that drivers are not accurate in their perception of risk in the automotive environment (Figure 22). This finding contributes to our understanding of risk homeostasis, and enables us to improve future traffic safety interventions, through engineering, enforcement, or education. Such interventions will, unfortunately, remain secondary to the responsibility of each individual driver. Everyone contributes to risk on the road, and everyone can promote traffic safety.

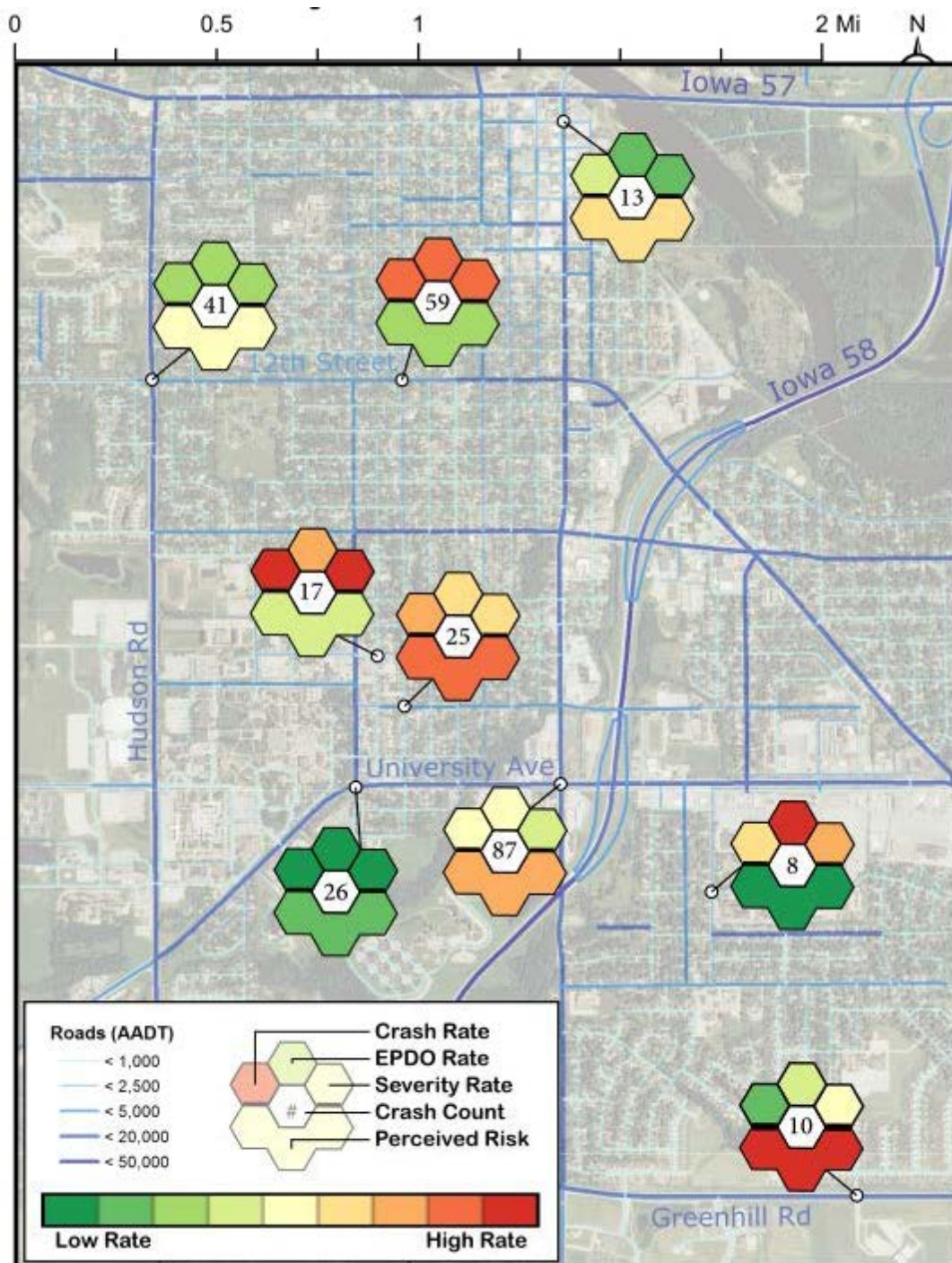


Figure 22: Mapping Risk-Rate Indices and Perceived Risk. Surveyed junctions in Cedar Falls show a lack of concordance between risk perception and actual risks along common residential connectors and commuter thoroughfares.

CHAPTER VI

CONCLUSIONS

Traffic Safety

To increase traffic safety, and to prevent unnecessary injury and death, our society must strive towards a culture that prioritizes safety for all participants in the automotive environment (Ward et al., 2010). This is not new thinking, as during the proliferation of American car culture it was noted that “[accident prevention] can only come through the joint and cooperative efforts ... of the great majority of Americans” (Bennet, 1950, p. 372). We have tried the four E’s (education, enforcement, engineering, and emergency response), and yet we return our focus back to the fifth E: Everyone (IaDOT, 2013, p. 1). This means you too, dear reader, because “the sad truth is that the way we drive is responsible for a good part of our traffic problems,” including the unacceptably high counts of crashes resulting in serious injury and death (Vanderbilt, 2008, p. 128).

We lie to ourselves about the extent of our traffic safety problems, and the cause. When involved in a crash, “drivers tend to explain accidents by circumstances which have least culpability compatible with credibility” (Baker, 1967, p. 591; Vanderbilt, 2008, p. 72). We even cast blame from ourselves onto vulnerable children. In a London study, children were held accountable for their involvement in a crash in 78% of cases; further, any observable reduction in children-pedestrian crash types over the last several decades is likely just a side effect of fewer children walking, and more riding in cars to school every day (Hillman, Adams, & Whitelegg, 1990). The shirking of responsibility

is not solely the fault of the car driver; rather there is an overall willingness evident throughout our society. Take for example, cases where we cast blame onto cars themselves (Figure 23), such as when newspapers reported a pickup incredulously driving itself through the front doors of a Wal-Mart shopping center (Abrams, 2016; Boroff, 2016; Hider, 2016; Maricle, 2016; Rodgers & McGowan, 2016). Three were killed by the truck in that “accident” (another point to be driven home shortly). The unfortunate reality is that cars (and trucks) don’t kill people; *people* kill people.

Clearly, the problem with traffic safety is the drivers. What is needed is a traffic safety culture, but even then, that type of program must start with the individual. We need to provide self-knowledge solutions. This solution demands an increased effort to



Figure 23: Headlines from a 2016 crash. The crash resulted in 3 fatalities and 2 injuries — the driver was not among the fatalities.

demonstrate the potential for human error, and to make apparent the resulting consequences (Reason, 1990, p. 248). What we need is to instill in drivers the “sustained realization that every time you step on the throttle, death gets in beside you, hopefully waiting for his chance” (Furnas, 1935, p. 21). This type of self-knowledge is already alive and well, on full display during the winter time, when despite terrible conditions, drivers actually get in significantly fewer wrecks (Hillman et al., 1990).

One easy start to these self-knowledge solutions is through simple use of language. We should call a spade a spade, and rarely is a crash an accident despite what you might read in the papers. This sensitivity to language is free (Stewart & Lord, 2003). Furthermore, the idea of affecting this language is not new, as in 1976, Ilya Ehrenburg lamented the evolution in language that transformed car crashes from ‘catastrophes’ into ‘accidents.’ Before Ehrenberg, and before crashes were catastrophes, the colloquial term was most poignant: people called fatal crashes motor-killings (“Nation roused,” 1924; Mars et al., 2013). The call for accurate language has already been reignited in our generations, led by the efforts of the Transportation Alternatives organization in their 2015 #CrashNotAccident social media campaign (Badger, 2015; Zumhagen, 2015).

There are simpler and more direct solutions to reducing dangerous driving. The severity of judicial punishments could be increased, and cars could be built with stringent speed governors (using either or both traditional radio-wave or modern satellite technologies). We can save lives, but as a society we lack the social and political willpower to make it happen. We willingly choose to accept unregulated freedom of mobility in exchange for rampant death and destruction (Humes, 2016, p. 132).

Unbridled Optimism

Many detractors of traffic safety (and yes, they do exist) would argue that the concerns expressed in this thesis are oversold. These types would suggest that engineering will eliminate the danger of our cars, and that automation will even supplant the driver. Such thoughts are optimistic at best, and downright wrong at their worst.

Improvements in safety technologies rarely reach their predicted potential. Safety technologies generally appear to increase our risk-taking behaviors. Wilde (2001) would interject his theory of risk homeostasis at this point. Taken a step further, Peltzman (1975) suggests that the consequences of this increased risk taking are mostly felt by innocent parties (pedestrians, cyclists, and other drivers). Aside, safety technologies are already available and often ignored; a significant number of crash injuries are to victims' heads, yet no one seems to be pushing for a helmet law (Vanderbilt, 2008, p. 265).

Automation in driving has become a trendy new topic of its own. Amidst the excitement and optimism, boosters promise an improvement in injuries and fatalities just as soon as we can eliminate the driver. This could be five years, or fifty, but many of these automation enthusiasts are content to sit back and wait while their friends and family buzz recklessly through the countryside. Even if this automation arrives within the decade, however, there is no guarantee of eliminating the human driver. People like to be in control (and especially like to be in control of their risk). Gambling on a future where people, governments, and engineers all see eye to eye seems a risky business all of its own. In the meantime, the death toll is still climbing.

There is another hidden truth in this story: the reality that the planet will likely never support one car for every person. The implication, then, is that we must go beyond optimism. We must go beyond traffic safety, and take aim at reducing automobility in favor of more sustainable public and active transit alternatives.

The issues inhibiting a transportation revolution are partly structural but also an ingrained part of our culture (Ladd, 2008). The personal car has replaced nearly every alternative, and thereby made the car a compulsory asset in the rural and suburban United States (Gorz, 1973). The American highway acts as a centrifugal force acting against our daily and personal spaces (Dimendberg, 1995; Jackson, 1984). This centrifugal age of “hypermobility” has embedded itself in our economies, and encouraged increasing wealth disparity, social dispersion, and anonymity. Meanwhile, our newborn suburbs have become placeless symbols of our newly adopted “McCulture” (Adams, 1999, pp. 95–96).

Practical Solutions

There are simple solutions to reversing the damage of our car culture (including the impacts to our environments, the sprawling of our cities, and the social and economic inequities). Something as simple as choosing to own and drive smaller cars would have significant implications for revitalizing dense urban spaces, and also address the closely related issue of expansive parking accommodations. Above all, however, we must seek to “reinstate the pedestrian” as a vital cornerstone of our places — we must rebrand the automotive environment as a human-friendly environment (Mumford, 1968, p. 8).

The first key to reducing our transportation footprint (and our transportation risk) is to reduce our daily trip distances. Before we ever face the choice of whether to drive or walk, we first choose where to live. That choice has control over our daily travel distances, and influences our modal choices. Reducing our daily travel distance to the point where walking, cycling, or public transit are preferable to a daily drive saves us a significant amount of risk (Lucy, 2003). This effect is compounded by removing yourself from the road during the most dangerous driving hours of the day: the commute. It also saves money, and as a bonus, cycling or walking doubles as daily exercise.

A second key is to push for reasonable legislation. With adequate social and political willpower, we can modify the incentives to favor transit and pedestrianism. We should increase the price for parking (Shoup, 2017), charge roads and gas taxes that cover the cost of maintenance, and we could lower speed limits and give right-of-way to pedestrians and cyclists. We can do all of these things and more, which would not only reduce the social and economic externalities of automobility, but also reduce the associated risks. Less cars means less crashes, and increased pedestrianism results in better behaved drivers (Speck, 2013, p. 98; Vanderbilt, 2008, p. 85)

Let us ignore the big picture for now. Let us ignore the environment, and our escalating consumption of natural resources. Let us ignore our sprawling urban capitals, our dwindling natural spaces and rising obesity. Let us ignore the simple economics, and the social inequities of casting a luxury good as a necessity. Instead, let us reiterate our focus on traffic safety, on the thousands killed every year, and the millions injured. We are the most dangerous creatures in our automotive environment, and we hold the keys.

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APPENDIX A
DATA SAMPLES

Table A1:
Exploratory Regression Data Inputs

County-Scale Regression Inputs								
County	C#	Area	Urban %	Pop	PP	Inc	Hwy	TN Hwy
Polk	93413	1532.02	38.2796	349332	1.1	60061	473.39	177.91
Scott	38565	1213.40	25.9843	133403	1.0	55114	342.81	102.72
Linn	32366	1875.95	16.2585	170386	0.9	59322	272.47	0.00
Black Hawk	24461	1482.27	19.6710	106859	1.6	48369	299.57	0.00
Johnson	22887	1612.97	9.0139	114221	1.3	55700	244.16	58.53
Woodbury	22279	2275.09	7.7313	78489	2.1	46720	229.96	62.57
Pottawattamie	20919	2484.58	5.9465	73416	2.3	51976	478.55	200.83
Dubuque	19243	1597.15	8.0092	76221	1.9	54605	286.22	0.00
Story	15517	1484.65	7.7664	79053	2.4	50438	256.09	50.79
Clinton	10422	1839.53	8.4284	38584	3.5	50498	207.79	0.00
Cerro Gordo	10001	1487.91	8.9034	35633	2.3	46122	210.04	54.67
Dallas	9418	1531.28	10.1851	55653	2.4	76320	162.13	50.42
Webster	8801	1860.37	4.0465	30162	5.3	42408	134.21	0.00
Des Moines	8432	1112.55	5.2934	31962	1.9	44423	133.84	0.00
Marshall	6861	1483.53	4.6148	31845	3.6	53351	70.52	0.00
Warren	6834	1482.67	6.3645	36762	1.7	64447	168.48	44.98
Lee	6218	1394.78	5.1134	28700	2.7	43312	144.86	0.00
Wapello	5729	1128.25	4.6398	28224	2.0	42095	163.94	0.00
Jasper	5363	1896.05	2.7696	29582	4.2	55033	155.65	60.08
Marion	4962	1476.14	3.4082	26076	3.2	54693	0.00	0.00
County: Name				Pop: 16 and Older				
C#: Crash Count (2007-2016)				PP: Perc. Pop. Agriculturally Employed				
Area: Square Kilometers				Inc: Median Household Income				
Urban %: Percentage Land in Incorporated Cities				Hwy: Kilometers State Highway				
TN Hwy: Kilometers of Transnational Interstate Highway								

Table A2:
Sample Rows and Key Columns of Survey Data

Sample of Rows and Key Columns from Survey																							
Dur	G	R	A	Ex	Ab	BC	B1	B2	B3	B4	B5	B6	B7	B8	RP	J1	J2	J3	~	J18	J19	J20	LT
312	F	N	24	1	4	37	5	4	4	5	5	4	5	5	3.8	4	5	3		3	3	4	MC
312	M	Y	33	3	5	25	5	4	2	1	3	2	4	4	2.8	2	4	1		3	5	2	MC
313	M	Y	29	2	6	28	4	5	4	3	3	3	2	4	3.4	3	2	3	~	5	3	1	MC
314	M	N	33	2	7	25	5	3	5	1	5	2	2	2	3.6	3	3	4		4	3	3	MC
314	M	Y	33	4	5	20	4	3	2	1	2	1	4	3	3.25	3	3	3		3	3	2	MC
314	M	Y	46	4	6	18	4	3	2	1	4	2	1	1	3.85	4	3	2	~	5	5	4	GEN
315	M	Y	23	3	6	32	4	4	4	3	4	4	5	4	2.8	2	2	3		3	3	2	MC
321	M	Y	27	3	5	19	4	4	2	1	2	3	1	2	2.95	2	2	2		3	6	2	AC
323	M	Y	22	3	7	29	4	5	3	4	4	4	2	3	3.3	2	2	2	~	3	4	3	PRO
327	M	Y	49	3	6	18	4	2	4	1	4	1	1	1	3.15	3	3	2		3	4	3	MC
330	F	Y	29	3	6	19	4	3	2	2	2	2	2	2	1.95	1	1	2		2	3	2	DRV
330	M	Y	40	3	6	24	5	4	4	2	2	2	2	3	3.8	4	4	4	~	3	5	3	MC
330	M	Y	49	3	6	24	3	4	4	2	1	2	4	4	3.55	2	2	4		3	5	3	MC
332	M	N	37	2	6	22	4	4	2	1	4	3	3	1	3.05	2	1	2		4	3	3	BC
334	M	Y	20	2	4	23	4	5	2	4	1	2	1	4	3.9	2	4	4	~	3	4	5	AC
334	M	Y	42	2	5	21	5	5	2	1	4	2	1	1	3.5	1	2	2		3	6	3	MC
337	M	Y	24	4	6	29	5	3	3	2	5	3	4	4	3.9	4	4	3		4	5	4	MC
337	M	Y	48	3	7	16	3	3	2	1	4	1	1	1	3.8	3	3	3	~	5	3	3	PRO
338	M	Y	39	3	7	28	1	1	5	4	4	3	5	5	3.6	5	4	4		3	3	3	PRO
340	M	Y	21	3	7	31	5	5	4	2	4	3	5	3	2.85	4	2	3		2	5	3	MC
341	F	Y	21	2	6	10	2	1	1	1	2	1	1	1	3.6	3	3	2	~	4	3	3	BC
342	M	Y	21	2	6	22	4	4	2	1	3	2	3	3	2.8	2	2	2		3	4	3	AC

Dur: Duration	Ex: Miles/Year	RP: Avg. Risk Perc.	J18: 324N
G: Gender	Ab: Self-Rate Ability	J1: 684N	J19: 736W
R: US Resident	BC: BSSS Sum	J2: 684S	J20: 736N
A: Age	B#: BSSS#	J3: 1100N	LT: Link Tracking

APPENDIX B
LAB AND FIELD MATERIALS

Computer Hardware

ACER CB3-111 Chromebook (Figure B1)

- Intel Celeron 2.16 GHz Single-Core
- 2 gigabytes DDR3 RAM memory
- 16 gigabytes Solid State Drive

- Benchmark. Browserbench.org/Speedometer
 - Test 1: 25.6 +- .28 (1.1%)
 - Test 2: 24.3 +- .81 (3.3%)

Dell Precision T1700 Workstation (Figure B2)

- Intel Xeon E3 1245, 3.40 GHz Quad-Core
- 64-Bit Processor and Operating System
- 32GB RAM
- NVIDIA Quadro K600 Graphics Display Adapter

- Benchmark. Browserbench.org/Speedometer
 - Test 1: 129.8 +- 1.3 (.96%)
 - Test 2: 132.2 +- 1.3 (.96%)

Computer Software

ACER Chromebook CB3-111 and Dell Precision T1700

- Google Chrome Web Browser 62.0.3202.94
- Google Drive Based Applications
 - Google Docs 0.10
 - Google Sheets 1.20
 - Google Slides 0.10
- Qualtrics Research Core Cloud-Based Software Suite

ACER Chromebook CB3-111

- ChromeOS Operating System 61.0.3163.120

Dell Precision T1700 Workstation

- Windows 10 Professional
- Microsoft Professional Productivity Suite 16.0.8730.2046
 - Word
 - Excel
 - Powerpoint
- ARCGIS Suite 10.4.1
 - ArcMap
 - Network Analyst Extension
- Adobe Photoshop CS2

- Adobe Acrobat DC Professional
- GNU Image Manipulation Program 2.8.16
- Inkscape 0.92.2
- RStudio 0.99.442
- TIBCO Spotfire S+ 8.2.0

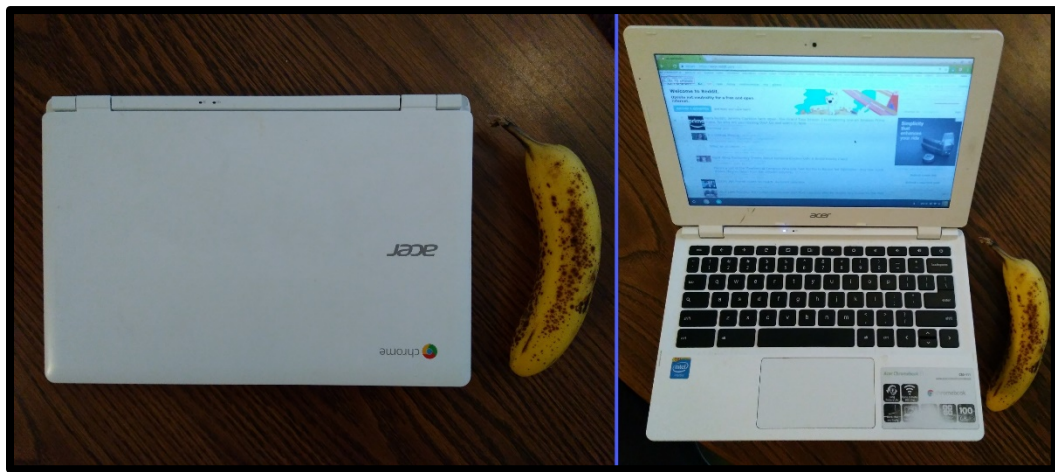


Figure B1: Acer Chromebook Portable Workstation; banana for scale (Alfonso, 2013).

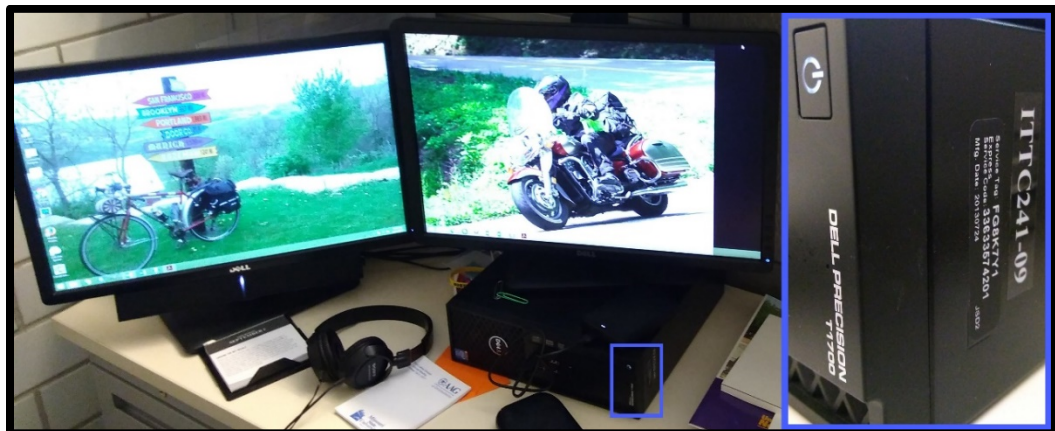


Figure B2: Dell Precision T1700 and Dual Monitor Configuration

Field Equipment

Kawasaki Vulcan Nomad 1600D “Classic Tourer”, 2007 (Figure B3)

- 1552 cc (94.70 cu.in.), liquid-cooled
- 4-stroke Single Overhead Cam, 50-degree V-Twin-cylinders
- 5-speed transmission, shaft-driven final drive
- Dual hydraulic front disc brakes (300mm), single rear hydraulic disc (300mm)
- Curb mass: 832lbs
- Modifications:
 - Cobra Steel Lightbar (#04-0442)
 - Vance & Hines Bagger Slash-Cut Dual Exhaust (#18369)
 - Cobra Tubed Sissy Bar Luggage Rack (#02-3501)



Figure B3: Kawasaki Vulcan. Vehicular platform used for photography in this research (Photo taken June of 2017, Highway NC-28; 35.439679 N, 83.785046 W).

ACTIVEon CX Action Camera (Figure B4)

- 5MP CMOS
- Full High Definition (FHD) 1080p Video Mode
- F/2.4
- 4 Field-of-View settings: Narrow, Medium, Wide, Super-wide (170°)

USA Gear Roll Bar and Handlebar Action Camera Mount

- Tripod Screw and Pivot Action Style Camera Mounting



Figure B4: Camera Equipment: Cobra Lightbar, Handlebar Mount, and Action Camera.

APPENDIX C

HOTSPOT ANALYSIS PYTHON SCRIPT

Overview

In this research, crash-record data points were assigned to intersection points according to their spatial location within buffered polygons. However, the creation of the buffered polygons for each intersection point resulted in many overlapped polygons; this resulted in crash records being double-counted through assignation to multiple intersections. Further exploration revealed, that in many cases, these overlapping buffers were a result of secondary intersections near to a much larger, primary intersection. Therefore, it was deemed best to eliminate this overlap, and to do so by preserving the polygon-buffer with the highest average annual daily traffic (AADT).

This python script runs within the ArcGIS ArcPy code environment. It requires an input table of polygon features with overlapping areas; within this research, these polygons are derived from buffered junction points which have been processed with the Union tool (“Junction_Union”). The Union tool splits polygons into smaller fragments wherever two or more polygons overlap (Figure C1). The script adds Centroid X and Y coordinates for each polygon fragment, then creates the output table (“Junction_Centroid”) by dissolving the union-polygons based on these coordinates. The dissolved output has no overlaps, but also no other attributes.

An iterative loop moves through each row of the Centroid output table; for each Centroid feature, a second loop accesses rows of the original Union polygons. It

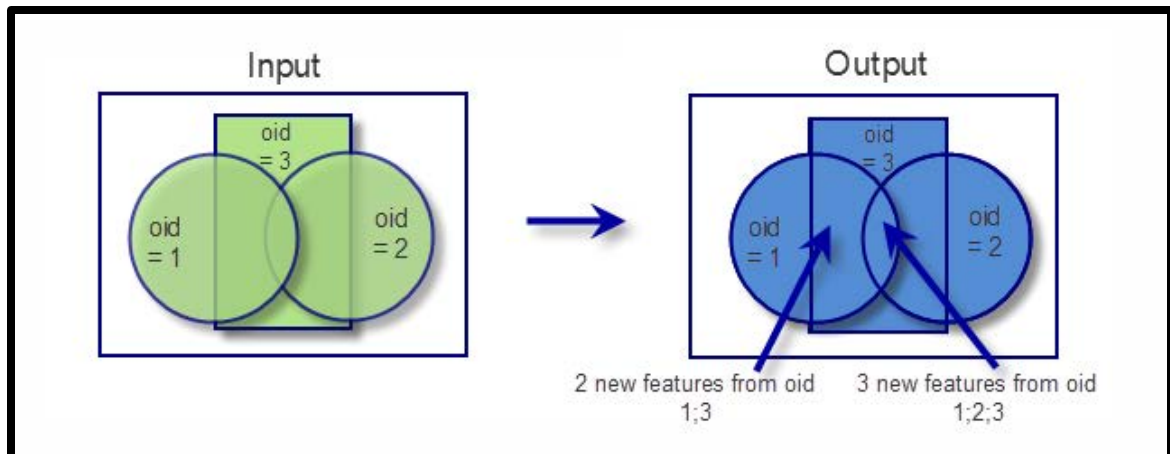


Figure C1: Union Tool Input and Output Example (Environmental Systems Research Institute, 2017).

compares and records the highest AADT amongst identical and overlapping polygon fragments, and then records this as the primary Junction ID (or “PrimJ”). The resulting Centroid output table has no overlaps, and features two key attributes, a Junction ID and the highest observed AADT. This output is Dissolved using these key fields, resulting in the complete reconstruction of the primary junction buffers.

Preparation of Workspace

- `arcpy.AddGeometryAttributes_management("Junction_Union", "CENTROID")`
- `arcpy.env.workspace = "D:\2017F\Thesis\Thesis_Junctions.gdb"`
- `arcpy.env.outputCoordinateSystem =`
`arcpy.Describe("Builder/Builder_2_BlackHawk_Union").spatialReference`
- `arcpy.Dissolve_management("Builder/Builder_2_BlackHawk_Union",`
`"Builder/Builder_2_BlackHawk_Centroid",["CENTROID_X", "CENTROID_Y"])`
- `arcpy.AddField_management("Builder/Builder_2_BlackHawk_Centroid",`
`"PrimeJunction_OID", "LONG")`
- `arcpy.AddField_management("Builder/Builder_2_BlackHawk_Centroid",`
`"HighestAADT", "LONG")`

Reset/Prime Columns

```

· with
  arcpy.da.UpdateCursor("Builder/Builder_2_BlackHawk_Centroid",["CENTROID_X",
  "CENTROID_Y","PrimeJunction_OID","HighestAADT"]) as rowsCentroid:
· for rowC in rowsCentroid:
·     newAADT = -12345678
·     newPrimJ = 87654321
·     rowC[3] = newAADT
·     rowC[2] = newPrimJ
·     rowsCentroid.updateRow(rowC)

```

Iterative Loop to Select Highest AADT Buffer

```

· with
  arcpy.da.UpdateCursor("Builder/Builder_2_BlackHawk_Centroid",["CENTROID_X",
  "CENTROID_Y","PrimeJunction_OID","HighestAADT"]) as rowsCentroid:
· for rowC in rowsCentroid:
·     refCentroidX = rowC[0]
·     refCentroidY = rowC[1]
·     newAADT = -1
·     newPrimJ = -1

·     with
      arcpy.da.SearchCursor("Builder/Builder_2_BlackHawk_Union",["CENTROID_
      X","CENTROID_Y","ORIG_FID","SUM_AADT"]) as rowsUnion:
·         for rowU in rowsUnion:
·             if rowU[0] == refCentroidX:
·                 if rowU[1] == refCentroidY:
·                     if rowU[3] > newAADT:
·                         print("Will update PrimJ --- RowU: ",rowU[3]," >
·                         New AADT:",newAADT)
·                         newAADT = rowU[3]
·                         newPrimJ = rowU[2]
·                     else:
·                         print("Preserved Existing Data --- RowU
·                         :",rowU[3]," < ",newAADT)

·         rowC[3] = newAADT
·         rowC[2] = newPrimJ
·         rowsCentroid.updateRow(rowC)

```

APPENDIX D

HORIZONTAL IMAGE RECTIFICATION

Due to stability issues with the tripod style ball-mount, some raw images included tilt from the true horizon. This was corrected in the GNU Image Manipulation Program. Imagery was imported, then rotated (often less than 5°). A selection box was created using a fixed aspect ratio (matching the ratio of the raw image). The image was cropped to this selection box, then exported to the Joint Experts Photographic Group image format (“.jpg”). This method avoided image distortion, and limited loss of viewshed.

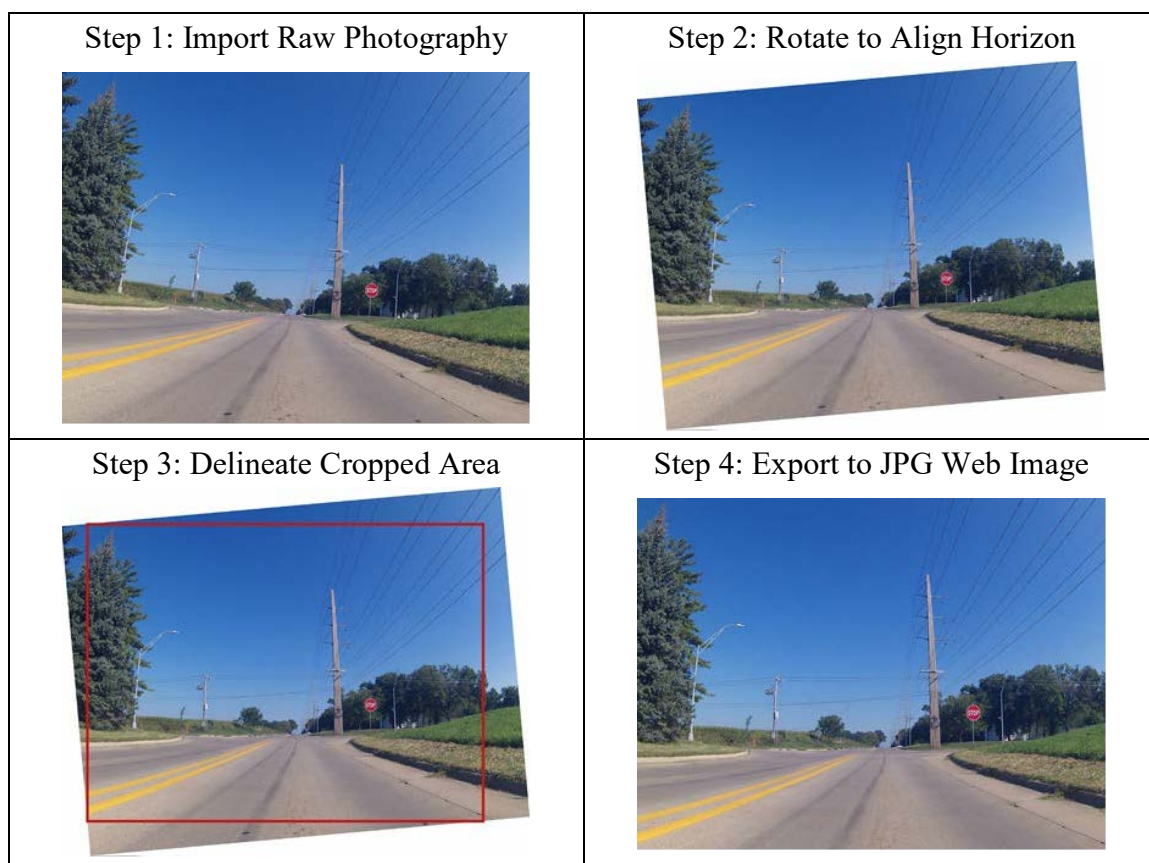


Figure D1: Horizontal Image Rectification Procedure

APPENDIX E
SURVEY IMAGERY



Figure E1: Survey Imagery



Figure E2: Survey Imagery (continued)

APPENDIX F

SURVEY QUESTIONNAIRE

◆ This survey aims to research the perception of risk in driving environments. The questionnaire begins with a short demographic section. Following this, participants are presented with 23 photographs of road intersections, and asked to rate the risk of each intersection.

This survey should only take 5-10 minutes of your time, requires minimal personal information, and poses very little risk to participants. Due to the nature of digital communications the security of these forms cannot be guaranteed; however, once received, survey results will remain secure and completely anonymous. The Institutional Review Board at the University of Northern Iowa has reviewed and verified these statements. The survey is voluntary, and may be stopped at any time.

- I am willing to participate in this survey.
- I am not willing to participate at this time.

◆ Are you 18 years of age or older?

- Yes
- No

◆ Do you have a valid driver's license?

- Yes
- No

◆ What is your gender?

- Male
- Female
- Other

◆ Are you a resident of the United States?

- Yes
- No

◆ What is your age?

- | | | | |
|--------------------------|--------------------------|--------------------------|-----------------------------------|
| <input type="radio"/> 18 | <input type="radio"/> 30 | <input type="radio"/> 42 | <input type="radio"/> 54 |
| <input type="radio"/> 19 | <input type="radio"/> 31 | <input type="radio"/> 43 | <input type="radio"/> 55 |
| <input type="radio"/> 20 | <input type="radio"/> 32 | <input type="radio"/> 44 | <input type="radio"/> 56 |
| <input type="radio"/> 21 | <input type="radio"/> 33 | <input type="radio"/> 45 | <input type="radio"/> 57 |
| <input type="radio"/> 22 | <input type="radio"/> 34 | <input type="radio"/> 46 | <input type="radio"/> 58 |
| <input type="radio"/> 23 | <input type="radio"/> 35 | <input type="radio"/> 47 | <input type="radio"/> 59 |
| <input type="radio"/> 24 | <input type="radio"/> 36 | <input type="radio"/> 48 | <input type="radio"/> 60 |
| <input type="radio"/> 25 | <input type="radio"/> 37 | <input type="radio"/> 49 | <input type="radio"/> 61 |
| <input type="radio"/> 26 | <input type="radio"/> 38 | <input type="radio"/> 50 | <input type="radio"/> 62 |
| <input type="radio"/> 27 | <input type="radio"/> 39 | <input type="radio"/> 51 | <input type="radio"/> 63 |
| <input type="radio"/> 28 | <input type="radio"/> 40 | <input type="radio"/> 52 | <input type="radio"/> 64 |
| <input type="radio"/> 29 | <input type="radio"/> 41 | <input type="radio"/> 53 | <input type="radio"/> 65 or older |

◆ What age did you receive your first driver's license?

- | | | | |
|-------------------------------------|--------------------------|--------------------------|-----------------------------------|
| <input type="radio"/> Before Age 14 | <input type="radio"/> 17 | <input type="radio"/> 21 | <input type="radio"/> 25 |
| <input type="radio"/> 14 | <input type="radio"/> 18 | <input type="radio"/> 22 | <input type="radio"/> Over Age 25 |
| <input type="radio"/> 15 | <input type="radio"/> 19 | <input type="radio"/> 23 | |
| <input type="radio"/> 16 | <input type="radio"/> 20 | <input type="radio"/> 24 | |

◆ Approximately, how many miles do you drive in a typical year?

- Less than 5,000 miles. Between 10,000 and 20,000 miles.
 Between 5,000 and 10,000 miles. Over 20,000 miles.

◆ Please rate your driving ability:

- | | | | | | | |
|-----------------------|--------------------------------|------------------------------|-----------------------|------------------------------|--------------------------------|-----------------------|
| Far above
average | Moderately
above
average | Slightly
above
average | Average | Slightly
below
average | Moderately
below
average | Far below
average |
| <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

◆ Please respond to the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I would like to explore strange places	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I get restless when I spend too much time at home	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to do frightening things	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like wild parties	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would like to take off on a trip with no preplanned routes or timetables	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer friends who are excitingly unpredictable	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would like to try bungee jumping	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would love to have new and exciting experiences, even if they are illegal	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

◆ Different intersections pose varying levels of risk of a car crash. The following section will present 23 photographs of various suburban intersections. We would like your estimation of risk at the given intersections, recorded on a multiple-choice scale from below average risk to above average risk. The photography is not meant to be misleading in any way; feel free to respond as quickly as possible, providing us with your first impressions.

◆ Estimate the risk of a car crash at the following intersection:



Far below average

Far above average

◆ *(Intersection Question Structure Repeated for Each of 23 Images)*

◆ Please enter your birth year:

◆ Do you have any comments, suggestions, or feedback for this study?

APPENDIX G
RESPONDENT COMMENTS

Hypotheses

Blind Spots Raise Threat

- I look at sight lines and obstructions. If there are obstructions to the drivers being able to see oncoming and threat-traffic when they are parked at the stopsign/light/driveway line, then that is a recipe for them to try and pull out past the line and hit cyclists and pedestrians, as they try to get out far enough to see the traffic.

Risk = Severity

- It's not so much the "chance of a collision" as the severity of the collision. Stop sign intersections are likely for a fender-bender, but faster roads are more likely for a serious crash.

Low Traffic = Low Risk (caveat, familiarity = negligence)

- No traffic at ANY of these intersections so they all look relatively safe.
- As a motorcycle rider I find intersections where someone could pull out in front of me as particularly risky. I've also been rear ended twice at simple 4 way lights in town due to driver distraction. Residential uncontrolled are usually pretty low due to the number of cars and low speed limit, but people familiar with the neighborhood rarely stop completely or look for cross traffic. Hopefully my answers show this.

Markings Mean Safe...

- It seems like most of the pictures were on streets that did not have double yellow centerlines... I would think that alone would keep them off the lowest notch. I didn't see any with vision potentially blocked by vegetation or objects.
- I rated intersections as more dangerous when driving lanes were not clearly marked[...], options to proceed were not clear, [...]
- 2-way stop v's 4-way stop would make a significant difference to the risk

...Though Not Always

- It would be nice to know, statically, how dangerous each type of intersection is, especially for motorcyclists. I believe it is when a smaller road tee's into a larger road, with only a stop sign to control traffic flow.
- It would be interesting to see what the empirical risks for these intersections are, or at least for intersections with and without traffic lights (and more or less obstruction to visibility). It's somewhat unclear to me whether traffic lights (presumably placed at high-traffic intersections) increase or decrease risk as running one by mistake probably leads to a crash.

Traffic Potential

- that was interesting. I looked at the total traffic potential and the opportunity to intersect. Protected turn lanes are typically somewhat dangerous. Sight lines play a big role, too.
- I rated intersections as more dangerous when [...] my perceived number of vehicles was higher.
- More lanes, more dangerous the intersection. Hello from /r/motorcycles!

LimitationsQualtrics "Random"

- I noticed some intersections are pictured twice from multiple angles/approaches. I only notice this because those photos are sequential. If more spread out it would be easier to fool me (and others). :)

Additional Factors in RiskDemographics

- An option to identify the survey taker as a professional or amateur driver might yield more interesting information.

Time of Day / Sun, Conditions

- I agree with your assertion that motorcyclists assess risks differently to car drivers. Since we are far more vulnerable the cost of even a minor accident is high. It might help your survey if you could include other vehicles, since this also has an important bearing on how dangerous an intersection might be. Also weather and the time of day are important factors.
- Knowing the direction of travel at each intersection would be helpful as the time of day and direction of the sun can play a major role in the safety of an intersection and the ability of the drivers to see clearly. I was only able to make opinions based on that moment in time, roadway markings, lights and signs and current conditions at the time of the picture. All of which can play a factor but are not always the most important things to consider.

Intersection Sample

- Where do you live for that many 4 way intersections to have no stops in any of the ways ?
- There should be more variety. They all seem like they are from the same town in the US. My main concern is when the roads are too wide - it makes them feel safer when they are not.

“Traffic or Situations”

- Hard to judge based on a photograph. Moving images would be better
- It's hard to evaluate the intersections based on a photo, I couldn't really see as well as I could if I was there - things like whether or not it was a four way stop or if it was crowded or if cars were likely to make a U-turn.. etc. But that's not the fault of the study.
- At least one photo did not encompass a complete intersection. Pretty much all intersections were average because I assumed daytime traffic. Some could have used better signage or striping. No traffic or speed limit sign information was provided though. It's more like driving at 3a.m. Very safe as there were no cliffs or construction sites. This is a pretty incomplete driving situation to assess.
- The pictures make it hard to tell exactly what's going on. You can judge risk based on lines of sight, traffic volume of road, and other factors that are hard to capture from a single picture."

Speed Limits

- Hard to tell which intersections will be dangerous without knowing the speed limits of the roads intersecting.
- Having some speed limit signs would help assess the different risk levels.
- No speed limit indicators, couldn't tell if 4 way stop or not, no way to have much indication of traffic volume or time of day.

Respondent Fatigue

- After about the 8th intersection I stopped caring

Photos

Other stop signs / 4-way Identification

- Some of the intersection photos didn't make it easy to determine what types of traffic control features were present.
- Hard to tell if other traffic had stop signs as well.
- It was difficult to gauge a lot of the stop sign regulated intersections. I couldn't see/tell if it was an all way stop or not.
- I think the photos seem overly biased toward semi-rural or residential areas. Also in many cases, I couldn't tell whether there were stop signs on the crossing streets in many cases. 2-way stop v's 4-way stop would make a significant difference to the risk

Small/Blurry

- Pictures of the intersection are inadequate to accurately judge the intersection. The images appear distorted and make it difficult to determine rough distances and potential clearances. Recommend updated pictures, diagrams, or different intersections.
- The photos are quite small. It's difficult to make out detail.
- Wide angle lens distorts depth of field significantly.

Perspective

- If I were to conduct this experiment again, I'd use the same vehicle and driver with a dash or head mounted camera to capture images more consistently representing what drivers would see in real time."
- It is very difficult to estimate the dangers because the pictures do not show the amount of overview you have of the roads on the left and right.
- Perspective is important. Without knowing how high the camera was, it is difficult to tell whether roadside obstacles would block the view of oncoming or crossing traffic. Picture 1 is a good example. Combined with the distortion from the camera lens, the grass berm on the right and bushes to the left could make seeing cross traffic difficult without entering the intersection.
- camera angle seems low, estimates are based on still images without seeing further into the intersection from the right left from and behind. Chance of accidents are always there. Some was easier to identify blind spots many looked the same 4 way intersection. Some where 3 way intersection, which helps identify threat or chance of oncoming vehicle.

Foreigner Perception?

- As a UK driver most of my decisions were based on UK rules, so may not apply to the USA
- Non-American responses may differ significantly from American responses since they're less familiar with US intersection design
- "Not sure how useful allowing us forinurs to participate, VERY different road setup i.e. very few intersections, more lots of roundabouts. differnet rules on what happens at these places too.

What is Average?

- Intersections have to be rated above average or below average. What if I consider the intersection to be average?
- It's not so much the "chance of a collision" as the severity of the collision. Stop sign intersections are likely for a fender-bender, but faster roads are more likely for a serious crash.
- most intersections are the same and same level of control.

- The questions are in relation to "average". Average of all images shown? Average of any given intersection in the US? Average based on my experiences? It seems a bit too open to interpretation.
- There is no "average" option on the estimate of how dangerous the intersection is.

Shared Experiences

- The vehicle that one drives must play a large role in predicting dangerous circumstances. While on my motorcycle, many of these scenarios would be alarming. In contrast, being in a car would warrant a different assessment.

Self-ascribed a higher risk

- As a newbie rider i tend to feel more risky going through intersections
- I drive very seldomly and live in a large metro area. My education level is a 2nd year college student.

Self-described their driving experience or abilities

- I ride Motorcycles on the road more than driving a car.
- "I'm on 41st year of driving and 50th year of riding motorcycles. I have never had any fear of a motorized vehicle be it land, sea or air (I was a Coast Guard rescue boat captain and have solo'ed in a single engine plane. I have also road raced motorcycles with WERA for over 20 years). The only thing that frightens me on the road is other drivers, most of who I find woefully inadequate at the operation of a vehicle. I lived in Germany for a year...they treated driving as a privilege and obtaining a license was similar to a pilots license in the US. We should adopt that policy!"
- Long haul trucker here, almost three years experience.
- My primary transport is a Kawaski En500, followed by a Ford F-250.
- No accidents or tickets (moving or not) in my entire driving career.

APPENDIX H

STATISTICAL CODING AND TESTS

Processing completed in the RStudio R coding environment (R Core Team, 2013).

Brief Sensation Seeking Scale Correlations

Inter-item Multicollinearity

Correlations

```
> df <- data.frame(Survey_ DATA)
> mCorr <- data.frame(df$BSSS1, df$BSSS2, df$BSSS3, df$BSSS4,
+   df$BSSS5,df$BSSS6, df$BSSS7, df$BSSS8)
> cor(mCorr, mCorr)
## Output Omitted
```

Correlation P-Values Matrix (Rinker, T., 2012; Zoonekynd, V., 2012)

```
> df <- data.frame(Survey_ DATA)
> cor.test.p <- function(x){
+   FUN <- function(x, y) cor.test(x, y)[["p.value"]]
+   z <- outer(colnames(x), colnames(x),
+     Vectorize(function(i,j) FUN(x[,i], x[,j])))
+   dimnames(z) <- list(colnames(x), colnames(x))
+   z}

> cor.test.p(mCorr)
# Output Omitted
```

Variable Inflation Factor Test

Multicollinearity Test using Variable Inflation Factor
(Naimi, Hamm, Groen, Skidmore, and Toxopeus, 2014)

```
> df <- data.frame(Survey_ DATA)
> vifcor(cbind(df$BSSS1, df$BSSS2, df$BSSS3, df$BSSS4, df$BSSS5, df$BSSS6,
+   df$BSSS7, df$BSSS8))
```

Output:

-- No variable from the 8 input variables has collinearity problem.

The linear correlation coefficients ranges between:

min correlation (V4 ~ V2): 0.008529956 max correlation (V8 ~ V4):
0.4871724

----- VIFs of the remained variables -----

Variables	VIF
1 V1	1.274485
2 V2	1.250898
3 V3	1.590967
4 V4	1.442226
5 V5	1.261420
6 V6	1.602118
7 V7	1.290714
8 V8	1.726975

Cronbach's Alpha

> alpha(x = BSSSItems)

Output:

Reliability analysis

raw_alpha	std.alpha	G6(smc)	average_r	S/N	ase	mean	sd
0.71	0.71	0.73	0.24	2.5	0.025	3.2	0.69

Confidence Intervals	lower	alpha	upper
	0.66	0.71	0.76

Item	raw_alpha	std.alpha	G6(smc)	average	_r S/N	alpha se
BSSS1	0.70	0.70	0.71	0.25	2.4	0.026
BSSS2	0.72	0.72	0.72	0.27	2.5	0.024
BSSS3	0.64	0.64	0.67	0.21	1.8	0.032
BSSS4	0.69	0.70	0.71	0.25	2.3	0.027
BSSS5	0.70	0.70	0.71	0.25	2.4	0.026
BSSS6	0.65	0.65	0.67	0.21	1.9	0.030
BSSS7	0.69	0.69	0.71	0.24	2.2	0.027
BSSS8	0.64	0.65	0.66	0.21	1.8	0.032

Descriptive Demographic Data and Correlations with BSSS Items

```
> df <- data.frame(Survey_ DATA)
> cor.test(df$BSSS1, df$DrvExp)
> cor.test(df$BSSS2, df$DrvExp)
## Repeated for each correlation (BSSS Items 1 through 8 and the BSSS total score,
## for Age, Experience, Ability, and Risk Perception.
```

Community Correlations

Linear Model using BSSS Items to Predict Community Affiliation

```
> df <- data.frame(Survey_ DATA)
> fit <- lm(as.numeric(df$Link.Tracking)~df$BSSS1+df$BSSS2
+   +df$BSSS3+df$BSSS4+df$BSSS5+df$BSSS6+df$BSSS7+df$BSSS8)
> summary(fit)
```

Output Omitted

*## A Cellular Reference Model was used to identify distinctions between Communities
and their response to BSSS items (Ogorek, 2012). Data was first prepared using
Microsoft Excel. This included duplicating the survey response rows (this
unfortunately inflates the sample size and degrees of freedom of ## this test). The
Link-Tracking attributes of the duplicated entries were replaced with “A1”; this
assured it would be treated first in the Linear Model (and thus, used as a Reference
Cell representing the aggregate response to the BSSS survey question Items).*

```
> df <- data.frame(Survey_ DATA_PrepForReferenceCellModel)
> fit <- lm(BSSS1 ~ df$Link.Tracking)
> summary(fit)
```

Output

Call:

```
lm(formula = df$BSSS1 ~ df$Link.Tracking)
```

Residuals:

Min	1Q	Median	3Q	Max
-3.4205	-0.4000	0.0526	0.6967	1.4000

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	4.30333	0.04802	89.607	< 2e-16	***
df\$Link.Tracking Academic	-0.04246	0.17997	-0.236	0.813553	
df\$Link.Tracking Bicyclist	0.09667	0.15928	0.607	0.544148	
df\$Link.Tracking Driver	-0.30333	0.23565	-1.287	0.198514	
df\$Link.Tracking General	-0.35596	0.19678	-1.809	0.070964	.
df\$Link.Tracking Motorcyclist	0.11718	0.07651	1.531	0.126189	
df\$Link.Tracking Professional	-0.70333	0.1921	-3.661	0.000273	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8318 on 593 degrees of freedom

Multiple R-squared: 0.03865, Adjusted R-squared: 0.02893

F-statistic: 3.974 on 6 and 593 DF, p-value: 0.0006578

The reference cell model was repeated for each Item of the BSSS,

and for the composite score of the BSSS.

Correlations between Subjective and Objective Risk by Photograph

Results were recorded manually for correlations between each communities'
perception of photography, and for each of 5 measures of risk.

```
> df = data.frame(RiskEstimatesForSurveyPhotography)
```

```
> cor.test(df$CR, df$ACAD)
```

Output

Pearson's product-moment correlation

data: df\$CR and df\$ACAD

t = -0.58778, df = 18, p-value = 0.564

alternative hypothesis: true correlation is not equal to 0

95 percent confidence interval:

-0.5465595 0.3250292

sample estimates:

cor

-0.1372296

```
## Correlation test repeated for severity rate, EPDO rate, crash frequency, and average
## severity. These correlations were then repeated for each community, academics,
## bicyclists, drivers, general, motorcyclists, and professionals, and for low and
## high BSSS scores.
```

Comparison of Different Perspectives of the Same Intersection

```
## Paired T-Test
```

```
> df = data.frame(IntersectionVariance)
> t.test(df$N, df$W, paired=TRUE)
```

```
## Output
```

Paired t-test

```
data: df$N and df$W
t = -0.89171, df = 8, p-value = 0.3986
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.4542311  0.2008978
mean of the differences
 -0.1266667
```