PEDESTRIAN ENVIRONMENT AROUND SCHOOLS AND TRAFFIC SAFETY: SOCIAL DISPARITY ISSUES IN CHILD PEDESTRIAN CRASHES IN AUSTIN, TX

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF URBAN PLANNING

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May 2016

Major Subject: Urban and Regional Planning

ABSTRACT

Pedestrian safety from the motor vehicle traffic crash is one of the major concerns of the transportation planning and public health fields. Especially, school-aged children are more vulnerable to being struck by a motor vehicle than other age groups. Many American cities have devoted time and effort to improve the pedestrian safety, providing a desirable pedestrian environment to their neighborhoods. However, there are some controversies about the unequal distribution of the benefits from a quality pedestrian environment. Thus, we investigated: 1) whether school neighborhoods provide safer pedestrian environments than other neighborhoods in terms of school-aged child pedestrian crashes, and 2) whether there are social disparity issues in the safe pedestrian environments around schools in Austin, TX. Using both bivariate and multivariate analyses, this study also examined differences in contributing factors of child pedestrian crashes across neighborhoods with contrasting socio-demographic characteristics. Results show that child pedestrian crashes occur less frequently near school neighborhoods. However, those school neighborhoods with higher proportions of Hispanic populations and lower-income households showed higher likelihood of crashes than their counterparts. Also, this paper identified that significant contributing factors of child pedestrian injuries varied by neighborhood characteristics. These findings suggest that planners and policy makers should pay more attention to the provision of safe pedestrian environments and the equitable distribution of their benefits to ensure the social justice.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Kenneth Joh, and my committee members, Dr. Chanam Lee and Dr. Xuemei Zhu, for their guidance and support throughout the course of this research.

Thanks also go to the department faculty and staff for making my time at Texas A&M University a great experience. I also want to extend my gratitude to the Texas A&M Transportation Institute (TTI), which provided the research information. I am also thankful to my colleagues at TTI for their wonderful collaboration and support.

Finally, thanks to my mother, father, and brother for their encouragement and to my fiancé for her patience and love.

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CHAPTER I

INTRODUCTION

Providing a desirable pedestrian environment to promote healthy and safe communities has been one of the predominant agendas for urban and transportation planners, policy makers, and public health professionals in recent years. A quality pedestrian environment encourages people to choose active modes of transportation such as walking and biking. Particularly, walking is a highly affordable and an easily undertaken form of physical activity in our daily life (Ainsworth & Macera, 2012). For school-aged children, especially, walking can provide several benefits such as normal bone development, biological maturation, and behavioral development (Strong et al., 2005; Texas Department of State Health Services, 2014). Walking to school provides school-aged children with an opportunity to participate in regular physical activities, improving their health through daily routines (Cooper, Andersen, Wedderkopp, Page, & Froberg, 2005). Children who walk to school have higher daily physical activity levels than others who commute by automobile (Loucaides & Jago, 2008; Sirard & Slater, 2008).

However, children are one of the most vulnerable age groups when they are on the street. Due to the vulnerability of children, such as their immature bodies and undeveloped cognitive skills, they are exposed to the greater risks of traffic accidents than other age groups (World Health Organization, 2004). In addition, children's smaller physical stature raises a problem that limits their ability to recognize the risk of traffic crashes or to be recognized (World Health Organization; Unicef, 2008). In 2008 and 2009, motor vehicle traffic crashes represented the top ranked cause of death in the U.S. for children and youth aged between 8 and 20 and the second ranked cause for young children aged between 4 and 7 (Subramanian, 2012). Besides fatality, traffic injuries caused by pedestrian-vehicle collisions in children are also a leading cause of disabilities sustained in crashes (World Health Organization; Unicef, 2008). This threat has remarkable effects especially on child pedestrians. A report released by the National Highway Traffic Safety Administration (NHTSA) identified that among children from birth to 14 years old killed in traffic crashes, 21% of them were pedestrians in 2013 (NHTSA, 2015). Traffic injuries cause approximately 70% of deaths of children aged 5 to 19 years in the United States and the United Kingdom (Keppel-Benson, Ollendick, & Benson, 2002). Beyond these kinds of physical injury threats, children pedestrian crashes contribute to a significant proportion of public healthcare costs as well. According to the recent research on the national economic estimates of pedestrian crashes for children aged under 19, pediatric pedestrian injuries cost about $300 million in inpatient hospital care in 2003 (Conner et al., 2010).

The unequal burden of traffic injury among children with different socio-demographic characteristics is another issue to be addressed. Prior research has reported that the risks of pedestrian crashes were higher in neighborhoods with particular socio-demographic characteristics, such as low-income and high proportion of ethnic minority. For both developed and developing countries, children from ethnic minority groups and low-income families have a higher possibility of being victims of traffic crashes (World

Health Organization, 2004). In the U.S. nationwide, although African-Americans and Latinos comprise only about 13% and 13.5% of the population, respectively, they account for nearly 20% and 16% of pedestrian deaths, respectively (Surface Transportation Policy Project, 2004). Loukaitou-Sideris, Liggett, and Sung (2007) reported that pedestrian collisions were concentrated in those neighborhoods consisting of high proportion of low-income Latino populations in Los Angeles. In a comparison between the Atlanta metropolitan statistical area and the rest of the U.S., the pedestrian fatality rates were higher for males, Hispanic, and age groups of 15-34 and 35-54 (Beck, Paulozzi, & Davidson, 2007). Zhu and Lee (2008) found that schools with a high proportion of Hispanic students were located in neighborhoods with higher risks of traffic crashes and violent crimes in Austin, TX.

To address the traffic safety issues, various interventions supporting safe pedestrian environments have been undertaken. Walsh (2012) found that many U.S. cities and communities have formulated policies and practices for implementation, including guidelines, planning and land development regulations, financing sources, and the measurements of operations. There were several noticeable interventions providing safe pedestrian environments for children. For example, the city of Burlington, Vermont created the Traffic Calming and Neighborhood Enhancement program in 1996 that includes activities for improving to roadway safety for children by controlling possible threats, such as traffic conflict points, vehicle speeds, and vehicle volumes. In Santa Barbara, California, the city government developed the *Santa Barbara's Pedestrian Master Plan* which has a goal to increase the number of children who commute to school by walking and biking. New York City also published the document, *Active Design Guidelines: Promoting Physical Activity and Health in Design*, to establish design guidance. Specifically, the guidance encourages public spaces to improve their pedestrian environment and safety by providing access to transit and parking, children's play areas, parks, open space, and recreational facilities, and so on. In Austin, TX, there are several programs, which enhance the physical environment in the neighborhood to provide safe pedestrian environments around schools. For instance, the city of Austin has developed the Access Austin program in cooperation with Austin's regional public transit provider (Capital Metro), Austin Independent School District (AISD), and the City of Austin Urban Trails Program. Access Austin aims to reinforce street connectivity and accessibility by completing high priority pedestrian infrastructure needs within a quarter-mile of all identified schools and bus stops in the city's jurisdiction (City of Austin, 2015).

At the U.S. national level, there was a noteworthy intervention for children walking to school. Since the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) was enacted in 2005, the legislation established the Federal Safe Routes to School (SRTS) program with a total funding of over $1 billion (National Center for Safe Routes to School, 2015). This program contains several policies and actions that focus on increasing children's physical activity and enhancing their safety on the way to school by improving the physical environment (Boarnet, Day, Anderson, McMillan, & Alfonzo, 2005). From 2005 through 2010, under the guidance of the federal government, $800 million was allocated to the state departments of transportation to accomplish the goals of the SRTS program, providing safer pedestrian environments, such as sidewalks, bike lanes, pathways, and safer crosswalks (Safe Routes to School National Partnership, 2010). State and local communities play key roles in the success of the SRTS program. In 2012, the U.S. Congress passed a new transportation bill MAP-21, the Moving Ahead for Progress in the 21st Century Act (MAP-21). This new bill consolidated various funding of pre-MAP-21 programs, including SRTS, into a united funding source (i.e., the Transportation Alternative Program) and granted the control over local transportation projects to state and regions (U.S. Department of Transportation Federal Highway Administration; Safe Routes to School National Partnership, 2014). As a result, the local governments were given the authority to judge how much funding should be allocated for the SRTS program, as well as which communities should be supported for improvement of the pedestrian environment safety along the routes for children's school travel.

Traffic injuries in children are a significant burden for communities. To address traffic injury issues and support safe pedestrian environments for children, more urban planning and public health professionals emphasized the importance of the quality pedestrian environments that may encourage more children to have safe pedestrian activities. While many studies have already examined pedestrian crashes, there is limited understanding of child pedestrian's safety from motor vehicle crashes specifically around schools. Furthermore, little is known about the social inequality issues in the distribution of benefits from safe pedestrian environments within the vicinity of schools. While related research have noted the high risk of traffic crashes in children and its racial/ethnic disparity issues, this paper attempts to specifically examine the child pedestrian crashes in the vicinity of schools in the Austin, Texas jurisdiction areas to identify whether pedestrian safety is equally guaranteed for school-aged children. Thus, this paper is intended to address differences in the probability of child pedestrian crashes across different neighborhoods to determine whether and how the risk varied by socio-demographic characteristics, such as median household incomes and proportion of ethnic minority populations (i.e., Hispanics in Austin, TX). The effects of explanatory variables on child pedestrian crashes are analyzed through both bivariate and multivariate analyses. Based on the findings from this paper, appropriate policy interventions for each of the neighborhoods will be proposed in the planning perspective for local governments to achieve the social justice in child pedestrian safety.

This paper is organized as follows: Firstly, Chapter II includes a literature review on various determinants of and methodologies for studying pedestrian crashes. The study area, descriptive statistics of crash patterns and contributing factors, and research methods will be presented in Chapter III, followed by a summary statistics and the results of analyses in Chapter IV. Lastly, in Chapter V, discussions of empirical results and the consequential policy implications will be suggested.

CHAPTER II

LITERATURE REVIEW

II.1. Factors Influencing Pedestrian Crashes

Previous research revealed and examined the effects of diverse factors related to pedestrian crashes, including traffic exposures, driver's characteristics, weather, road conditions, pedestrian's behavior, built environment, and socio-demographic factors. However, this study focused on the effects of built environment and socio-demographic factors, considering traffic exposure because the objectives of this study are to identify the differences of a pedestrian environment across different neighborhoods. While it would be better to control other factors, such as personal behavior or characteristics, they are exempted in this study due to the lack of availability.

Most of the contributory factors in traffic accidents for the general population have similar effects on children as well (World Health Organization; Unicef, 2008). Out of the various contributing factors to pedestrian crashes, previous literature have revealed that the physical environmental and socio-demographic factors are mostly related to higher risks of traffic crashes involving pedestrians (Cottrill & Thakuriah, 2010). Many policies and programs that aim to provide safe pedestrian environments have also focused on improving and enhancing the physical, or built, environment in communities. The built environment consists of urban infrastructures and neighborhood characteristics in our community that affect people's lifestyle (Sallis & Glanz, 2006).

Previous studies have stated that the built environment plays an important role in accounting for the determinant effects not only on people's travel mode choice but also on the traffic safety issues in terms of pedestrian crashes. The following paragraphs describe typical factors that are considered to have significant effects on pedestrian safety.

II.1.1. Traffic Exposure

Several authors have noted that traffic exposure factors are related to pedestrian safety as well as people's mode choice. Intuitively, pedestrian crashes are more likely to occur where more people walked. Also, the number of pedestrian crashes across different units of analysis vary by size of unit of analysis: larger units possibly show a greater number of crashes. Thus, to account for the different effects of exposure, the number of pedestrians and/or the areal size of units should be included as a control variable. However, in the pedestrian safety research, it has been difficult to obtain the exact number of pedestrians at the site-specific level due to the lack of resources (Miranda-Moreno, Morency, & El-Geneidy, 2011). To address the issue of data availability, previous literature commonly used a proxy variable, such as population density for the measure of pedestrian exposure (Loukaitou-Sideris et al., 2007). Prior studies have stated that higher population density may be related to higher number of pedestrians regardless of trip purpose, heightening the risk of pedestrian traffic injuries (Cottrill & Thakuriah, 2010; Ewing & Dumbaugh, 2009). Several previous studies have provided evidence of the positive relationship between population density and pedestrian accidents (Dumbaugh, Li, & Joh, 2013; Huang, Abdel-Aty, & Darwiche, 2010; Wedagama, Bird, & Metcalfe, 2006). For child pedestrians, LaScala, Gruenewald, and Johnson (2004) found that greater density of youth population is related to more child pedestrian collisions. Clifton and Kreamer-Fults (2007) also found that population density around schools in Baltimore City, Maryland has a positive association with pedestrian crash count per school enrollment.

Besides population density, there are other variables considered to increase exposure of pedestrians to the risk of traffic crashes by generating a high level of pedestrian activity. Recent literature suggest transit accessibility as one of the key pedestrian exposure factors (Dumbaugh et al., 2013). Accessibility to the transit system has been commonly measured using the number of transit stations, such as bus or rail transit stops (Miranda-Moreno et al., 2011; Pulugurtha & Repaka, 2008; R. Schneider, Arnold, & Ragland, 2009). Usually, transit stops may generate more pedestrian activities. Pulugurtha and Repaka (2008) found that a higher number of transit (bus) stops is associated with more pedestrian activities in general. R. Schneider et al. (2009) also reported a positive association between the presence of regional transit stations and the pedestrian volume. This kind of pedestrian generators may increase the risk of exposure to traffic crashes. Miranda-Moreno et al. (2011) argued that more bus stops are correlated to both more pedestrian activity and the frequency of pedestrian-vehicle crashes. However, sometimes the results seem to be mixed. Around the school area, greater transit accessibility (percentage of households within a quarter mile of transit stops) was related to less pedestrian crashes for all age groups (Clifton & Kreamer-Fults, 2007). These confounding results imply mixed effects between transit stops and pedestrian safety. Without adequate provision of pedestrian facilities, such as signals, sidewalks, and crosswalks, pedestrians would likely be exposed to the risk of traffic crashes around the transit stops (Pulugurtha & Repaka, 2008).

II.1.2. Built and Road Environments

The absence or inadequate installation of pedestrian facilities, such as sidewalks and crosswalks, are generally found to be associated with more pedestrian crashes. The presence of complete sidewalk networks may lead pedestrians to walk on the sidewalks instead of the street or the shoulder, making pedestrians safer from traffic injuries (Boarnet et al., 2005). Previous literature has reported the relationship between the presence or absence of sidewalks and pedestrian crashes. Ossenbruggen, Pendharkar, and Ivan (2001) found that the probability of traffic crashes or injuries is twice as high in the site without sidewalks than the site with sidewalks. Wang and Kockelman (2013) reported sidewalk provision may reduce severe-crash rates in Austin, Texas. Findings from the study of pedestrian crashes on the campus of the University of North Carolina at Chapel Hill also indicate that incomplete sidewalk network is associated with greater risk of observed and perceived pedestrian crashes (R. J. Schneider, Ryznar, & Khattak, 2004). Sidewalk completeness or coverage, furthermore, may influence children's mode choice to travel to school. The missing sidewalks had a negative effect on the rate of children's active mode choice to or from school (Banerjee, Bahl, & Uhm, 2012; Dalton et al., 2011; Ewing, Schroeer, & Greene, 2004; Larsen, Buliung, & Faulkner, 2013). Ewing and Dumbaugh (2009) have argued that sidewalks are absolutely necessary for all through-streets in developed areas for pedestrian safety from vehicle collisions.

The presence of crosswalks may also have effects on the risk of pedestrian-vehicle crashes, but previous research has produced confounding results. While the presence of crosswalk signs is considered as a protective factor, Dai, Taquechel, Steward, and Strasser (2010) reported more than 50% of the locations with crosswalk signs involved pedestrian crashes around an urban university campus in downtown Atlanta, Georgia. Rothman, Buliung, Macarthur, To, and Howard (2013) stated that crosswalks may indicate more children walking and be related to increased exposure and/or increased child pedestrian crashes depending on the adequacy of its design or use. Zegeer, Stewart, Huang, and Lagerwey (2001) revealed that the effects of crosswalks varied by other built environmental factors, such as the type of crosswalks (i.e., marked versus unmarked one), the number of lanes on street segment, the presence of median, and traffic volume. Specifically, the presence of a marked crosswalk at a location without traffic signals or stop sign on the two-lane streets was associated with no difference in pedestrian crash rate, compared with unmarked crosswalks. On the other hand, after controlling for other site factors, the pedestrian crash rate was higher at a marked crosswalk on multilane roads with traffic volumes above about 12,000 vehicles per day, compared with at an unmarked crosswalk.

While considerable research also included intersections as one of the contributing factors for predicting crashes, its effect was mixed. Usually, higher intersection density is associated with higher street connectivity (Dill, 2004). Carver, Timperio, Hesketh, and Crawford (2010) found that intersection density is positively associated with the increased use of active transport among adolescent boys. Ladrón de Guevara, Washington, and Oh (2004) examined the effects of road network and socio-demographic variables on pedestrian crashes, and identified negative associations between intersection density and the fatal crash in Tucson, Arizona. The authors stated that urban intersections are generally associated with crash restraint elements (i.e., slower speeds, higher levels of congestion, and more adjacent land use densities). However, in other studies, the effect of intersections was contrasting. Hadayeghi, Shalaby, and Persaud (2003) and Hadayeghi, Shalaby, Persaud, and Cheung (2006) developed similar prediction models, but found a positive association between intersection density and pedestrian crashes in the city of Toronto, Canada. The model indicated that the traffic analysis zones with higher intersection densities have more traffic accidents. Huang et al. (2010) also argued that intersections may commonly generate more traffic conflicts, and they found the positive association between intersection density and the risk of pedestrian crashes at the county level. Furthermore, for child traffic safety, Blazquez and Celis (2013) found that child pedestrian crashes were concentrated in the areas situated in urban areas with a high intersection density. Because of the mixed effects of intersections from previous literature, researcher should pay more attention to inferences on the relationship between intersections and traffic crashes.

WHO reported that high speeds is one of the principal risk of traffic injury (World Health Organization; Unicef, 2008). The presence of high speed roads may increase the probability of pedestrian crashes. Rothman et al. (2013) found that higher traffic speed or posted high-speed has a positive correlation with less walking and more child traffic incidences. The report released by Transportation for America revealed that over 50% of fatal pedestrian crashes occur on the high capacity and high-speed roads (Ernst, Lang, & Davis, 2011). The speed of traffic is also perceived by parents as one of the most hazardous factors for active transportation to school (Vaughn et al., 2009). Dumbaugh et al. (2013) found that there are two possible reasons why the high-speed facility, such as arterial roads, is the problem. Firstly, driver's range of vision is decreased by high-speeds and thereby drivers will be less likely to recognize the potential traffic conflicts on the part of pedestrians. Secondly, driver's braking distance is increased by high speeds, making them difficult to stop when they face dart-out pedestrians.

Block length that can be measured from the centerline of the street intersection has been also used to represent the street connectivity (Dill, 2004). Low connectivity, characterized by long block length and large block size, are barriers to direct travel. The few route choices also discourage people to choose active transportation (Saelens, Sallis, & Frank, 2003). For child pedestrian activity as well as that of adults, a large block size within the residence area of a child reduces the number of children walking to schools

(Lin & Chang, 2010). Block size also influences the risk of pedestrian crashes. Loukaitou-Sideris et al. (2007) found that high-collision intersections had some hazardous characteristics, such as long block length, narrow sidewalks, the presence of bus stops, and so forth. Ewing and Dumbaugh (2009) also stated that traditional or "Smart Growth" patterns, mostly small or short blocks, dense streets and intersections, and more transit services, sometimes showed lower traffic crash rates than their counterparts. Motorists may be driving at relatively slow speeds in the area with higher connectivity, thus having the lower crash rate and less likelihood of severe traffic crashes (Clifton, Burnier, & Akar, 2009).

Particular land uses, such as commercial or retail that generates a high pedestrian demand, have shown positive associations with more pedestrian collisions, whereas industrial and office land uses have shown a lower collision with counter-effects (Loukaitou-Sideris et al., 2007). Wier, Weintraub, Humphreys, Seto, and Bhatia (2009) examined the relationship between pedestrian crashes and predictor variables, and found that potential pedestrian attractors, such as neighborhood commercial districts, contribute to increased vehicle-pedestrian collisions. Miranda-Moreno et al. (2011) have reported that commercial land uses have statistically significant effects on the increase of pedestrian activity as well as a higher frequency of pedestrian collisions. In Austin, Texas, the Census tracts with greater mixed uses of residential and commercial land uses showed the higher pedestrian crash risk (Wang & Kockelman, 2013). Kerr, Frank, Sallis, and Chapman (2007) have also found that youths aged between 5 and 18 in Atlanta who lived in neighborhoods with more than one commercial land use showed higher likelihood of walking as twice as those without commercial land use. When examined around schools, commercial land uses still showed the same result: it was positively associated with pedestrian traffic crash rates (Clifton & Kreamer-Fults, 2007). From the results of a study on child pedestrian crashes in Santiago, Chile, Blazquez and Celis (2013) found that areas with concentrated commercial land use have more crashes.

II.1.3. Neighborhood Characteristics and Spatial Disparity Issues in Pedestrian Crashes

In addition to the built environment and road characteristics, socio-demographic factors also account for a portion of the risk of traffic crashes. In the previous literature, socio-demographic characteristics of neighborhood residents have been reported to be related not only to pedestrian behavior, but also to traffic crashes. Generally, both walking rates and pedestrian crash rates are higher in the disadvantaged population groups, such as low-income families or ethnic/racial minority (Beck et al., 2007; Loukaitou-Sideris et al., 2007; Surface Transportation Policy Project, 2004; World Health Organization, 2004; Zhu & Lee, 2008). Above all, the rate of walking to school is also almost two times higher for children from low-income families than their counterparts, thereby these children have greater potential risks to be involved in pedestrian crash injuries (Gavin & Pedroso, 2010; McDonald, 2008). It is speculated that certain population groups are less likely to own motor vehicles, so that they have no choice but walking or biking, being exposed to the risk of traffic crashes (Surface Transportation Policy Project, 2004). However, higher exposure is not only the reason for the variation in probability of traffic crashes among different socio-demographic groups. Besides the exposure, lower socio-demographic groups tend to have poorer and less pedestrian facilities, such as poor maintained sidewalks (Franzini et al., 2010). The same results apply to children. The pedestrian crash rates are higher for children who lived in the low-income neighborhood (Blazquez & Celis, 2013; Dougherty, Pless, & Wilkins, 1989; McArthur, Savolainen, & Gates, 2014). Ethnic minority children, such as Hispanic students, traveled to and from school in the neighborhood with a poorer pedestrian environment (Zhu & Lee, 2008). Likewise, although socio-demographic characteristics of neighborhood is not directly related to the risk of pedestrian crashes, it accounts for the variation of the risk among different population groups.

While several authors have reported the differentials in the risk of pedestrian crashes between neighborhoods, there is limited understanding of the differences within the particular neighborhoods around schools. Because schools and surrounding environments are significant places contributing to children's education as well as residents' social and recreational activities, these places deserve more attention (Haug, Torsheim, Sallis, & Samdal, 2010; Wechsler, Devereaux, Davis, & Collins, 2000). Therefore, one of the objectives of this paper is to examine which factors account for differentials in child pedestrian crashes in those contrasting neighborhoods (e.g., low-income versus high-income neighborhoods or high-percentage of Hispanic versus low-percentage of Hispanic population neighborhoods around schools).

II.2. Methodologies of Previous Studies

With diverse built environment and socio-demographic factors we discussed above, several previous studies have examined the effects of those variables on the pedestrian crashes to understand typical attributes of accident locations using various empirical methods. Because the crash frequency data are non-negative integers, researchers have typically applied count-data regression models or other methods that can properly resolve the integer nature of the data (Lord & Mannering, 2010). Although most statistical analyses prefer the standard ordinary least squares (OLS) because of its benefits, such as transparency for understanding the relationship between variables, the count-data cannot be applied as a dependent variable in the OLS model. Because of the non-negative integer attribute, the OLS regression model, which assumes a continuous dependent variable, is not appropriate for the count-data. Thus, to take advantages of the OLS model, some studies transformed the crash data. LaScala, Gerber, and Gruenewald (2000) examined the number of pedestrian crash injuries per street lengths in the census tracts within the city of San Francisco, using a regression model that has been corrected for the spatial autocorrelation with contributing variables including alcohol availability, road system environment, and socio-demographic characteristics. They used a natural logarithm transformation for the rate of pedestrian crashes. Similarly, Wier et al. (2009) also developed an area-level regression model of pedestrian collisions using environmental and population data in 176 census tracts of San Francisco. They included street, land use, and population characteristics as predictor variables of OLS regression model to predict the variation in the natural log of the number of vehicle-pedestrian injury collisions per census tract. Clifton and Kreamer-Fults (2007) transformed the count of pedestrian crashes around schools into crash rates per school enrollment, and used OLS regression model to examine general and child pedestrian crashes around schools in Baltimore, Maryland. LaScala et al. (2000), Wier et al. (2009), and Clifton and Kreamer-Fults (2007) transformed the dependent variable from count-data to continuous data in order to apply OLS regression model, assuming the approximate normal distribution for the dependent variable. However, when the crash event is relatively rare and the mean is low, the transformation of a count variable to a continuous one may draw incorrect inferences (Quddus, 2008). To address this issue, recent studies have employed the count-data regression models, including the Poisson, negative binomial, random-effects, etc., preserving the integer attribute of count data (Cottrill & Thakuriah, 2010; Dumbaugh et al., 2013; Ukkusuri, Hasan, & Aziz, 2011). More detailed information of methodology will be discussed in the following Chapter, and only brief review is described in this chapter.

The Poisson model is the basic approach for most of the count-data regression models. In the Poisson models, the probability of traffic accidents is estimated by specifying the Poisson parameters to be explanatory variables (Poch & Mannering, 1996). Although the Poisson models have been used for traffic crash analyses as a starting point, it cannot handle the data which has over- or under-dispersion because the

Poisson model restricts the mean and variance to be equal (Lord & Mannering, 2010).[1] To overcome the dispersion issues, various methods have been derived from the Poisson model, including the negative binomial approach.

In addition to the integer nature, the count data has another attribute which needed more careful attention, called spatial correlation. This is because if roadways where crashes occur are spatially close, they may share unobserved effects, setting up a correlation of disturbances (Lord & Mannering, 2010). Thus, to account for the relationship between close spatial units, random-effects methodologies have been employed in conventional count-data regression models. Lord and Mannering (2010) explained the random-effects models as follows: “To account for such correlation, random-effects models (where the common unobserved effects are assumed to be distributed over the spatial/temporal units according to some distribution and shared unobserved effects are assumed to be uncorrelated with explanatory variables) … can be considered.” In the same vein, Ukkusuri et al. (2011) used the negative binomial regression model with random-effects to predict pedestrian crash frequencies at the census tract level, controlling the demographic data, land use patterns, and traffic system characteristics. These count-data regression models can be applied to examine the frequency of crashes at both an area-wide and a specific entity (street segment or intersection) level.

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[1] Over-dispersion happens when the variance of cash counts exceeds the mean value. On the contrary to this, under-dispersion is that the mean of crash counts is greater than the variance (Lord & Mannering, 2010).

As well as the count-data regression models for the crash frequency analyses, researchers also used logistic regression models to predict the probability of crash events, and identify the effects of contributing factors to traffic crash risk. In this method, crash events were treated as a binary data (i.e., 1=Yes; 0=No). Several studies used logistic regression models to examine the probability of traffic crashes and the influence of the risk factors (Al-Ghamdi, 2002; Yan, Radwan, & Abdel-Aty, 2005; Yu, 2015). For the logistic regression model, the parameter is usually estimated by the maximum likelihood method. However, for the binary dependent variables with rare events, it is difficult to explain and predict because of the biased probability resulted from the conventional logistic regression (King & Zeng, 2001). Also, in this rare event analysis, a failure of the likelihood maximization to convergence issue in logistic regression, known as complete separation, commonly occurs (Allison, 2008). To account for this issue, recent literature have used Firth's penalized likelihood method, instead of the maximum likelihood method for the standard logistic regression, not only to reduce bias in the parameter estimates, but also to address the complete or quasi-separation (De Ceunynck et al., 2013; Firth, 1993; Gim & Ko, 2016; Martin, Holden, Chen, & Quinlan, 2006; Mattos, Grzebieta, Bambach, & McIntosh, 2014; Polders, Daniels, Hermans, Brijs, & Wets, 2015).[2]

The previous literature has examined the frequency and probability of crashes at diverse geographic units, both at the macro and the micro scale levels. Some studies

[2] A complete or quasi-separation happens when the outcome variable separates a predictor variable or a combination of predictor variable completely or to certain degree (Bruin, 2006).

used a relatively large scale as a unit of analysis, such as census tracts (LaScala et al., 2000; Ukkusuri et al., 2011; Wier et al., 2009) and independent school districts (Rothman, Macarthur, To, Buliung, & Howard, 2014); but some others explored smaller levels, such as roadway segments (Ma, Kockelman, & Damien, 2008; Qin, Ivan, & Ravishanker, 2004), intersections (Bao & Boyle, 2009; Lee & Abdel-Aty, 2005; Poch & Mannering, 1996), and a certain vicinity (e.g., 0.25-mile, 0.5-mile, 1-mile, etc.) of crashes or facilities (Abdel-Aty, Chundi, & Lee, 2007; Clifton & Kreamer-Fults, 2007; McArthur et al., 2014; Yu & Zhu, 2015). When using macro-level units to examine the area-wide traffic crashes with aggregate information at the macro level, we had to lose the disaggregated finer information of specific units of area (Galster, Tatian, & Smith, 1999; Woo, Joh, & Van Zandt, 2015). On the other hand, the micro level allows researchers to use disaggregated information, but one challenge is that comparison of the risk between selected area and beyond the specific area is difficult. For example, when researcher examines the risk of pedestrian crashes at the specific area, such as 0.25-mile around schools, it would be hard to compare the risk between the specific area of schools and beyond those specific areas.

To overcome these limitations, some literature used various geographic scales at the same time. Zhu and Lee (2008) evaluated social disparity issues in overall walkability and pedestrian safety to support children walking to school at the macro (school's attendance area) level as well as street segment level. Nevertheless, the school's attendance area is too large to predict more specific risks of pedestrian crashes, and also to represent the socio-demographic characteristics of the neighborhood around schools. Also, their empirical methodologies primarily focused on the bivariate analysis (simple regression model) which cannot control the effects of other contributing factors.

Zahabi, Strauss, Manaugh, and Miranda-Moreno (2011) used five different sizes of buffer zones around the accident locations to identify the relationship between the built environmental factors and pedestrian/cyclist crashes. Mitra and Buliung (2012) also explored correlation between built environment and active school transportation, using different geographic scales (four buffer zones, Census dissemination area, and traffic analysis zone). However, this literature focused only on general pedestrian or cyclist crashes and/or active transportation, thereby questions concerning child pedestrian crashes and school-aged children's traffic safety around school areas still remain.

Although several literatures has found the effects of various contributing factors to traffic injuries, only few of them specifically studied the child pedestrian safety around school areas to understand the social equity issues. This paper builds upon the previous literature, examining the risk of child pedestrian crashes at both macro (census tract) and micro (street segment) levels. Figure 1 shows a conceptual framework that organizes the relationship between influencing factors and pedestrian-vehicle crashes involving school-aged children. Based on the previous literature, three major factors – built environments, traffic exposure, and neighborhood characteristics– are assumed to be related to pedestrian crashes. To identify whether child pedestrian crashes occurred less around schools, this paper compares the frequency of the crash between the vicinity of schools and beyond that areas, using random-effects Poisson regression model which may address the unobserved spatial heterogeneity at the area level. Also, examining the specific differences of contributing factors at street segment level, this paper identifies whether and how the risk of child pedestrian crashes varies by socio-demographic characteristics of neighborhood around schools.

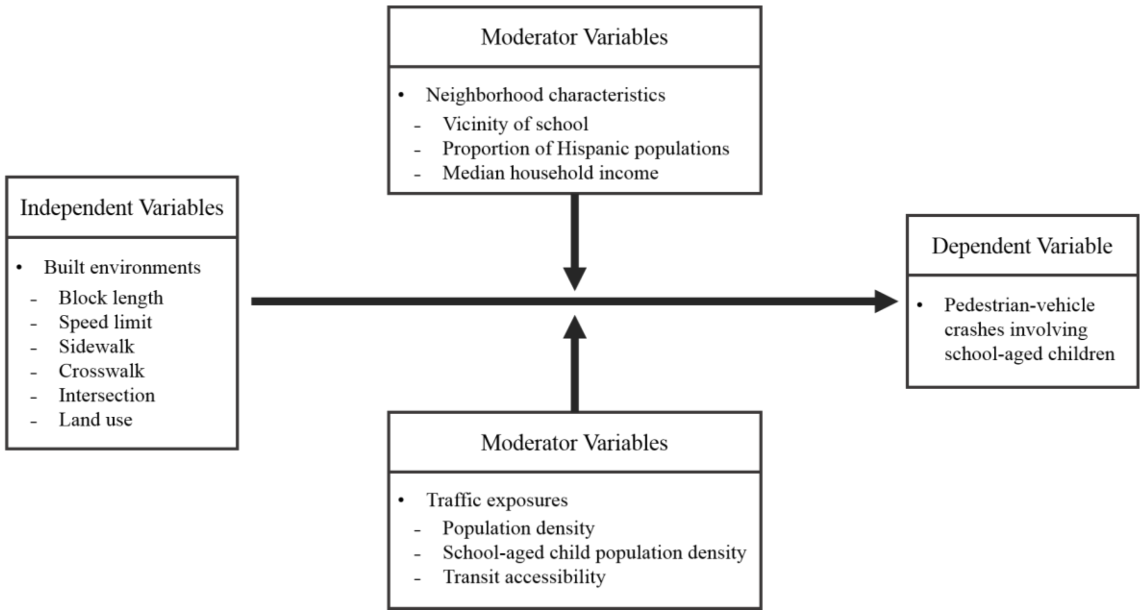

Figure 1 Conceptual framework

CHAPTER III

METHODS

III.1. Study Area

In 2011, Texas was the top-ranked state for traffic crash fatality in children aged 14 and younger; a total of 119 children died in Texas due to traffic crashes, while the national average by state was 22.4 (NHTSA, 2013). In Austin, Texas, there were 71 traffic fatalities in all age groups in 2013, and pedestrians comprised 29.6% of those fatalities. The fatality rate per 100,000 population was 2.37 in Austin, and this number is greater than that of the state of Texas, 1.81 (NHTSA, 2015). Furthermore, the data for pedestrian crashes between 2010 and 2014, provided by the Texas Department of Transportation (TxDOT), shows that among 33 urbanized areas in Texas, Austin was ranked in the fifth place for total number of pedestrian crashes in children aged between 5 and 19 (see Appendix Table A - 1).[3] However, there is limited understanding about whether school-aged child pedestrian crashes occurred near the school area because the report only showed the entire city of Austin region. The goal of this paper is to analyze child pedestrian crashes within Austin, Texas, focusing on the neighborhoods around schools to identify whether the vicinity of schools are safer than beyond the vicinity, as

[3] Urbanized areas were selected based on the 2010 U.S. Census data. The pedestrian crash data used in this paper were collected by TxDOT, and provided by the Texas A&M Transportation Institute (TTI).

well as to determine whether and how the distribution of child pedestrian crashes varies by socio-demographic characteristics of the neighborhood around schools.

III.1.1. Unit of Analysis

To examine child pedestrian crashes around schools in the study area, public schools at all levels were selected within the Austin Independent School District (AISD). In 2013, AISD operated 119 regular campuses (84 elementary schools, 18 middle schools, and 17 high schools) and 10 special campuses/alternative education centers. Among these 129 schools, 124 schools were selected and five schools/campuses were excluded due to the lack of information or very small enrollment.[4] One of the objectives of this paper is to identify whether the vicinity of schools are safer from child pedestrian-vehicle collisions than areas outside of the vicinity. Hereafter, the vicinity of schools is defined as "school-neighborhood", and the outside area of the vicinity is defined as "beyond school-neighborhood."

The previous literature that examined traffic crashes at the vicinity of certain point, such as school location or point of accident, used a particular distance of circular (radial) buffer zone (Clifton & Kreamer-Fults, 2007; Mitra & Buliung, 2012; Zahabi et al., 2011). While the distance used in previous literature varies, a quarter-mile or 400m

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[4] National Center for Education Statistics (NCES) has no information on the 2013 enrollment for Allan Elementary (Pre-K Program), IDEA Allan In-District Charter School, IDEA Allan 6-12 (In-District Charter School), and the redesigned Learning Support Center. The Elementary Disciplinary Alternative Education Program was also excluded because it had only 4 students in 2013.

was commonly used and represents the general walking distance of people to get to their destinations (Clifton & Kreamer-Fults, 2007; Ewing, 1996; Ewing & Dumbaugh, 2009; McCormack, Giles-Corti, & Bulsara, 2008; McMillan, 2007; O'Sullivan & Morrall, 1996; Yang & Diez-Roux, 2012). Although most of the previous studies used conventional circular buffers, this paper created 0.25-mile street network buffers around schools to establish the approximate and more accurate area that students can actually walk to and from schools. This constitutes a more accurate approach to examining built environment and socio-demographic characteristics (Frank, Schmid, Sallis, Chapman, & Saelens, 2005). In this paper, the 0.25-mile network buffers around schools were defined as the “school-neighborhoods.” This network buffer was created using the network analysis network analysis function in ArcGIS. To measure more accurate distances to access the school area, 0.25-mile was calculated from the land use parcel that contains a school instead of calculating from the point of schools (see Figure 1).

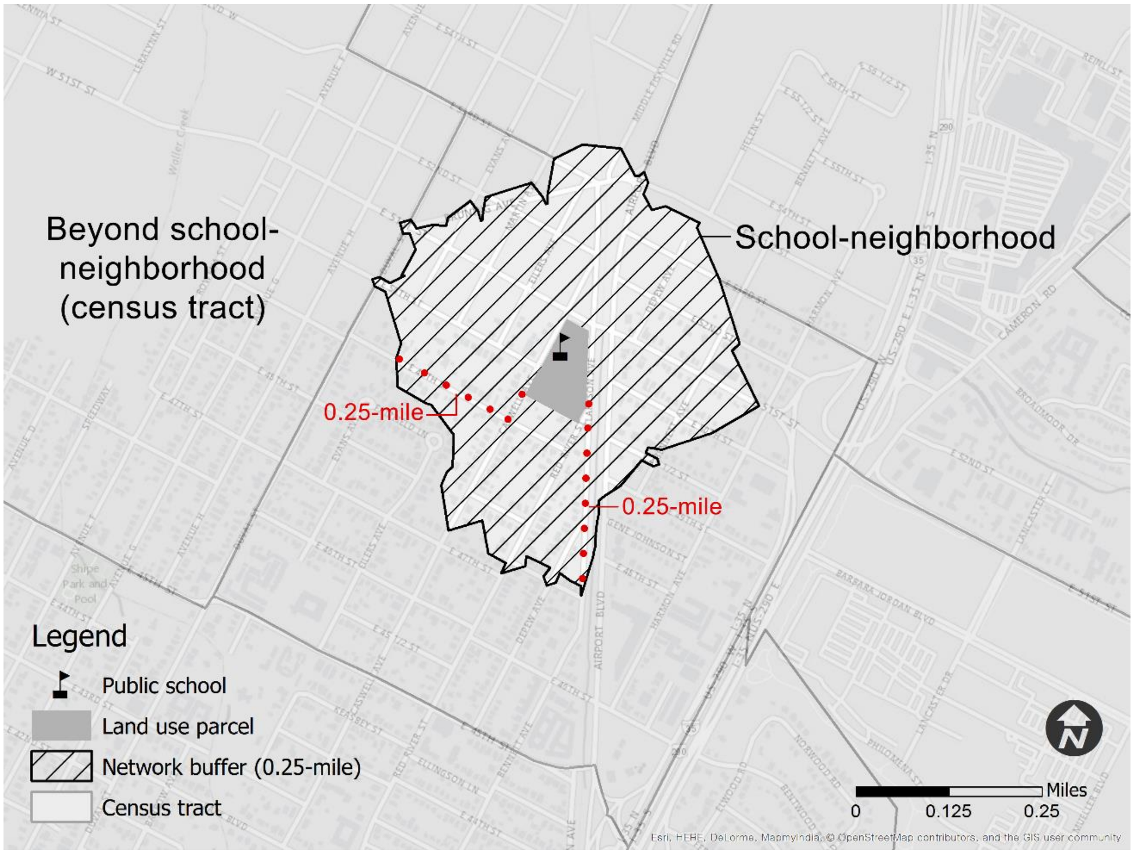

Figure 2 The concept of the school-neighborhood and the beyond school-neighborhood

For comparison of child pedestrian safety between school-neighborhoods and beyond school-neighborhoods, this paper also utilized U.S. census tracts as the counterpart of the school-neighborhoods. When they are overlapped, this paper excluded the network buffer area from the census tracts to ensure the accuracy of comparison. Hence, for the "beyond school-neighborhoods," this paper used census tracts which have no school-neighborhoods and parts thereof (i.e., the remaining parts of census tracts) within the study area. Among the 218 census tracts that comprise Travis County, only 178 census tracts that overlapped with the AISD area were selected (see Figure 2). As a result, to identify child pedestrian safety around schools, two different area-wide scales were used in this paper: 124 school-neighborhoods; and 178 beyond school-neighborhoods.

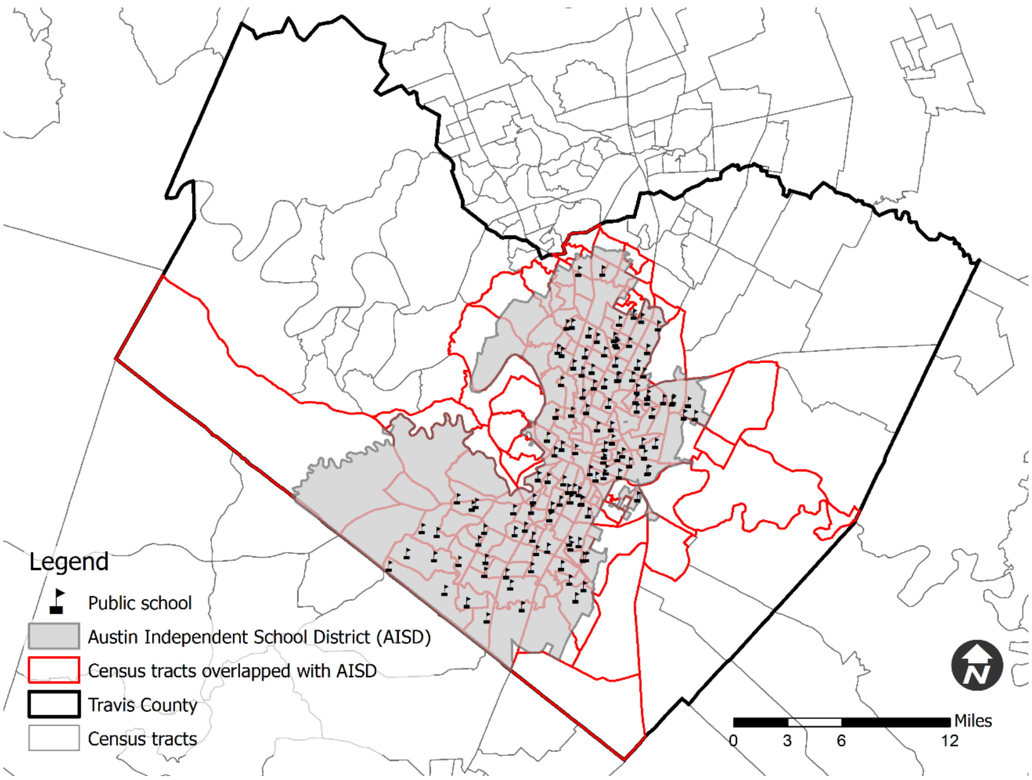

Figure 3 The concept of selecting census tracts overlapped with AISD

Additionally, this paper also attempted to examine whether and how the differences in factors influencing child pedestrian crashes vary by neighborhood characteristics. For more specific information of accident related variables, disaggregated information was obtained by utilizing the street-segment units (see Figure 3). Unlike the area-wide scales, street segments allow the use of more detailed information, such as segment length, the presence of sidewalks, crosswalks, or bus stops, and dominant land uses at the segment level. With this finer information, this paper compared the crash related factors among different neighborhoods after dividing segments into each neighborhood category. At the street segment level, road environment was measured by using 100-feet buffers along each street segment. This buffer distance was determined considering the minimum width of lanes, shoulders, and medians for different road classes (i.e., freeways/interstate highways, arterial roads, city collectors, and local roads). Also, the 100-feet is wide enough to measure detailed roadway information listed above as well as being reasonably narrow to avoid excessive overlaps among the street buffers with each other (Yu, 2015).[5]

[5] The highway has at least 2 lanes in each direction with minimum 12 feet lane width. The widths of shoulders for highways are, on average, 4 to 12 feet. For this case, the minimum total width would be 96 feet (Yu, 2015). Thus, a hundred feet is reasonable distance to cover the roadway environment for all road classes.

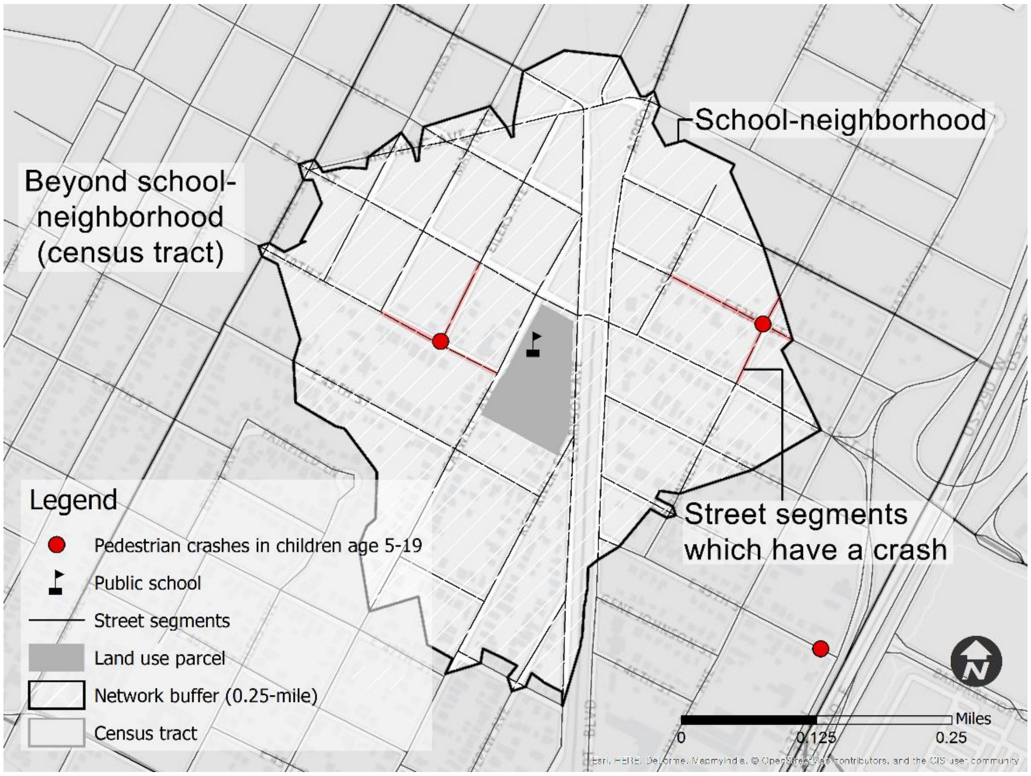

Figure 4 The concept of units of analysis (school-neighborhood, beyond school-neighborhood, and street segment)

III.2. Data Description

The pedestrian crash data used in this paper was collected from 2010 through 2014. In the entire state of Texas, the dataset included a total of 25,376 records of pedestrian crashes with general information such as X-Y coordinates of accident point, crash date, and pedestrian age. Among the records, this paper extracted the crashes that occurred within the city of Austin for geocoding crash locations on the map to estimate the spatial distribution of pedestrian crashes. To identify child pedestrian crashes, this paper used a specific age group, ages 5 through 19, which has been defined as school-aged children in the previous literature (DiMaggio & Li, 2013; Linakis, Amanullah, & Mello, 2006; Miller & Spicer, 1998). The distribution of pedestrian crashes in school-aged children within the study area is shown in Figure 4. Overall, child pedestrian crashes were concentrated in downtown Austin which potentially implies spatial autocorrelation. At the area-wide (i.e., school-neighborhood and beyond school-neighborhood) level, the frequency of pedestrian crashes in school-aged children was aggregated for each neighborhood. However, at the street segment level, the crashes were not aggregated, but transformed into binary-data which present the occurrence of the crashes on the segment (1: Yes; 2: No) to examine the probability of pedestrian crash risk. Among the total 5,703 street segments within the school-neighborhoods, only 23 segments (0.4%) had two or more child pedestrian crashes thereby this small variance did not influence the result.

Among the total number of street segments within the school-neighborhoods, 103 segments have at least one pedestrian crash involving school-aged children. Meanwhile, there are 687 segments that overlap two or more times with different school network buffers, when the schools are close enough to create overlapped network buffers. In this case, the overlapped segments were counted twice or more and included in the regression models, because the corresponding school-neighborhood and roadway environments may influence on the crashes that occur on these segments (Yu, 2015). Also, the consistent tests that used both the unique-segment dataset (which excluded overlapped segments) and the double or more counted segment dataset showed acceptably similar results, implying that the regression models including double or more counted segments are not biased.

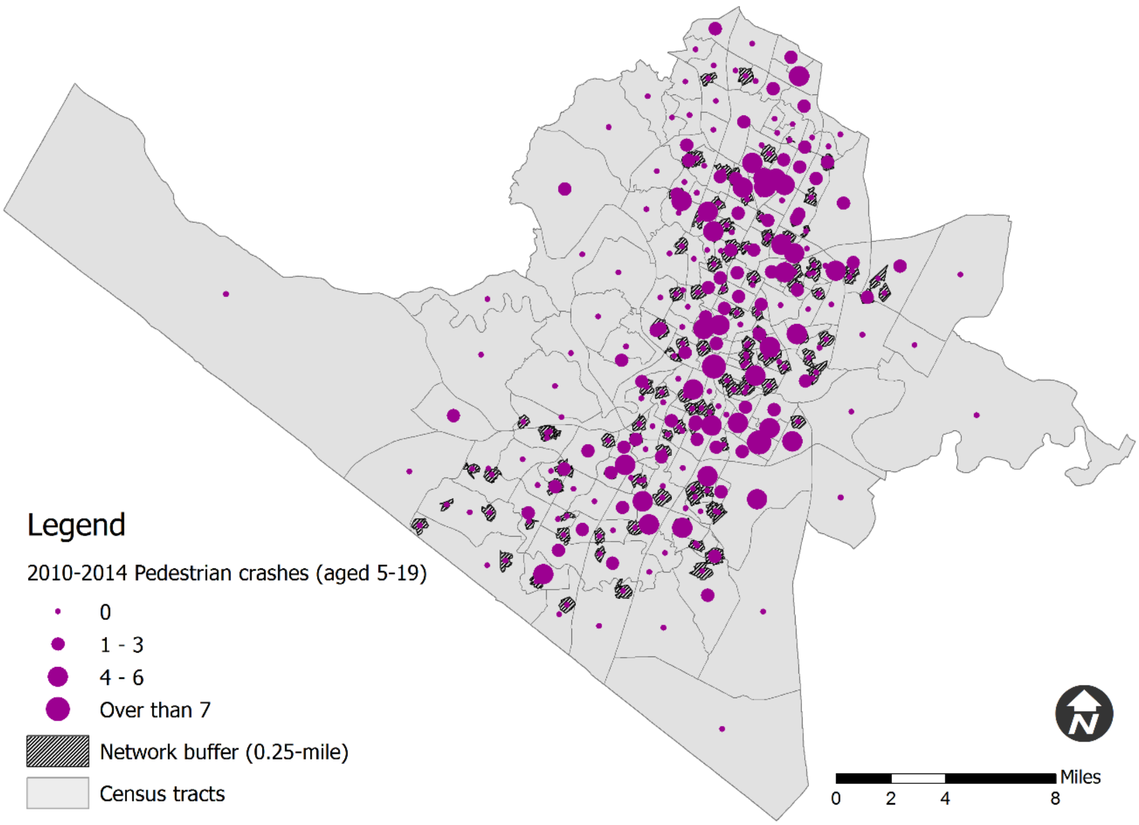

Figure 5 2010-2014 child pedestrian crashes in the study area

Along with child pedestrian crash data, built environment and socio-demographic characteristics were examined to analyze the relationship between the crashes and contributing factors. Table 1 shows the measurements, descriptive statistics, and data sources for dependent and independent variables at the area-wide (neighborhood) scale. All data for built environmental variables, except the bus stop data, were obtained from the Open Data Portal of the city of Austin.[6] The transit accessibility is derived from the density of Capital Metro bus stops, using the data obtained from Capital Metro-Austin Public Transit. At the area-wide scale analysis, block length was measured from the mean length of street segments within each neighborhood (Cervero & Kockelman, 1997; Dill, 2004). All other built environments were also aggregated into percentage or density at the neighborhood level.

Additionally, to determine whether and how school-aged child pedestrian crashes vary by neighborhood characteristics within the school-neighborhoods, this paper defined “high-Hispanic school-neighborhood” as those neighborhoods with a higher proportion of Hispanic population than the study area average (34.36%). “Low-income school-neighborhood” was also defined as school-neighborhoods with median household income below than 50% of area median household income in 2014 ($37,700).[7]

[6] ftp://ftp.ci.austin.tx.us/GIS-Data/Regional/coa_gis.html

[7] The U.S. Department of Housing and Urban Development (HUD) defined “Low and Moderate Income” under the Community Development Block Grant program. “For CDBG, a person is considered to be of low income only if he or she is a member of a household whose income would qualify as "very low income" under the Section 8 Housing Assistance Payments program. Generally, these Section 8 limits are based on 50% of area median.” In 2014, HUD limited $37,700 as a very low income in Austin-Round Rock-San Marcos, TX MSA area (https://www.huduser.gov/portal/datasets/il/il2014/2014summary.odn).

The 2014 American Community Survey (ACS) 5-year estimates were used for socio-demographic information, such as population and income level. For the beyond school-neighborhood that does not overlap with any school-neighborhoods, the ACS census tract data were utilized without conflicts. However, it was difficult for both the school-neighborhood and the beyond school-neighborhood overlapping with at least one school-neighborhood to keep the original census tract information, due to the mismatch of areal shape. To address this problem and estimate more accurate demographic information, this study employed the network length binary dasymetric areal interpolation, which produced precise results in previous research (Qiu, Zhang, & Zhou, 2012). The binary dasymetric method uses ancillary data (such as land use and street length) that provide a binary divide between populated and unpopulated units. In this paper, street network was used as a binary dasymetric interpolation to distribute population only to populated units (Qiu et al., 2012).

Table 1 Definition and descriptive statistics for study variables at area-wide level

Variable	Measurement	Descriptive Statistics	Data Source
Dependent Variable			
School-aged (5-19) child pedestrian crashes	Total number of school-aged child pedestrian crashes within the neighborhood (2010-2014)	Obs.: 302[a] Mean: 0.96 S.D.: 1.96[b]	TxDOT
Traffic Exposure			
Area of units	An area of school-neighborhoods and beyond school-neighborhoods	Obs.: 302 Mean: 1.53 S.D.: 5.47	Census tract: 2014 US Census Bureau
Population density	A thousand population / neighborhood area (sq. mi.)	Obs.: 302 Mean: 4.90 S.D.: 3.53	2014 ACS 5-year estimates
School-aged child population density	Population aged 5-19 / neighborhood area	Obs.: 302 Mean: 866.11 S.D.: 1,144.59	
Bus stop density	Total number of bus stops within the neighborhood / neighborhood area	Obs.: 302 Mean: 21.02 S.D.: 22.25	Capital Metro-Austin Public Transit
Neighborhood Characteristics			
School-neighborhood	Network buffer area with public school (Yes: 1; No: 0)	Obs.: 302 1: 124 (41.1%) 0: 178 (58.9%)	2013 NCES
High-Hispanic School-neighborhood	School-neighborhood with Hispanic population more than 34.36% (Yes: 1; No: 0)	Obs.: 302 1: 29 (23.4%) 0: 95 (76.6%)	2014 ACS 5-year Estimates

Table 1 Continued

Variable	Measurement	Descriptive Statistics	Data Source
Neighborhood Characteristics - Continued			
Low-income School-neighborhood	School-neighborhood with median household income below than 50% of area median household income (Yes: 1; No: 0)	Obs.: 302 1: 62 (50.0%) 0: 62 (50.0%)	HUD FY2014 Income Limits Summary
Median household income	A thousand dollars median household income[c]	Obs.: 302 Mean: 55.79 S.D.: 31.90	2014 ACS 5-year Estimates
Independent Variables (contributing factors – built environment in the neighborhood)			
Mean block length	Total street lengths (mi.) / number of street segments within the neighborhood	Obs.: 302 Mean: 0.07 S.D.: 0.03	The city of Austin
% of high-speed roads	[Total lengths of high-speed roads (≥ 35 mph) / total street lengths in the neighborhood] × 100	Obs.: 302 Mean: 52.27 S.D.: 18.23	
% of missing sidewalks	[Total lengths of street segments missing sidewalks / (2 × total street segment lengths in the neighborhood)] × 100	Obs.: 302 Mean: 43.90 S.D.: 22.67	
Crosswalk density	Total number of crosswalks within the neighborhood / neighborhood area	Obs.: 302 Mean: 104.21 S.D.: 112.21	
Intersection density	Total number of intersections within the neighborhood / neighborhood area	Obs.: 302 Mean: 95.24 S.D.: 53.27	

Table 1 Continued

Variable	Measurement	Descriptive Statistics	Data Source
Independent Variables (contributing factors – built environment in the neighborhood) - Continued			
Land use diversity	Entropy index[d]	Obs.: 302 Mean: 0.66 S.D.: 0.14	The city of Austin
% of residential use	(Land use k area in the neighborhood/ neighborhood area) × 100	Obs.: 302 Mean: 49.58 S.D.: 21.83	
% of commercial use		Obs.: 302 Mean: 6.51 S.D.: 8.55	
% of office use		Obs.: 302 Mean: 4.09 S.D.: 7.12	
% of industrial use		Obs.: 302 Mean: 3.67 S.D.: 7.83	
% of park use		Obs.: 302 Mean: 6.86 S.D.: 10.55	

[a.] The number of observations
[b.] Standard Deviation
[c.] Median household income of each neighborhood was measured at census tract level. For school-neighborhood, median household income refers to that of census tract where the school is located.
[d.] Entropy index of land use diversity = $-\frac{\sum_k (p_k \ln p_k)}{\ln N}$, where $p_k = \frac{\text{Land Use } (k) \text{Area (sq.mi.)}}{\text{Target Area (sq.mi.)}}$ (Kockelman, 1997; Leslie et al., 2007; Zhang, 2004)

Table 2 Definition and descriptive statistics for included variables at road segment level

Variable	Measurement	Descriptive Statistics	Data Source
Dependent Variable			
School-aged (5-19) child pedestrian crashes	The occurrence of school-aged child pedestrian crashes on the segment (Yes: 1; No: 0)	Obs.: 5,703[a] 1: 103 (1.8%) 0: 5,600 (98.2%)	TxDOT
Traffic Exposure			
Population density	A thousand population in the school-neighborhood / neighborhood area	Obs.: 5,703 Mean: 5.69 S.D.[b]: 2.47	2014 ACS 5-year estimates
School-aged child population density	Population aged 5-19 in the school-neighborhood / neighborhood area	Obs.: 5,703 Mean: 995.86 S.D.: 685.60	
Bus stop density – street segment level	Total number of bus stops on the segment / segment length	Obs.: 5,703 Mean: 0.19 S.D.: 0.71	Capital Metro-Austin Public Transit
Neighborhood Characteristics			
High-Hispanic School-neighborhood	Segment on the school-neighborhood with Hispanic populations more than 34.36% (Yes: 1; No: 0)	Obs.: 5,703 1: 1,323 (23.2%) 0: 4,380 (76.8%)	2014 ACS 5-year Estimates
Low-income School-neighborhood	Segment on the school-neighborhood with median household income below than 50% of area median household income (Yes: 1; No: 0)	Obs.: 5,703 1: 1,800 (31.6%) 0: 3,903 (68.4%)	HUD FY2014 Income Limits Summary
Median household income	A thousand dollars median household income[c]	Obs.: 5,703 Mean: 53.36 S.D.: 27.16	2014 ACS 5-year Estimates

Table 2 Continued

Variable	Measurement	Descriptive Statistics	Data Source
Independent Variables (contributing factors – road environments at segment level)			
Block length	Street centerline lengths in 100m	Obs.: 5,703 Mean: 1.01 S.D.: 0.78	The city of Austin
High-speed roads	High-speed (≥ 35 mph) segment (Yes: 1; No: 0)	Obs.: 5,703 1: 2,900 (49.2%) 0: 2,803 (50.8%)	The city of Austin
% of missing sidewalks	[Total lengths of street segments missing sidewalks / (2 × total street segment lengths)] × 100	Obs.: 5,703 Mean: 1.01 S.D.: 0.78	The city of Austin
Crosswalk density	Total number of crosswalks on the segment / segment length	Obs.: 5,703 Mean: 0.66 S.D.: 1.07	The city of Austin
Land use diversity	Entropy index[d]	Obs.: 5,703 Mean: 0.39 S.D.: 0.36	The city of Austin
% of residential use	(Total number of land use *k* on the segment / segment length) × 100	Obs.: 5,703 Mean: 80.25 S.D.: 34.15	The city of Austin
% of commercial use	(Total number of land use *k* on the segment / segment length) × 100	Obs.: 5,703 Mean: 7.76 S.D.: 20.58	The city of Austin

Table 2 Continued

Variable	Measurement	Descriptive Statistics	Data Source
Independent Variables (contributing factors – road environments at segment level) - Continued			
% of office use	(Total number of land use *k* on the segment / segment length) × 100	Obs.: 5,703 Mean: 4.59 S.D.: 15.09	The city of Austin
% of industrial use		Obs.: 5,703 Mean: 1.26 S.D.: 7.75	
% of park use		Obs.: 5,703 Mean: 2.29 S.D.: 11.09	
Independent Variables (contributing factors – built environment at neighborhood level)			
Crosswalk density	Total number of crosswalks within the neighborhood where the segment is located / neighborhood area	Obs.: 5,703 Mean: 184.20 S.D.: 141.11	The city of Austin
Intersection density	Total number of intersections within the neighborhood where the segment is located / neighborhood area	Obs.: 5,703 Mean: 135.17 S.D.: 51.06	
Bus stop density	Total number of bus stops within the neighborhood where the segment is located / neighborhood area	Obs.: 5,703 Mean: 66.94 S.D.: 58.51	Capital Metro-Austin Public Transit

Table 2 Continued

Variable	Measurement	Descriptive Statistics	Data Source
Independent Variables (contributing factors – built environment at neighborhood level) - Continued			
% of residential use		Obs.: 5,703 Mean: 43.23 S.D.: 14.84	
% of commercial use		Obs.: 5,703 Mean: 4.30 S.D.: 5.59	
% of office use	(Land use *k* area in the neighborhood where the segment is located/ neighborhood area) × 100	Obs.: 5,703 Mean: 2.69 S.D.: 5.79	The city of Austin
% of industrial use		Obs.: 5,703 Mean: 1.38 S.D.: 3.82	
% of park use		Obs.: 5,703 Mean: 5.56 S.D.: 9.07	

[a.] The number of observations; [b.] Standard Deviation; [c.] Median household income refers to that of census tract where the school is located; [d.] Entropy index of land use diversity = $-\frac{\sum_k (p_k \ln p_k)}{\ln N}$, where $p_k = \frac{\text{Land Use }(k)\text{Area (sq.mi.)}}{\text{Target Area (sq.mi.)}}$ (Kockelman, 1997; Leslie et al., 2007; Zhang, 2004)

III.3. Methods of Statistical Analysis

With these variables, this paper firstly conducted the difference-in-means tests (t-test) to identify the possible disparity issues in the frequency of pedestrian crashes involving school-aged children between the high-Hispanic school-neighborhoods and the low-Hispanic school neighborhoods, as well as between the low-income school-neighborhoods and the high-income school-neighborhoods. While these comparisons are reasonable among the school-neighborhoods that have relatively similar areal size, it is not acceptable to simply compare the frequency of crashes between school-neighborhood and beyond school-neighborhood due to the inconsistency of areal size (see Table 3). Thus, this paper used multivariate analyses, random-effects Poisson regression models, to determine whether the school-neighborhoods are safer than beyond school-neighborhoods, controlling for other factors to be constant.

Table 3 An area by neighborhood characteristic

	SN[a]			BSN[b]		
	Obs.	Mean	S.D.	Obs.	Mean	S.D.
An area (sq. mi.)	124	0.18	0.05	178	2.47	6.98

[a.] School-neighborhoods; [b.] Beyond school-neighborhoods

The conventional Poisson regression model predicts the probability $P(y_i)$ of having y_i number of school-aged child pedestrian crashes per 5-year (2010-2014) at neighborhood *i* as follows:

$$P(y_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!} \qquad (1)$$

where λ_i is the Poisson parameter for neighborhood i, which is equal to expected number of school-aged child pedestrian crashes per 5-year ($E[y_i]$) in neighborhood *i*. The Equation 1 can be estimated by specifying the Poisson parameter λ_i as a function of explanatory variables. Following is the most common functional form:

$$\lambda_i = \exp(\beta \mathrm{X}_i) \qquad (2)$$

where X_i is a vector of explanatory variables and β is a vector of estimable parameters. However, Poisson regression model restricts the mean and variance of the number of accidents to be equal ($E[y_i] = Var[y_i]$), consequently drawing incorrect inferences (Lord & Mannering, 2010). To address this issue and correct spatial correlations, the random-effects models rework the Poisson parameter as follows:

$$\lambda_{ij} = \exp(\beta \mathrm{X}_{ij})\exp(\eta_j) \qquad (3)$$

where λ_{ij} is the expected number of child pedestrian crashes for neighborhood *i* belonging to group *j* (i.e., spatial group expected to share unobserved effects), X_{ij} is a vector of explanatory variables, β is a vector of estimable parameters, and η_j is a random-effects for observation group *j*.[8] The most common random-effects Poisson

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[8] In this paper, spatial group *j* for school-neighborhoods is defined as the census tract where the school is located.

model assumes that η_j is randomly distributed across spatial groups, such that $\exp(\eta_j)$ is gamma-distributed with mean one and variance α (Hausman, Hall, & Griliches, 1984; Lord & Mannering, 2010). Thus, the unobserved heterogeneity across different spatial groups is accounted by random-effects. With random-effects, Poisson regression has a different variance to mean ratio, $1 + \frac{\lambda_{ij}}{(1/\alpha)}$, with the conventional one. Using the random-effects Poisson models, this paper attempted to identify the statistical significance of differences in traffic safety between school- and beyond school-neighborhoods, controlling for other factors. For this comparison of traffic safety, this paper included a set of dummy variable (School-neighborhood variable in Table 1). By comparing the direction of these vector variables, the child pedestrian safety around school can be interpreted. In the same manner, the frequency of child pedestrian crashes can be compared among high- and low-Hispanic school-neighborhoods; and low- and high-income school-neighborhoods, by using another set of dummy variables (see neighborhood characteristics variables in Table 1). Also, this paper examine the percentage changes in the frequency of child pedestrian crashes by each statistically significant contributing factors through the interpretation of the incidence rates ratio, $\exp(\beta_k \delta)$, which can be derived as follows (Long & Freese, 2006):

$$\frac{\mathrm{E}(y|\mathrm{X}, x_k + \delta)}{\mathrm{E}(y|\mathrm{X}, x_k)} = e^{\beta_k \delta} \tag{4}$$

where $\mathrm{E}(y|\mathrm{X}, x_k)$ is the expected count of child pedestrian crashes for a given X, which is explicitly noted as the value of x_k variable, and $\mathrm{E}(y|\mathrm{X}, x_k + \delta)$ is the expected count after changes in x_k of any amount δ. This can be computed the percentage change in the expected count for a δ-unit change in x_k, holding other variables constant:

$$100 \times (e^{\beta_k \delta} - 1) \qquad (5)$$

Long and Freese (2006) suggested the interpretation as follows: "Percentage change for δ: For a change of δ-unit in x_k, the expected count of the crash changes by $100 \times (e^{\beta_k \delta} - 1)$%, holding other variables constant."

On the other hand, Table 2 shows the variables used for the analyses at the specific geographic scales. To use disaggregated finer information, such as road environments, this paper also included the analyses of street segment scale for school-neighborhood. By using this detailed information, the differentials in crash contributing factors were examined across the school-neighborhoods with the information of their Hispanic proportion and median household income level. Thus in the street segment level analyses, only the street segments within the network buffers were used to specifically compare the differentials among the school-neighborhoods: all the beyond school-neighborhoods were excluded from the segment scale analyses.

The crash data used in this paper showed rare frequency of school-aged pedestrian crashes in the Austin area. Thus, among the school-neighborhoods, there are many street segments that have a similar set of predictor variables, so that the outcome variable will separate the explanatory variables into different groups (King & Zeng, 2001). When the outcome variable separates a predictor variable or a combination of predictor variables completely or to certain degree, the complete or quasi-separation issue happened, resulting in a failure of the likelihood maximization to convergence problem in logistic regression. To overcome this separation issue and predict an accurate probability of school-aged child pedestrian crashes at the street segment level, this paper applied the logistic regression with Firth's penalized likelihood, avoiding a separation (Firth, 1993; Martin et al., 2006; Mattos et al., 2014). The following is the formulation for the fitted logistic regression models for this paper (Polders et al., 2015):

$$\mathrm{logit}(P) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad (6)$$

where P is probability of child pedestrian crashes on the segment, X_k is contributing factors to the crashes, and β_k is partial logistic regression coefficient. Odds ratios, $\exp(\beta_k)$, were also calculated for each factor to make the interpretation more meaningful. As in the random-effects Poisson model, the odds ratios can be transformed into the percentage change (Long & Freese, 2006):

$$\text{percentage change in odds} = 100 \times (\exp(\beta_k) - 1) \quad (7)$$

Long and Freese (2006) suggested the interpretation of this percentage change as for a unit change in X_k, the odds are expected to change by $100 \times (\exp(\beta_k) - 1)\%$, holding all other variables constant. The results of empirical analyses will be presented in the following chapter.

CHAPTER IV

RESULTS

Table 4 shows the result of the difference-in-mean test (t-test) of mean number of pedestrian crashes involving school-aged children between the high-Hispanic and low-Hispanic school-neighborhoods. The school-neighborhoods were divided into two groups by proportion of Hispanic population in the neighborhood (i.e., high-Hispanic and low-Hispanic school-neighborhoods). The t-test for these groups shows that there is potential disparity in the frequency of school-aged child pedestrian crashes. While the mean of child pedestrian crashes for high-Hispanic school-neighborhood was 2.91, that for low-Hispanic school-neighborhood was 0.62 ($p < 0.01$).

Table 4 The result of t-test between high-Hispanic and low-Hispanic school-neighborhoods

	HHSN[a]			LHSN[b]			Mean difference
	Obs.	Mean	S.D.	Obs.	Mean	S.D.	
School-aged child pedestrian crashes	23	2.91	4.45	101	0.62	1.57	2.29**

* $p < 0.05$; ** $p < 0.01$ (two-tailed test); [a.] High-Hispanic school-neighborhoods; [b.] Low-Hispanic school-neighborhoods

Similar result of t-test for mean frequency of child pedestrian crashes between low-income and high-income school-neighborhoods is presented in Table 5.

Table 5 The result of t-test between low-income and high-income school-neighborhoods

	LISN[a]			HISN[b]			Mean difference
	Obs.	Mean	S.D.	Obs.	Mean	S.D.	
School-aged child pedestrian crashes	38	1.84	3.24	86	0.70	2.05	1.14*

* $p < 0.05$; ** $p < 0.01$ (two-tailed test); [a.] Low-income school-neighborhoods; [b.] High-income school-neighborhoods

In like manner with the t-test for Hispanic school-neighborhoods, the mean of child pedestrian crashes was higher in the low-income school-neighborhood than its counterpart, possibly implying the disparity in the crashes between the two neighborhoods ($p < 0.05$). These findings presumably indicate the unequal distribution of school-aged child pedestrian crashes across the school-neighborhoods. To determine more statistically accurate results as well as to identify the child pedestrian safety in the school-neighborhoods, random-effects Poisson regression models were applied.[9]

[9] Multicollinearity test was conducted with VIF tests.

Model 1 included two sets of dummy variables, such as school-neighborhood and high-Hispanic school-neighborhood, while Model 2 included school-neighborhood and low-income school-neighborhood. The difference in frequency of child pedestrian crashes between school-neighborhood and beyond school-neighborhood can be identified consistently in Model 1 and Model 2, by interpreting the school-neighborhood variable (see Table 6). The results of likelihood-ratio test of α and Akaike's and Schwarz's Bayesian information criteria (AIC and BIC) tests for both models indicate that the panel estimators with random-effects are better than the pooled (Poisson) estimators: the outputs of AIC and BIC for random-effect Poisson regression models are smaller than simple Poisson models.

In both Model 1 and Model 2, school-neighborhood variable showed a negative coefficient, meaning that school-aged child pedestrian crashes occur less in the school-neighborhoods. In the school-neighborhood, the expected number of child pedestrian crashes decreased by around 50%, holding other variables constant (IRR = 0.483, $p < 0.01$ in Model 1; IRR = 0.488, $p < 0.05$ in Model 2).

Table 6 The results of random-effects Poisson regression for identifying the difference in the frequency of school-aged child pedestrian crashes between high-Hispanic and low-Hispanic school-neighborhoods

	The expected number of school-aged (5-19) child pedestrian crashes					
	Model 1			Model 2		
Variables	β[a]	IRR (C.I.)[b]	*z*[c]	β[a]	IRR (C.I.)[b]	*z*[c]
Neighborhood Characteristics						
School-neighborhood	-0.727**	0.483 (0.303, 0.770)	-3.06	-0.718*	0.488 (0.280, 0.850)	-2.53
High-Hispanic School-neighborhood	1.029**	2.798 (1.642, 4.768)	3.78			
Low-income School-neighborhood				0.610*	1.840 (1.035, 3.269)	2.08
Median household income	-0.004	0.996 (0.987, 1.005)	-0.89	-0.002	0.998 (0.988, 1.009)	-0.32
Traffic Exposure						
Population density	0.093	1.098 (0.994, 1.211)	1.85	0.122*	1.130 (1.018, 1.254)	2.30
School-aged child population density	0.000	1.000 (1.000, 1.000)	-1.04	0.000	1.000 (1.000, 1.000)	-1.36

Table 6 Continued

	The expected number of school-aged (5-19) child pedestrian crashes					
	Model 1			Model 2		
Variables	β[a]	IRR (C.I.)[b]	*z*[c]	β[a]	IRR (C.I.)[b]	*z*[c]
Traffic Exposure - Continued						
Area of units	-0.019	0.981 (0.903, 1.065)	-0.45	-0.022	0.978 (0.896, 1.068)	-0.50
Bus stop density	0.004	1.004 (0.996, 1.013)	1.00	0.004	1.004 (0.995, 1.012)	0.83
Built environments (neighborhood level)						
Mean block length	-4.117	0.016 (0.000, 2035.108)	-0.69	-6.345	0.002 (0.000, 254.872)	-1.05
% of high-speed roads	-0.006	0.994 (0.979, 1.009)	-0.82	-0.009	0.991 (0.977, 1.006)	-1.16
% of missing sidewalks	0.006	1.006 (0.997, 1.015)	1.33	0.003	1.003 (0.994, 1.012)	0.63
Crosswalk density	0.002	1.002 (0.999, 1.005)	1.46	0.002	1.002 (0.999, 1.005)	1.16

Table 6 Continued

	The expected number of school-aged (5-19) child pedestrian crashes					
	Model 1			Model 2		
Variables	β[a]	IRR (C.I.)[b]	*z*[c]	β[a]	IRR (C.I.)[b]	*z*[c]
Built environments (neighborhood level) – Continued						
Intersection density	0.002	1.002 (0.995, 1.010)	0.60	0.004	1.004 (0.996, 1.011)	0.92
Land use diversity	0.258	1.294 (0.259, 6.461)	0.31	-0.087	0.916 (0.178, 4.727)	-0.10
% of residential use	-0.024**	0.976 (0.962, 0.992)	-3.03	-0.028**	0.972 (0.957, 0.988)	-3.45
% of commercial use	0.040**	1.041 (1.018, 1.063)	3.61	0.035**	1.036 (1.013, 1.059)	3.15
% of office use	-0.033*	0.967 (0.936, 0.999)	-2.00	-0.041*	0.960 (0.930, 0.991)	-2.51
% of industrial use	0.023	1.023 (0.996, 1.051)	1.67	0.021	1.022 (0.994, 1.050)	1.54
% of park use	-0.002	0.998 (0.979, 1.018)	-0.17	0.002	1.002 (0.983, 1.021)	0.21

Table 6 Continued

	The expected number of school-aged (5-19) child pedestrian crashes					
	Model 1			Model 2		
Variables	β[a]	IRR (C.I.)[b]	*z*[c]	β[a]	IRR (C.I.)[b]	*z*[c]
Intercept	0.342	1.408 (0.132, 15.023)	0.28	0.963	2.621 (0.239, 28.769)	0.79
Observations	302			302		
LR test of $\alpha = 0$[d]	106.02 (0.000)			124.79 (0.000)		

* $p < 0.05$; ** $p < 0.01$ (two-tailed test)

[a.] Coefficient; [b.] Incidence Rate Ratio (95% Confidence Interval); [c.] z-statistics; [d.] Likelihood-ratio chi-square test. Prob ≥ $\bar{\chi}^2$ is shown in parentheses

Furthermore, Model 1 indicates a statistically significant disparity in the frequency of child pedestrian crashes between high-Hispanic and low-Hispanic school-neighborhoods at the 1% level. In the high-Hispanic school-neighborhood, the expected number of child pedestrian crashes increased by almost 180%, controlling for other variables (IRR = 2.798, $p < 0.01$). Also, Model 2 implies the child pedestrian safety varies by income level of school-neighborhoods: the expected number of child pedestrian crashes was greater in the low-income school-neighborhoods by 84%, holding other factors constant (IRR = 1.840, $p < 0.05$). Additionally, in Model 1, certain land uses had a statistically significant contribution to child pedestrian crashes in both regression models: for an increase of 1% in residential and office uses area in the neighborhood, the expected count of the child pedestrian crashes deceased by 2.4% (IRR = 0.976, $p < 0.01$) and 3.3% (IRR = 0.967, $p < 0.05$), respectively, holding other factors constant. In contrast, a one-percentage increase in commercial land use area in the neighborhood increased the expected frequency of the crashes by 4.1%, controlling for other factors (IRR = 1.041, $p < 0.01$). Model 2 also represented similar results as the Model 1 for land uses (residential use: IRR = 0.972, $p < 0.01$; office use: IRR = 0.960, $p < 0.05$; and commercial uses: IRR = 1.036, $p < 0.01$).

Table 7 The result of logistic regression for identifying factors influencing the probability of school-aged child pedestrian crashes in the school-neighborhoods

	The probability of school-aged (5-19) child pedestrian crashes		
	Model 3 (School-neighborhoods)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]
Road environments (segment level)			
Block length (100m)	0.373**	1.452 (1.152, 1.830)	3.16
High-speed roads	1.379**	3.971 (2.041, 7.729)	4.06
% of missing sidewalks	0.003	1.003 (0.998, 1.009)	1.22
Crosswalk density	0.289**	1.336 (1.127, 1.583)	3.33
Bus stop density	-0.118	0.888 (0.672, 1.174)	-0.83
Land use diversity	0.150	1.161 (0.596, 2.262)	0.44
% of residential use	-0.004	0.996 (0.983, 1.008)	-0.67
% of commercial use	0.017*	1.017 (1.004, 1.030)	2.53
% of office use	0.011	1.011 (0.994, 1.029)	1.23
% of industrial use	-0.002	0.998 (0.966, 1.030)	-0.14
% of park use	-0.022	0.979 (0.936, 1.023)	-0.96

Table 7 Continued

	The probability of school-aged (5-19) child pedestrian crashes		
	Model 3 (School-neighborhoods)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]
Built environments (neighborhood level)			
Crosswalk density	-0.002	0.998 (0.995, 1.002)	-0.81
Intersection density	-0.006	0.994 (0.985, 1.002)	-1.48
% of residential use	-0.005	0.995 (0.973, 1.017)	-0.47
% of commercial use	0.103**	1.109 (1.069, 1.150)	5.56
% of office use	-0.161**	0.851 (0.761, 0.952)	-2.83
% of industrial use	0.034	1.035 (0.961, 1.114)	0.90
% of park use	-0.001	0.999 (0.963, 1.036)	-0.05
Traffic exposure			
Population density (1,000 people)	0.285**	1.329 (1.115, 1.586)	3.17
School-aged child population density (1,000 people)	0.000	1.000 (1.000, 1.001)	0.71
Bus stop density (neighborhood level)	-0.118	0.888 (0.672, 1.174)	-0.83

Table 7 Continued

	The probability of school-aged (5-19) child pedestrian crashes		
	Model 3 (School-neighborhoods)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]
Neighborhood characteristics			
Median household income ($1,000)	-0.012	0.988 (0.976, 1.001)	-1.85
Intercept	-6.382**	0.002 (0.000, 0.011)	-6.65
Observations	5,703		
	Wald χ^2 (22) = 188.94 (p = 0.000); penalized log likelihood = -293.976		

* $p < 0.05$; ** $p < 0.01$ (two-tailed test)

[a.] Coefficient; [b.] Odds Ratio (95% Confidence Interval); [c.] z-statistics

Model 3. Initial log likelihood: -417.4280; Final log likelihood: -293. 9758; Pseudo R^2: 0.296

Table 8 The result of logistic regression for identifying the differentials in influencing factors the probability of school-aged child pedestrian crashes between high-Hispanic (HHSN) and low-Hispanic school-neighborhoods (LHSN)

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 4 (HHSN)			Model 5 (LHSN)		
Variables	β[a]	OR (C.I.)[b]	z[c]	β[a]	OR (C.I.)[b]	z[c]
Road environments (segment level)						
Block length (100m)	0.644**	1.905 (1.264, 2.871)	3.08	0.345*	1.413 (1.041, 1.918)	2.22
High-speed roads	1.874**	6.516 (2.499, 16.989)	3.83	0.894	2.446 (0.830, 7.210)	1.62
% of missing sidewalks	0.010**	1.010 (1.003, 1.016)	2.88	-0.010	0.990 (0.979, 1.001)	-1.80
Crosswalk density	0.463**	1.589 (1.239, 2.038)	3.65	-0.015	0.985 (0.712, 1.362)	-0.09
Bus stop density	-0.544	0.581 (0.22, 1.529)	-1.10	0.164	1.178 (0.834, 1.662)	0.93
Land use diversity	0.745	2.106 (0.635, 6.978)	1.22	0.397	1.488 (0.601, 3.685)	0.86
% of residential use	-0.015	0.985 (0.967, 1.004)	-1.54	-0.001	0.999 (0.980, 1.019)	-0.10
% of commercial use	-0.014	0.986 (0.964, 1.009)	-1.21	0.023*	1.024 (1.004, 1.043)	2.43

Table 8 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 4 (HHSN)			Model 5 (LHSN)		
Variables	β[a]	OR (C.I.)[b]	z^c	β[a]	OR (C.I.)[b]	z^c
Road environments (segment level) - Continued						
% of office use	-0.003	0.997 (0.962, 1.032)	-0.19	0.017	1.017 (0.994, 1.041)	1.48
% of industrial use	0.010	1.010 (0.976, 1.046)	0.58	-0.004	0.996 (0.954, 1.040)	-0.17
% of park use	-0.218	0.804 (0.581, 1.112)	-1.32	0.001	1.001 (0.969, 1.035)	0.08
Built environments (neighborhood level)						
Crosswalk density	-0.002	0.998 (0.988, 1.008)	-0.39	-0.010**	0.990 (0.983, 0.997)	-2.78
Intersection density	0.002	1.002 (0.969, 1.037)	0.13	0.003	1.003 (0.991, 1.016)	0.54
% of residential use	0.050	1.052 (0.964, 1.147)	1.14	-0.023	0.977 (0.945, 1.010)	-1.37
% of commercial use	0.136*	1.145 (1.001, 1.31)	1.97	0.121**	1.128 (1.073, 1.186)	4.74
% of office use	0.222	1.248 (0.474, 3.291)	0.45	-0.151*	0.860 (0.761, 0.971)	-2.43

Table 8 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 4 (HHSN)			Model 5 (LHSN)		
Variables	β[a]	OR (C.I.)[b]	z^c	β[a]	OR (C.I.)[b]	z^c
Built environments (neighborhood level) - Continued						
% of industrial use	0.001	1.001 (0.814, 1.23)	0.01	0.103	1.108 (0.988, 1.243)	1.76
% of park use	0.048	1.049 (0.941, 1.169)	0.86	0.021	1.022 (0.974, 1.072)	0.87
Traffic exposure						
Population density (1,000 people)	0.698*	2.009 (1.006, 4.013)	1.98	0.222	1.249 (0.977, 1.595)	1.78
School-aged child population density (1,000 people)	-0.002	0.998 (0.995, 1)	-1.85	0.000	1.000 (0.999, 1.001)	-0.80
Bus stop density (neighborhood level)	-0.010	0.990 (0.974, 1.007)	-1.16	0.017*	1.017 (1.004, 1.030)	2.52
Neighborhood Characteristics						
Median household income ($1,000)	0.053	1.054 (0.93, 1.194)	0.83	-0.021*	0.979 (0.962, 0.997)	-2.32

Table 8 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 4 (HHSN)			Model 5 (LHSN)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]	β[a]	OR (C.I.)[b]	*z*[c]
Intercept	-10.904**	0.000 (0, 0.003)	-4.23	-5.388**	0.005 (0.000, 0.077)	-3.74
Observations	1,323			4,380		
	Wald χ^2 (22) = 63.95 (p = 0.000); penalized log likelihood = -68.493			Wald χ^2 (22) = 142.73 (p = 0.000); penalized log likelihood = -100.559		

* $p < 0.05$; ** $p < 0.01$ (two-tailed test)

[a.] Coefficient; [b.] Odds Ratio (95% Confidence Interval); [c.] z-statistics

Model 4. Initial log likelihood: -122.7726; Final log likelihood: -68.4925; Pseudo R^2: 0.442

Model 5. Initial log likelihood: -205.0715; Final log likelihood: -100.5587; Pseudo R^2: 0.510

Table 9 The result of logistic regression for identifying the differentials in influencing factors the probability of school-aged child pedestrian crashes between low-income (LISN) and high-income school-neighborhoods (HISN)

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 6 (LISN)			Model 7 (HISN)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]	β[a]	OR (C.I.)[b]	*z*[c]
Road environments (segment level)						
Block length (100m)	0.141	1.151 (0.836, 1.585)	0.86	0.765**	2.148 (1.506, 3.066)	4.22
High-speed roads	1.861**	6.431 (2.296, 18.014)	3.54	1.181*	3.258 (1.183, 8.976)	2.28
% of missing sidewalks	0.007*	1.007 (1.001, 1.014)	2.15	-0.007	0.993 (0.983, 1.004)	-1.23
Crosswalk density	0.260*	1.296 (1.051, 1.600)	2.42	0.299	1.348 (0.918, 1.980)	1.52
Bus stop density	-0.216	0.806 (0.486, 1.337)	-0.84	0.262	1.299 (0.868, 1.945)	1.27
Land use diversity	1.899**	6.678 (2.244, 19.877)	3.41	-0.721	0.486 (0.182, 1.304)	-1.43
% of residential use	-0.015	0.985 (0.968, 1.003)	-1.68	0.002	1.002 (0.983, 1.022)	0.24
% of commercial use	0.017	1.017 (0.999, 1.036)	1.82	0.015	1.015 (0.995, 1.035)	1.50

Table 9 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 6 (LISN)			Model 7 (HISN)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]	β[a]	OR (C.I.)[b]	*z*[c]
Road environments (segment level) - Continued						
% of office use	0.000	1.000 (0.976, 1.025)	0.03	0.018	1.018 (0.991, 1.045)	1.32
% of industrial use	0.006	1.006 (0.976, 1.037)	0.37	-0.063	0.939 (0.778, 1.133)	-0.66
% of park use	-0.158	0.854 (0.683, 1.069)	-1.38	-0.003	0.997 (0.960, 1.035)	-0.15
Built environments (neighborhood level)						
Crosswalk density	0.002	1.002 (0.995, 1.010)	0.56	-0.019**	0.981 (0.971, 0.992)	-3.56
Intersection density	-0.018	0.982 (0.960, 1.005)	-1.56	-0.001	0.999 (0.983, 1.015)	-0.12
% of residential use	0.006	1.006 (0.972, 1.041)	0.33	0.016	1.016 (0.968, 1.066)	0.64
% of commercial use	-0.025	0.975 (0.893, 1.065)	-0.56	0.264**	1.302 (1.183, 1.432)	5.41
% of office use	-0.200	0.819 (0.605, 1.108)	-1.30	0.018	1.018 (0.899, 1.153)	0.28

Table 9 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 6 (LISN)			Model 7 (HISN)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]	β[a]	OR (C.I.)[b]	*z*[c]
Built environments (neighborhood level) - Continued						
% of industrial use	-0.011	0.989 (0.879, 1.112)	-0.19	0.061	1.063 (0.914, 1.237)	0.80
% of park use	-0.152**	0.859 (0.769, 0.960)	-2.68	0.104**	1.110 (1.052, 1.171)	3.80
Traffic exposure						
Population density (1,000 people)	0.162	1.175 (0.841, 1.642)	0.95	0.218	1.243 (0.902, 1.713)	1.33
School-aged child population density (1,000 people)	0.001	1.001 (1.000, 1.002)	1.17	0.000	1.000 (0.999, 1.001)	-0.10
Bus stop density (neighborhood level)	0.001	1.001 (0.983, 1.019)	0.08	0.025**	1.025 (1.009, 1.041)	3.18
Neighborhood characteristics						
Median household income ($1,000)	0.158**	1.172 (1.062, 1.293)	3.15	-0.042**	0.959 (0.932, 0.987)	-2.88

Table 9 Continued

	The probability of school-aged (5-19) child pedestrian crashes					
	Model 6 (LISN)			Model 7 (HISN)		
Variables	β[a]	OR (C.I.)[b]	*z*[c]	β[a]	OR (C.I.)[b]	*z*[c]
Intercept	-9.962**	0.000 (0.000, 0.003)	-4.91	-7.894**	0.000 (0.000, 0.010)	-4.71
Observations	1,800			3,903		
	Wald χ^2 (22) = 83.76 (p = 0.000); penalized log likelihood = -83.666			Wald χ^2 (22) = 91.04 (p = 0.000); penalized log likelihood = -69.971		

* $p < 0.05$; ** $p < 0.01$ (two-tailed test)

[a.] Coefficient; [b.] Odds Ratio (95% Confidence Interval); [c.] z-statistics

Model 6. Initial log likelihood: -164.6144; Final log likelihood: -83.6664; Pseudo R^2: 0.492

Model 7. Initial log likelihood: -161.6844; Final log likelihood: -69.9710; Pseudo R^2: 0.567

The results from the logistic regression model for all street segments within each school-neighborhood are presented in Table 7 (Model 3). Most significant factors are consistent with previous literature. For a hundred meter increase in block length, the odds of the occurrence of child pedestrian crash on the segment are expected to increase by 45%, holding all other variables constant (OR = 1.45, $p < 0.01$). If segments are a high-speed street that has higher than a 35-mph speed limit, its odds of child pedestrian crashes are almost 4 times larger than its counterparts, holding other variable constant (OR = 3.97, $p < 0.01$). Holding other factors constant, 34% increase in the odds of child pedestrian crashes is expected for a one-unit increase in crosswalk density (OR = 1.34, $p < 0.01$). Moreover, a one-percent increase of the number of commercial land use parcel on the street segment increases the odds of the occurrence of child pedestrian crashes by about 2%, controlling for the other factors (OR = 1.02, $p < 0.01$).

In addition, Table 8 and Table 9 show the results from separate regression models to determine the differences in factors influencing pedestrian crashes involving school-aged children between high-Hispanic and low-Hispanic school-neighborhoods (Model 4 and Model 5); as well as between low-income and high-income school-neighborhoods (Model 6 and Model 7). Block length was statistically significant for both high-Hispanic and low-Hispanic school-neighborhoods. For an increase of a hundred-meter in block length, the odds of child pedestrian crashes are expected to increase by 90.5% and 41.3% in the high- and low-Hispanic school-neighborhoods, respectively, controlling for other factors to be constant (OR = 1.90, $p < 0.01$; and OR = 1.41, $p < 0.05$, respectively). However, road characteristics, such as speed, sidewalks, and crosswalks are only statistically significant within the high-Hispanic school-neighborhoods, holding other factors constant: the odds of child pedestrian crashes are expected to increase by about 6 times for being a high-speed street (OR = 6.52, $p <$ 0.01); when the percentage of missing sidewalk rises by one-percent, the odds of child pedestrian crashes are increased by 1% (OR = 1.01, $p < 0.01$); and for an increase of one-unit in crosswalk density, the odds of child pedestrian collisions would go up by about 60% in the high-Hispanic neighborhoods (OR = 1.59, $p < 0.01$). Contrastively, commercial land uses on the segment was statistically significant only in the low-Hispanic neighborhoods: a one-percent increase of the number of commercially used parcel increases the odds of child pedestrian crash occurrence by 2.4% in the low-Hispanic school-neighborhoods, holding other factors constant (OR = 1.02, $p < 0.05$).

This paper also found some differentials in the factors correlated with child pedestrian crashes between the low-income and the high-income school-neighborhoods. Only in the low-income school-neighborhoods, road and built environments such as percentage of missing sidewalks, crosswalk density, and land use diversity on the segment are significant, holding all other variables constant: for a one-percentage increase of missing sidewalks, the odds of child pedestrian-vehicle collision occurrence are expected to increase by about 1.0% (OR = 1.01, $p < 0.05$); an increase of one-unit in the crosswalk density increases the odds of child pedestrian crashes by almost 30% (OR = 1.30, $p < 0.05$); and for an one-unit increase of land use diversity index on the segment, the odds of child pedestrian crashes increase by six times (OR = 6.68, $p <$ 0.01). While the speed limit is statistically significant in both neighborhoods, block length was significant only in the high-income neighborhood: being a high-speed street segment increases the odds of child pedestrian collisions occurrence by about 6 and 3 times in low-income and high-income school-neighborhoods, respectively (OR = 6.43, $p < 0.01$; and OR = 3.26, $p < 0.05$, respectively); but an increase of 100-meter in block length increases the odds of child pedestrian crashes by about 1.2 times (OR = 2.15, $p < 0.01$) only in the high-income school-neighborhoods. These findings are also consistent with the prior research.

CHAPTER V

CONCLUSION

Pedestrian injury or death from motor vehicle related crashes are obviously critical public health concerns. More attention should be paid to providing safe pedestrian environments, especially for school-neighborhoods, because school-aged children are one of the most vulnerable groups to pedestrian crashes. Based on the results of this paper, the school-neighborhoods had a lower frequency of pedestrian crashes than the beyond school-neighborhoods in Austin, Texas. The results of multivariate (random-effects Poisson regression models) analyses show that the pedestrian environment around schools was safer than other neighborhoods. From the results of regression models (Model 1 and Model 2), this paper found that the expected number of pedestrian crashes involving school-aged children was lower in the school-neighborhoods. However, using the t-test, this paper also identified possible evidence of spatial disparity issues in child pedestrian crashes among the school-neighborhoods by their socio-demographic characteristics. In the high-Hispanic and low-income school-neighborhoods, the mean value of the number of child pedestrian crashes was higher than their counterparts. This evidence was determined by the regression models. Although both high-Hispanic and low-income school-neighborhoods showed a lower expected number of child pedestrian crashes than the beyond school-neighborhoods, the crash count was higher than their counterparts; the expected number of child pedestrian crashes was higher in the high-Hispanic and low-income school-neighborhoods when compared to low-Hispanic and high-income school-neighborhoods, respectively.

This research also found the differentials in the factors correlated to school-aged child pedestrian crashes by neighborhood characteristics (see Table 9). Certain factors, such as block length, speed limit, missing sidewalks, and percentage of commercial land use parcels on the segment, showed positive associations with pedestrian crashes involving children in the school-neighborhoods, regardless of neighborhood characteristics. However, in the high-Hispanic school-neighborhoods, several road environmental attributes (i.e., traffic speed, percentage of missing sidewalks, and crosswalk density on the street segment) were statistically significant: but not in the low-Hispanic school-neighborhoods. In contrast, percentage of commercially used parcels on the street segment had significant effects only in the low-Hispanic neighborhoods. Also, for both neighborhoods, block length showed a positive association with child pedestrian crashes. In the low-income school-neighborhoods, meanwhile, missing sidewalks, crosswalk density, and land use diversity factors were correlated to child pedestrian crashes: but not in the high-income school-neighborhoods. Block length was associated with the child pedestrian crashes in the high-income school-neighborhoods, and a speed limit of street segment was statistically significant in both neighborhoods.

Table 10 Road environmental factors influencing pedestrian-vehicle crashes involving school-aged children for each type of school-neighborhoods[a]

	SN[b]	HHSN[c]	LHSN[d]	LISN[e]	HISN[f]
Block length	**	**	*		**
High-speed roads	**	**		**	*
% of missing sidewalks		**		*	
Crosswalk density	**	**		*	
Bus stop density					
Land use diversity				*	
% of commercial use	*		*		

[a.] Statistically significant factors are marked with asterisks (**: $p < 0.01$; *: $p < 0.05$)
[b.] School-neighborhoods regardless of neighborhood characteristics; [c.] High-Hispanic school-neighborhoods; [d.] Low-Hispanic school-neighborhoods; [e.] Low-income school-neighborhoods; and [f.] High-income school-neighborhoods

For school-neighborhoods, interventions related to road environments may have an effect of reducing the probability of child pedestrian crashes. Specifically, for both high-Hispanic and low-income school-neighborhoods, this paper found that traffic speed on the roadways, the number of crosswalks on the street segment, and sidewalk completeness may need to be examined. As we discussed in the previous chapters, dense development patterns provide shorter block length in the neighborhoods. However, high density is also related to the high street connectivity, resulting in a greater number of intersections and possibly a greater number of crosswalks. In this case, appropriate policy interventions, such as requiring crossing guards around schools, should be applied to reduce the likelihood of pedestrian crashes (Ahlport, Linnan, Vaughn, Evenson, & Ward, 2008; Chriqui et al., 2012; Dumbaugh & Frank, 2007).

Additionally, in terms of built environments and vehicle speed, traffic calming approach can be one of the alternatives for school-neighborhoods. Many European countries have reported the positive effectiveness of traffic calming features (e.g., speed humps, road narrowing, changes in pavement color and texture, and speed tables) on reducing traffic crashes and controlling for motor vehicle volumes and driver's behavior (Jones, Lyons, John, & Palmer, 2005). Especially for small areas, traffic calming devices decreased child pedestrian injuries by 70% and contributed to a 9 mph decrease in traffic speeds (Towner, Dowswell, & Mackereth, 2001; Webster & Mackie, 1996). Therefore, provision of these kinds of traffic calming devices may help to reduce the risk of child pedestrian crashes in the school-neighborhoods.

Moreover, commercial land uses around schools should be controlled by planning interventions for general school-neighborhoods. When surveyed, children responded that commercial spaces are most often destinations for their favorite places (Banerjee et al., 2012). Also, the types and size of commercial uses affect pedestrian and cyclist crash rates in the neighborhood (Dumbaugh et al., 2013). Thus, appropriate land use planning and zoning regulations for excluding commercial land use or restricting types of commercial uses should be applied to these neighborhoods to reduce the risk of child pedestrian crashes (Yu & Zhu, 2015).

Although this paper identifies spatial disparity issues in pedestrian-vehicle collisions involving school-aged children and suggested different factors influencing the pedestrian crashes by school-neighborhood characteristics, there are a few limitations. Firstly, this paper focused on a quantitative measurement for road and built environments, excluding the qualitative assessment due to the limitation of data and resources. Nevertheless, the quality of the pedestrian environment can be an important predictor of perceived safety for pedestrians (Landis, Vattikuti, Ottenberg, McLeod, & Guttenplan, 2001). Furthermore, the maintenance of a built environment, such as sidewalks and street surfaces, may be different between neighborhoods (Zhu & Lee, 2008). Design factors may also affect the frequency of pedestrian-vehicle accidents. For example, the impact of the crosswalk on the pedestrian crashes would be different by its design or use (Rothman et al., 2013). Therefore, for future research, it is recommended to including street audit approaches to understand the quality of street segments. Secondly, more crash data may be needed to produce more accurate results. The data used in this paper showed a relatively small portion of school-aged child pedestrian crashes. While this paper attempted to control for possible issues of separation in logistic regression with Firth's penalized likelihood method, larger sample size or more crash data would be better to generate more accurate statistics. Thirdly, the time frames of GIS spatial data were not exactly matched with that of other information, such as crash and socio-demographic data, due to the availability. Although most of spatial data are related to the physical environments of neighborhood which are relatively insensitive to the time, matching information would be better to produce more precise results. Lastly, child pedestrian's exact information, such as address and commuting time, would be better to examine the roadway environment for their routes to schools. While network buffers used in this paper reasonably represent areas that have available paths for walking, more accurate routes for children who walk to and from school would be more helpful to understand the pedestrian environment for children and the school-neighborhoods. Also, this detailed information of time period would allow us to exactly measure the walking exposure.

Despite the limitations, this paper contributes to understanding traffic safety within the school-neighborhoods in Austin, Texas and identifies whether and how the factors correlated with child pedestrian crashes vary by socio-demographic characteristics of school-neighborhoods. To achieve the social justice in the child pedestrian safety, this paper proposes a few alternatives beyond the current efforts. One of the important contributions of this paper is to suggest local governments put the appropriate interventions and actions in the right places. The findings from this paper may allow local governments to apply more targeted strategies to different neighborhoods to provide our children with safe pedestrian environments around schools. While this paper clearly shows differences in child pedestrian crashes based on the neighborhood characteristics around schools, examining the contributions of quantitative factors will be an important merit for further research. Also, survey data for actual routes to school and commuting time period for children will improve the results of empirical analyses.

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APPENDIX A

TABLE

A - 1 Child pedestrian crash in urbanized areas in Texas (2010-2014)

Urbanized Area	**Pedestrian Crashes in Children (age 5-19)**
Dallas--Fort Worth--Arlington	911
Houston	707
San Antonio	600
El Paso	262
Austin	236
Laredo	146
Corpus Christi	125
Lubbock	109
Brownsville	71
Amarillo	66
McAllen	60
Odessa	52
Killeen	49
Denton--Lewisville	49
College Station--Bryan	42
Midland	38
Waco	38
Harlingen	35
Beaumont	30
Wichita Falls	26
Tyler	24
Abilene	21
Longview	20

A - 1 Continued

Urbanized Area	**Pedestrian Crashes in Children (age 5-19)**
San Angelo	18
San Marcos	17
McKinney	16
Texas City	13
Port Arthur	13
Conroe--The Woodlands	10
Sherman	9
Temple	9
Lake Jackson--Angleton	5
Victoria	3