A Review of Analysis Techniques and Data Collection Methods for Modeling Pedestrian Crossing Behaviors

Shrikanth V. Mamidipalli, MSCE Civil, Construction and Environmental Engineering University of Alabama at Birmingham Birmingham, AL, USA <u>shrivina@uab.edu</u>

Virginia P. Sisiopiku, PhD Civil, Construction and Environmental Engineering University of Alabama at Birmingham Birmingham, AL, USA vsisiopi@uab.edu

Abstract— A thorough literature review was performed in this study to gain an in depth understanding of current practices and existing knowledge gaps with respect to modeling pedestrian crossing behaviors and pedestrianvehicle interactions. The review of literature concentrated on a. current analysis methods and b. approaches for data collection and performance estimation. The synthesis presented in this paper aims at providing background information in support of future research efforts aiming at improving the modeling of pedestrian-vehicle interactions in multi-modal operational analyses.

Keywords—Pedestrian Crossing Behavior; Data Collection; Pedestrian-Vehicle Interactions

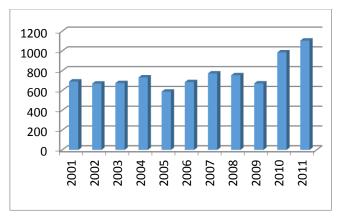
I. BACKGROUND

The urban transportation systems today are evolving continuously to improve goals of safety, accessibility, and mobility. A greater appreciation for non-motorized modes of transportation is also gaining momentum, owing to the traffic congestion and health benefits attributed. The transportation research and engineering community is gradually embracing the multi-modal perspective in operational and policy analyses. This is, for example, evidenced from the paradigm shift in capacity and serviceability analysis reflected in the recent revision of the Highway Capacity Manual [1].

The conventional transportation infrastructure design has been greatly inclined to maximize automobile throughput. At intersection locations right-of-way sharing among motorized and un-motorized modes has major traffic safety implications. Fig. 1 displays traffic safety trends in pedestrian fatalities over the last decade from failure to yield the right-of-way [2]. A glance of pedestrian fatalities resulting from failure to yield the right-of-way highlights the need for better understanding and analysis of pedestrian and vehicle interactions. Bastian Schroeder, PhD

Institute for Transportation Research and Education North Carolina State University Raleigh, NC, USA

Lily Elefteriadou, PhD University of Florida Transportation Institute University Of Florida Gainesville, FL, USA



 $_{\rm Fig}$ 1. Pedestrian Fatalities from Failure to Yield Right of Way (2001-2011)

This paper provides a comprehensive synthesis of earlier efforts towards modeling pedestrian crossing behaviors and pedestrian-vehicle interactions. First, the paper explores pedestrian movement and routechoice models pedestrian crossing behavior models and then it presents and contrasts pedestrian data collection options. The objective is to summarize current practices and identify possible gaps, thus paving the way for the development of new and enhanced methods that take under consideration pedestrian presence in future modeling efforts.

II. PEDESTRIAN MODELING REVIEW

A. Pedestrian Movement and Route-Choice Models

Pedestrian movement has been examined in several aspects like route choice, activity based movement, crowd evacuation model, and lane formation models. These types of movements are prominently modeled in simulation environments. Simulation development includes modeling pedestrian movement using continuous or discrete time domain methods, time or event based transitions. Macroscopic pedestrian models involve modeling pedestrian flows as traffic flow, queuing theory, and fluid or continuum mechanics.

In early studies, Borgers and Timmermans developed a stochastic micro-simulation tool for describing pedestrian movement and route choice within city centers and shopping areas. Multinomial logit model formulation was used to estimate the function of subjective utility, which serves as an underpinning for the route choice behavior [3].

Hunt and Griffiths modeled delay acceptance in pedestrian movement as a function of traffic volumes using a decision matrices approach [4]. Daamen, Hoogendorn and Bovy used controlled experiments to develop fundamental traffic flow relationships for pedestrian crowds inside and upstream of bottlenecks [5].

Some studies modeled pedestrian movements in cellular automaton. Cellular automata involve partitioning the network into grid of cells, each in one of the finite number of states at a discrete time period. The state of grid cell and its transition to other state is governed by a set of rules that are a function of states of adjoining neighboring cells.

Blue and Adler studied pedestrian lane formation in bi-directional pedestrian walkways. They modeled the flows under three distinct conditions, namely separated flow similar to un-interacting flow in opposite directions, interspersed flow in which pedestrians orient themselves in directional flow lanes to find their way, and dynamic lane formation involving emergence of lanes form interaction among pedestrian movements. The study used cellular automaton approach to describe behavioral rules like sidestepping, conflict mitigation, and temporary stand-off [6].

Lovas developed the stochastic microscopic simulation tool EVACSIM for modeling pedestrian evacuation dynamics. In this model he assumed that a pedestrian facility can be modeled as a network of walkway sections and the pedestrian flow in a network resembles to a queuing network process. In queuing network process, each pedestrian is treated as a flow object interacting with other objects. The proposed simulation model described the pedestrian behavior to be affected by head times between different pedestrians at high densities, whereas for low densities pedestrian behavior is affected by walking speed [7].

Lee and Lam used simulation rules and equations from previous models with some rules derived from observational data to calibrate a model for bidirectional pedestrian flow at crosswalks [8].

Wakim, Capperon, and Oksman used speed distribution to develop a Markovian model of pedestrian movement consisting four discrete choices: standing, walking, jogging, and running [9].

Antonini, Bierlaire, and Weber modeled pedestrian walking behavior using discrete choice analysis. The model consists of a choice set comprising walking alternatives based on speed (same speed, accelerate, decelerate), radial direction, and number of pedestrians present. Cross nested logit models and mixed logit models were tested on observed data, for generating utility functions [10].

B. Pedestrian Crossing Behavior Models

Literature review shows that the pedestrian crossing behavior has been investigated in different dimensions such as effectiveness of pedestrian safety treatments, pedestrian level of service, and delay to motorized modes of traffic. Pedestrian crossing modeling includes analysis of driver yielding and pedestrian gap acceptance behavior.

Himanen and Kulmala modeled probabilities of driver yielding for a pedestrian crossing in the marked crosswalks using multinomial logit method. The study considered the number of vehicles in platoon, vehicle speed, pedestrian distance from curb, number of pedestrians attempting to cross the street, city size as explanatory variables extracted from videotaped field observations [18].

Oxley et al. used explanatory variables such as curb delay, gap acceptance, crossing time, time-ofarrival for determining differences in crossing behavior of elderly pedestrians against younger pedestrians. The differences were obtained using t-tests [12].

Baltes and Chu adopted a stated preference approach to evaluate pedestrian crossing difficulty at mid-block locations. A continuous scale from 1 to 6 was used to describe crossing difficulty. The model used ordinary least squares to estimate pedestrian, roadway, crosswalk and traffic control variables [13].

Rosenbloom, Ben-Eliyahu, and Nemrodov examined differences in children's crossing behavior. It was observed in the study that when an adult accompanied children, they are more likely to commit unsafe crossing maneuvers [14].

Hui and Hongwei modeled pedestrians crossing decisions based on utility theory. The choice of crossing within or outside crosswalk was based on attributes like perceived safety level of crosswalk, compliance, and travel time [15].

Sun et al. analyzed pedestrian-motorist interactions by developing models of pedestrian gap acceptance and vehicle yielding. Pedestrian gap acceptance was modeled using probability distribution determining critical gap and binary logit model based on age, gender, waiting time, gap size, and number of pedestrians waiting on the curb [16].

Yang analyzed pedestrian gap acceptance considering the effect of enforcement. The model was developed based on stated preferences and revealed preferences obtained from video recordings [17].

The literature review and synthesis reaffirms that there is a need to develop robust pedestrian gap acceptance and driver yield behavior models based on a broad set of data collected at various locations, and to gain a better understanding of the true dynamics of pedestrians and vehicles at crossing locations. In doing so, collection of detailed data is needed to provide the basis for the development of enhanced models describing pedestrian-vehicle interactions. Given the complexity of such interactions, a need for state of art techniques for data acquisition, processing and analysis has been identified. Available data collection approaches are reviewed next, along with advantages and limitations of each approach.

III. DATA COLLECTION APPROACHES

A. Background

A scan of relevant literature identified several research efforts that aimed at studying driver attitudes and pedestrian crossing behaviors. For obtaining data in such studies, three different data collection techniques have been adopted, namely observational, instrumented vehicle, and driving/pedestrian simulator approaches [31].

Observational studies are the most traditional method employed in the collection of empirical driving and pedestrian behavior data. They can be used to obtain data from attributes that are fixed (such as vehicle type, pedestrian characteristics, geometric characteristics, etc.), those that change dynamically (e.g., vehicle speeds, pedestrian speeds, distance headways, traffic signal indications, etc.) as well as to record qualitative observations (such as driver or pedestrian distraction). Observational data are obtained from trained observers with the help of tally sheets, count boards, video surveillance equipment, and radar detection devices.

Instrumented vehicles, on the other hand, permit quantitative assessments of driver performance in the field. under actual road conditions. These measurements are not subject to the type of human bias that affects inter-rater reliability on a standard road test. Moreover, the internal network of modern vehicles makes it possible to obtain information from the driver's own automobile, providing opportunities to study in depth driver strategy, vehicle usage, upkeep, drive lengths, route choices, and decision-making [18]. The instrumentation enables researchers to record driver characteristics and vehicle operational parameters. Driver characteristics include galvanic skin response, heart rate, and muscle activity. Examples of vehicle operating characteristics that can be gathered using an instrumented vehicle include steering motion, braking actions, speed, distance and triaxial accelerations [19].

Laboratory simulators can also be employed to assess behavior in response to synthetic reality. Driving simulators make it possible to observe driver behavior in controlled environments without the risk of driving on the road. They offer a cost-effective alternative to real world naturalistic studies and allow independent variables to be systematically for manipulated so that driver behavior can be measured precisely and safely [18]. Since their introduction in the 1960s they have undergone many advances in terms of computing, visual display, and vehicle dynamics capabilities. Even the lower fidelity simulators are able to collect vast amounts of data, which is one of their reported advantages over naturalistic investigative methods. Typical dependent measures of driving performance that are collected in

driving simulation research studies include vehicle speed, acceleration, braking reaction time, and lane position. Similar to the driving simulators, pedestrian simulators also exist that can be used to study pedestrian behavior in controlled environments.

The following paragraphs summarize and contrast studies that employed the data collection methods highlighted above in an effort to highlight opportunities and challenges from implementation.

IV. DATA COLLECTION STUDIES

A. Observational

Observational data collection methods are widely employed in pedestrian behavior analysis. They are leveraged for manifold purposes including crash analysis, en-route choice modeling, and assessment of level of service for various facilities. A cursory note of these methods indicates either direct observation approach or video recording based approach as the major means to collect data. Many research efforts use observational methods to collect data for studying pedestrian crossing attributes (such as pedestrian crossing speed and pedestrian compliance) as well as pedestrian vehicle interactions (such as gap acceptance, and driver yielding behavior) for a variety of users and crossing types.

are several methods There employed in observational studies which vary with respect to ease of collection, post processing, and degree of human involvement. These include direct field observations using human observers, and automated data collection utilizing infra-red sensors, Radio Frequency Identifiers (RFID) sensors, detection based on Bluetooth sensors, or Light Detection and Ranging (LIDAR) sensors [20], [21], and [22]. These sensors are primarily used for measuring pedestrian speed. Bluetooth sensors were used to trace pedestrian trajectories in confines of study field. In majority of observational studies, video recording is used as data collection technique. Retrieval of study data from video recording is a major task. Post processing of data includes manual analysis of field recorded videos, semi-automated video analysis, or automated video analysis. The nature of the study and requisite parameters for model development govern specific methods over others.

For implementation of automated video data collection, detection of facility users and tracing the trajectories of these users is essential. This is accomplished mainly by the following techniques [22], [23]:

a) Tracking based on detection: A model of background is first developed and pedestrians are distinguished from the background. The moving pedestrians are tracked based on subtracting with background or deformable templates.

b) Tracking using flow: Determining few reference points and tracking them in successive frames provide object trajectories with the aid of clustering.

c) Tracking with probability: The tracking problem is considered as a probabilistic inference problem in Bayesian framework. The sequence of states generated and measured are assumed to follow a Markov chain process.

Avineri et al. used synthetic approach of observational data and brief survey to capture the study of pedestrian behavior. Microscopic variables (e.g. speed) were obtained from video recording and age, gender and fear of falling (FOF) were obtained using surveys [24].

Schroeder and Rouphail used a video recording technique for capturing driver yielding and pedestrian gap acceptance behavior. Vehicle speed was obtained using laser speed gun synchronized with video recording device. An observer recorded vehicle speed at multiple instances on the onset of pedestrian in the crosswalk. Such synchronized data gathering aided efficient manual post processing [25].

Guo et al. obtained field data using video recording method and Vehicle Detector Data Acquisition System (VDDAS). VDDAS provided vehicle counts, vehicle classification, headway distribution and mean speed by vehicle type [26].

Hoogendorn et al. conducted experiments to obtain microscopic variables relating to pedestrian behavior. In these experiments the variables obtained from automatic video analysis technique were bifurcated as stimuli-side and response-side [20]. Further stimuli variables were classified into experimental and context variables. Context variables render greater insights into model development by controlled experiments. Table 1 below provides detailed information about these variables [20].

TABLE I.	VARIABLES FOR PEDESTRIAN MODEL DEVELOPMENT [20]
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uli	Response	
Context Variables	Microscopic	Macroscopic
Free speed of individual	Walking speeds	Density
pedestrian		Space mean
	Walking	speed
Age of Pedestrian	directions	Intensity
	Passing	,
Grouping behavior	behavior	Desired speed
	Group	distribution
Gender of	formation	
Pedestrian		Time mean
	Walking directions	speed
	Context Variables Free speed of individual pedestrian Age of Pedestrian Grouping behavior Gender of	Context VariablesMicroscopicFree speed of individual pedestrianWalking speedsAge of PedestrianWalking directionsGrouping behaviorPassing behaviorGender of PedestrianGroup formationWalking WalkingWalking Walking

Ismail et al. summarized various pedestrian studies analyzing pedestrian walking speed. These studies employed field observations, manual video analysis, and semi-automated vide analysis techniques with different variables. The variation of the walking speed against the Manual of Uniform Traffic Control Devices (MUTCD) standard was also summarized [21].

Kerridge et al. introduced a real time pedestrian data acquisition and processing system based on low cost infra-red sensor array. Such detection system enables extraction of pedestrian trajectories. Post processing can output macroscopic variables such as density, flow rate, and volume of pedestrians [27]. Quan et al. conducted experiments for pedestrian speed determination using RFID. The speed error rate of 8.11% was observed when compared with true values. In contrast with conventional manual collection of data and video image processing techniques, the technique was found to be less labor intensive and lower in cost. However, interference caused by same spectrum devices and environment can cause increase in errors [28].

Ismail et al. utilized automated video analysis techniques to examine pedestrian vehicle conflicts. The study gathered pre- and post data of a scramble facility installation at an intersection. Simultaneous tracking of vehicles and pedestrians from frame to frame was cited as a major challenge in using such technique. Future advances in observational techniques may improve data collection and post processing for estimating the impacts of facility design and operations [21].

In other studies, Zeedyk and Kelly (2003) used unobtrusive observations of 123 adult-child pairs at pedestrian crossings to model the adult-child crossing behavior. Eight types of maneuvers were considered in this study: crossing within the confines of the crosswalk, curb stoppage, oral instruction from adult to child, pressing the button for pedestrian signal, checking for traffic emerging from either direction before initiating crossing, holding hands during crossing, and walking/running (child). Fischer's exact chi-square was used to compare the observations [29].

Hatfield and Murphy (2007) investigated the effect of mobile phone usage on crossing speed of pedestrians based of field observation data. The study group comprised of 270 females and 276 males. Both genders were observed to walk slowly when using a mobile phone during crossing. Females were found to be more likely to not look at the traffic before starting a crossing maneuver [30].

In a recent study, Schroeder et al. analyzed pedestrian and driver behavior at mid-block crosswalks based on targeted empirical observations of naturally occurring and staged crossings. Using an extensive set of field data collected at 27 mid-block pedestrian crossings in three states (Alabama, Florida, and North Carolina), they developed models describing driver yielding and pedestrian gap acceptance behavior and used them to enhance modeling procedures in the CORSIM traffic microsimulation environment [31].

Overall, current experience with observational data collection methods indicates that such methods require minimal investment in equipment, allow for direct observation of natural pedestrian crossings and driver decision making, and provide first source information to calibrate simulation models. The main shortcoming is the lack of control to cover a specific range of parameters as part of the experiment and isolate others that may bias the data sample.

B. Instrumented Vehicle

The review of the literature confirms that the use of instrumented vehicles to gather driver behavior measures in the context of driver-pedestrian

interaction has gained little attention as of now. Still, studies that utilized instrumented vehicles for gathering driving behavior data can provide some useful insights on experimental design, resource requirements, advantages and limitations.

For example, a study by Boyce and Geller conducted experiments using instrumented vehicles to assess risky driving behavior. The participant group comprised of 61 licensed drivers with ages ranging from 18 to 82 years. The participants were distributed in three groups: younger, middle aged and older. The risky behavior was assessed by means of speeding, on-task behavior, turn-signal use, and following distance [32].

A study by Rizzo et al. used instrumented vehicle to collect data for the assessment of fitness and knowhow of diverse young and old driving population and develop objective measures to distinguish normal and potentially unfit drivers [18].

Other research efforts used instrumented vehicles to study driver distraction. For example, an experiment by Texas Transportation Institute (TTI) investigated behavior under distraction driver using an instrumented vehicle. The experiment had three tasks, control, reading and writing, on which the driver performance was evaluated. Using the in-vehicle instrumentation and Pyschopy data collection software, data related to speed, lateral lane position, steering, brake, accelerator, light response times, and reading/texting rates were gathered. Some of the major observations of the study include lower mean speed than posted speed while texting and difficulty in maintaining lane discipline while texting [33].

C. Driving Simulators

A widely used approach to evaluate driver behavior is using driving simulators. However, there are not many instances where driving simulators were used to examine driver behavior with pedestrian crossing stimulus. In a relevant study, Pradhan et al. researched the yielding propensity of drivers at midblock crossings using a driving simulator. The participants were grouped in novice drivers (16-17 years), young drivers (19-29 years), and older drivers (60-75 years). Each group had 24 participants. The position of vehicle, velocity and point of driver's gaze The stopping propensity and eye were recorded. movement were used for developing indices of safe driving behavior. Some scenarios presented to drivers included right turn with walk signal, an intersection with hidden sidewalk, and truck parked in front of sidewalk [34].

In another study, Fisher and Garay-Vega conducted simulator based experiments for assessing driver behavior in sight limited, multi threat scenarios. The study participants were divided into two groups, each comprising of 18 subjects. A fixed base Saturn Sedan was used as the simulator vehicle and three screens with 150° horizontal and 30° vertical vision were used in the experiment. The simulator was equipped with audio input. The study assessed the likelihood that sight limited drivers who were presented

with a multi threat scenario would skim for pedestrians in the expected zone. The likelihood of yielding at a sudden appearance of a pedestrian on provision of advance yield signage was also assessed. The experiment recorded whether or not the driver identified the target zone, crosswalk time upon locating a pedestrian, and percentage of vehicle yielding [35].

Using a driver simulator, Edquist et al. investigated the effects of on street parking and visual complexity associated with the roadside environment on speed and reaction time. A low complexity and a high complexity scenario with different curb side parking assumptions were assessed in the simulator. The participant group comprised of 29 drivers, 15 of which were male. The ages of the study subjects varied from 20 to 53 years. Upon unexpected sight of pedestrian event, variables such as time to accelerator release, time to brake, minimum distance, minimum time to collision, and number of collisions were recorded and evaluated [36].

perception of Hazard elderly drivers and experienced drivers in regards to pedestrian presence was compared using two different approaches by Bromberg et al.. They compared the response to a traffic scene video against the response in a driving The participants were divided into two simulator. groups, namely experienced (28-40 years) and elderly experienced drivers (65 and above). The first group consisted of 22 participants and the second one of 20 participants. The participants had different visual acuity profiles ranging from 6/6 to 6/12 [37].

The validity of a driving simulator, in terms of its ability to reliably measure a given aspect of driving performance, depends on a number of factors associated with physical validity (simulator "fidelity") and behavioral validity [38]. The choice of whether to use a driving simulator should be based on whether the simulator is sufficiently accurate for the specific task or behavior under investigation [39].

D. Pedestrian Simulators

Charron et al. used a pedestrian simulator to gauge the risk taking behavior in child pedestrians. In this study, 80 children with median age of 10 years took the simulator test that requested subjects to maneuver the crosswalk. The experimental design consisted of reaching two targets (mailbox, cinema) one after another within a 3 minute timeframe. The targets were connected in such a way that it will take greater time to reach the targets by crosswalk usage. Variables recorded in this study included the subjects' decision to use the crosswalk or not, to walk or run, and to observe the vehicles while crossing [40].

Several studies point to marked differences in pedestrian crossing behavior based on age, able bodied condition, or crossing in groups. For instance, Simpson et al. used a virtual reality system to investigate the differences in crossing behavior between children and young adults. The study comprised of 24 participants equally distributed in the following age groups: 5-9, 10-14, 15-19, and >19 years. Each age group had equal number of male and female participants. The youngest age group was found to make the most unsafe crossings. The system collected collisions, tight fits (potential collisions with vehicle less than 1.5 s away from pedestrian), time headway, and rejected gaps for each crossing maneuver [41].

Some studies reported use of pedestrian simulators to study behavior of subjects (especially young adults) crossing the street with potential distraction due to multimedia devices. A study by Schwebel et al. found small but meaningful impacts caused by distraction due to multimedia devices. The participant group consisted of 138 college students subjected to cross a virtual street. The participants were randomly assigned to three distinct groups with distraction: talking on phone, texting, listening, with a fourth group without any of these distractions. The variables recorded to model the distraction included elapsed time after pedestrian finished the crossing maneuver and arrival of next vehicle in the crosswalk, left/right observation, looking away, hit instances, and missed crossing opportunities [42].

E. Summary of Data Collection Options

Among the existent data collection alternatives, the nature of study and available resources govern the choice of preferred alternative. Findings from the literature review show some advantages related to simulator based data gathering techniques for modeling driver and/or pedestrian distraction. However, it should be noted that the development of experiments appropriate to realistically model pedestrian/vehicle interactions for a wide range of users and facility types is a complex and expensive proposition.

The instrumented vehicle technique renders valuable insights in driver behavior analysis and can be effectively utilized in controlled experiments to study driver yielding behavior associated with pedestrian presence. Still, instrumented vehicle studies cannot provide insights about pedestrian gap selection, which is an important element in the study of pedestrian-vehicle interactions. Field observational studies, on the other hand, allow for observation of naturally occurring pedestrian crossings as well as driver actions in a coordinated fashion. Such studies allow observation of vehicle type, pedestrian type, gap size, pedestrian-vehicle conflicts etc. as well as gathering of data for determining the percentage of driver yielding, average observed speeds, pedestrian delay, and other variables important for the development of behavioral models for drivers and pedestrians. Thus such studies hold promise in providing detailed data to support the development improved models of pedestrian-vehicle interactions. A comparison of various data collection methods reviewed in the paper is offered in Table II.

V. CONCLUSION

There is resurgence in interest in describing pedestrian-vehicle interactions at pedestrian crossing locations. In order to support such efforts, different

TABLE II. COMPARISON OF DATA COLLECTION METHODS

Option	Advantages	Challenges/ Limitations
	Observational S	
Manual	Direct observation of	Lack of control to cover
Video Post	natural pedestrian	specific range of
Processing	crossings and driver	parameters
Tiocessing	decision making	parameters
	Post Processing	Human error
	software not	ridinari erioi
	required	
	roquirou	Labor and time
		intensive post
		processing
		Hard to obtain
		microscopic variables
Automatic	Direct observation of	Lack of control to cover
Video Post	natural pedestrian	specific range of
Processing	crossings and driver	parameters
rioccooling	decision making	parametere
	Microscopic	Difficult in complex
	variables can be	situations like
	measured	occlusion, high density,
	medearea	improper illumination
	Less processing	Moderate cost
	time and labor	
	intensive	
	Low degree of error	Lack of standard
	Lett degree et effet	validation techniques
RFID	Direct observation of	Lack of control to cover
	natural pedestrian	specific range of
	crossings and driver	parameters
	decision making	parametere
	Low cost equipment	High error rate, if
	_on coor equipment	external interference
		present
	Microscopic	Lack of standard
	variables can be	validation techniques
	measured	Validation tooliniquoo
	Ease of installation	
	Instrumented ve	hicles
	Microscopic	Vehicle instrumentation
	driver/vehicle data	is needed
	Low cost	Risky behavior may not
		be studied
	Data can be fused	
	with other data	
	sources	
	Simulator	
	Can be used to	High equipment cost
	study risky conflicts	
	Can be used in	Results may vary
	distraction studies	significantly from field
		behavior
	Microscopic data	Validity depends on
	(Driver / Pedestrian)	simulator fidelity and
	,	behavior validity
	Special event	
	behavior	1
	Denavior	

data acquisition methods can be employed including in-field data collection, instrumented vehicle. pedestrian and vehicle simulators. The nature and scope of research along with any cost constraints govern the choice of data acquisition method. Moreover, various methods have been proposed to model pedestrian choices and pedestrian crossing behaviors. Although not all-inclusive, the literature synthesis provided in this paper, contributes to an improved understanding of current practices and future pedestrian-vehicle opportunities modeling for interaction at pedestrian crossing locations and

developing enhanced methods that can be used in multi-modal traffic operational analysis in the future.

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