Chapter 2

Literature Review

2.1 Preface

In general, measures of road safety can be categorized into crash-based and non-crash-based. Examples of crash-based safety measures are observed changes in the number, rate, and severity of traffic accidents resulting from the implementation of safety countermeasures. Non-crash-based safety measures are indirect ways to measure safety. Surrogate safety measures (SSM) are the most common non-crash-based safety assessment tools. SSM-based safety assessments are more desirable when crash data are (a) not available, (b) insufficient, or (c) when a quick evaluation of safety is desirable. Errors in crash reports are inversely proportional to the income levels of countries [45]. With lower income levels, the condition of crash databases in developing countries is more aggravating [46, 47]. Therefore, the need to implement a safety evaluation methodology that does not require crash data becomes even more relevant for these countries. With rapid motorization and continuously increasing crash rates, there is an even greater need to develop a quick and accurate alternative for quantifying and improving road safety in non-lane-based heterogeneous traffic conditions that prevail in developing countries.

This chapter provides a literature review on SSM-based safety assessment in heterogeneous and non-lane-based traffic conditions. Literature from developing countries is reviewed to identify challenges associated with conflict data collection, selection of suitable conflict indicators, and modeling conflict in heterogeneous traffic conditions.

2.2 Review of Existing Literature

Over time, the unavailability of quality crash data has given rise to surrogate safety measures (SSMs) which were developed to measure road safety proactively based on non-crash events. Over the last 5 decades, numerous studies have used traffic conflicts as SSMs for road safety assessment in different traffic scenarios. Most of these studies have originated from developed countries where traffic is homogeneous and lane-based. Due to strict lane discipline, vehicular interactions in homogeneous traffic are mostly one-dimensional. Many researchers have reviewed literature on SSM and investigated the suitability of existing conflict measures in different conflict scenarios and road facilities. They highlighted the inconsistency in defining conflicts and selecting thresholds, non-representativeness of sample size for conflict surveys, challenges in modeling the conflicts. They also established the need for incorporating road user behavior and aggregating multiple indicators in defining conflict. Further, a few studies have also reviewed the application of SSM in mixed traffic which includes traditional and autonomous vehicles. A summary of the recent review studies on surrogate safety measures is presented in Table 2.1.

Table 2.1 Previous review studies on SSM

Authors	Scope of review	Major findings
Sarkar et al. [48]	SSM-based safety assessment at unsignalized intersections.	• TTC and PET although the most common SSMs, do not effectively measure the conflict frequency and severity. • Limited number of studies comparing SSM between developed and developing countries. • Not many studies that validate SSMs in heterogeneous traffic conditions.
Abdel-Aty et al. [49]	Computer vision applied to traffic safety assessment using SSMs.	• Real time vehicle trajectory extraction is challenging. • Video data from UAV and advanced computer vision techniques can be utilized for real time proactive safety assessment.

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Authors	Scope of review	Major findings
Nikolaou et al. [50]	Crash-based SSM modeling	• Observation period for conflict studies is much smaller than crash data. • Smart phone data can solve the problem of small sample size. • Generalized linear model (GLM) can effectively model crash and conflicts.
Singh et al. [51]	Contrasting SSM for homogeneous with heterogeneous traffic environments	• Conflict measures are primarily selected based the roadway facility. • Lack of safety studies utilizing micro-simulation models in heterogeneous traffic.

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Authors	Scope of review	Major findings
Das et al. [52]	SSM for traffic stream with human driven and autonomous vehicles.	• There is a need for defining SSM specific to traffic stream that composed of autonomous and human driven vehicles. • Due to scarcity of real-world data on connected automated vehicles, most of SSM studies are based on simulation and have not been validated.
Bonela and Kadali [53]	SSM based safety assessment at unsignalized T-intersection.	• While TTC and PET are used frequently, they are not suitable for quantifying conflict severity and may be integrated with evasive action-based indicators for better safety assessment.

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Authors	**Scope of review**	**Major findings**
Arun et al. [25]	Towards a unifying framework for traffic conflicts and SSM	• Selection of conflict indicators and their threshold is inconsistent. • Behavioral aspect such as spatial and temporal violations should be integrated in defining conflicts. • Crash-conflict relationship needs to be validated.
Arun et al. [54]	Defining conflict measures based on intersection types, traffic operation, road user types	• Conflict studies lack validation of conflict measures, and suitable measures to quantify conflict severity. • There are limited studies on conflict measures for vulnerable road users. • Signalized intersections are investigated far more frequently than other road facilities.

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Authors	Scope of review	Major findings
Pinnow et al. [55]	Suitability of SSM for different roadway geometries.	• Suitability of conflict indicators was observed to vary based on road geometry and conflict types. • Consistency in setting the threshold can be achieved by utilizing extreme value theory (EVT) methods.
Zheng et al. [56]	Modeling traffic conflicts	• Modeling traffic conflicts necessitates accounting for multidimensionality, short observation periods, temporal and spatial correlations, as well as unobserved heterogeneity. • Validating the relationship between crashes and conflicts requires the inclusion of road user behavior and conflict severity.

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Authors	**Scope of review**	**Major findings**
Wang et al. [57]	Application of SSM in assessing safety in traffic stream with connected and automated vehicles (CAV)	• Microscopic traffic simulation has been the primary tool for conducting safety studies concerning Connected and Autonomous Vehicles (CAVs) in the absence of real-world data. • Development of SSMs, tailored for CAVs at varying levels of automation and connectivity is imperative.
Sheykhfard et al. [58]	Pedestrian safety based on active and passive approaches.	• The passive approach, relying on crash databases and questionnaires, aids in identifying crash causes and discerning road users' safety attitudes. • The active approach, employing driving simulations and videography, facilitates a deeper understanding of road users' behaviors and attitudes.

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Authors	**Scope of review**	**Major findings**
Mahmud et al. [59]	Micro-simulation and SSM for traffic safety evaluation.	• Multi-vehicle conflicts, single-vehicle conflicts and overtaking conflicts have not been investigated enough. • Simulation based SSM for heterogeneous and non-lane traffic environments must be developed and calibrated.
Johnsson et al. [60]	SSM for vulnerable road users	• An integration of multiple indicators may more accurately capture different aspects of a traffic event. • Suitable conflict indicator should be chosen considering the respective traffic and road user behavior.

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Authors	Scope of review	Major findings
Mahmud et al. [20]	Proximity based conflict indicators for SSM studies.	• There are 38 proximity indicators used in the literature. • Some proximity indicators are more suitable for evaluating particular conflict/crash type.
Zheng et al. [61]	Research on traffic conflict techniques	• There are ambiguity and inconsistency in various traffic conflict frameworks. • There is a need for standards in determining proper thresholds and conflict indicators that can capture frequency and severity both are required.

Traffic in most developing countries is characterized as non-lane-based heterogeneous traffic. The two key aspects that contrast heterogeneous traffic with homogeneous traffic are vehicular heterogeneity and non-lane-based movements that lead to multi-vehicle interactions. This traffic condition is described in Section 1.4.

In this chapter, the focus is to highlight the challenges associated with SSMs in developing countries. These include issues with conflict data collection and extraction in disordered traffic, suitability of conflict indicators utilized to define conflict, segregation of conflicts, and modeling approach used in the literature to model vehicular heterogeneity.

Specifically, this chapter answers the five research questions based on the existing literature in developing countries:

1) What are the challenges associated with conflict measurement and data extraction in developing countries?

2) Which conflict indicators are more suitable for capturing traffic conflicts in non-lane-based traffic?

3) How is vehicular heterogeneity incorporated in estimating conflicts and crash risk?

4) How were critical conflicts segregated from safe and normal traffic interactions?

5) What modeling approaches are generally used in traffic conflict studies?

2.3 Analysis of Conflicts Studies

This section which is divided into 6 subsections presents the review of existing conflict studies from non-lane-based traffic. Section 2.3.1 describes how data collection and extraction has been taken up for conflict estimation. Section 2.3.2 describes various conflict indicators utilized in non-lane-based traffic conditions. The effect of heterogeneity in the assessment of crash risk is discussed in section 2.3.3. Conflict segregation and threshold selection techniques are discussed in sections 2.3.4 and 2.3.5 respectively. Section 2.3.6 describes the modeling of conflict and crash risk using conflict indicators.

2.3.1 Data Collection for conflict studies

Data for a traffic conflict study can be obtained in a number of ways namely (1) using roadside sensors, (2) deploying in-vehicle devices such as in case of naturalistic driving studies, (3) performing traffic microsimulation, and (4) using driver simulators as shown in Fig. 2.1. This section points out the characteristics and accuracy of data, along with various challenges associated with data collection in developing countries.

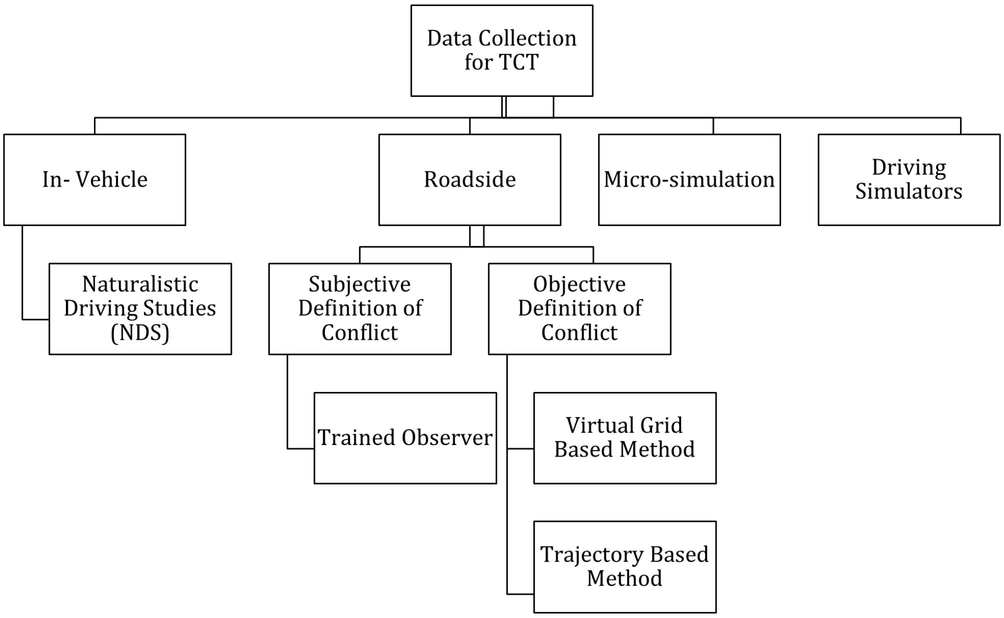

Fig. 2.1 Traffic conflict data collection

In the reviewed studies, conflict data collection was mostly based on two approaches namely (1) roadside sensing, and (2) microsimulation. Roadside sensing was further divided into three approaches. In the first approach, conflicts were identified in real-time or in recorded videos by trained observers. This approach is subjective and is usually coupled with other methods for more accurate conflict identification. In the second approach, a virtual grid-based technique was utilized to extract temporal indicators from videos recorded using a static camera or UAV. In this approach, the study area in the video image is overlaid with a rectangular image grid. Temporal indicators like post-encroachment time are computed within each grid by manual observation. The third and most common approach was defining conflict indicators using vehicle trajectory data obtained by automated or semi-automated methods. In semi-automated methods, a trained observer manually identifies and tracks the vehicles by using motion tracking software such as Traffic Analyzer [62]; Tracker [63]; Traffic Data Extractor [64]; Kinovia [65]; SAVETRAX [66]; T-analyst [67] and VeTre [68]. Since the video data are post processed in the lab at a later time, data collection and conflict estimation may also be performed for adverse weather and poor visibility conditions. However, this technique requires a high-quality camera and the task of manual extraction of conflict indicators may be tedious.

Computer vision and deep learning techniques have been frequently used for trajectory-based automated conflict estimation in homogeneous traffic [49]. Nevertheless, employing deep learning-based computer vision for traffic data collection in traffic stream with heterogeneous vehicle composition and disorderly movement has posed challenges. Most of the existing training datasets for vehicle identification such as ImageNet [35] and COCO [36] are limited to homogeneous traffic. Due to presence of multiple vehicle types and informal vehicles such as motorized three wheelers and non-motorized vehicles, vehicle classification and tracking using these algorithms will not be accurate. To counter this problem, few researchers have proposed novel approaches for automated vehicle tracking and conflict identification in heterogeneous traffic. Yao et al. [69] developed a deep learning framework for automated conflict identification in heterogeneous traffic. In a similar study, Tan and Kieu [70] developed an automated vehicle detection and tracking system for heterogeneous traffic stream. Recently few researchers have applied automated vehicle trajectory-based conflict estimation in heterogeneous traffic conditions as well [71, 72]. The summary of real-world conflict data collection methodology from developing countries is depicted in Table 2.2.

Table 2.2 Data collection and extraction of conflict indicators from field data

Method	**Extraction of conflicts from data**	**Merits**	**Demerits**	**References**
Trained observer based	Trained observers identify conflicts at site or from video data	Easy, customizable and effective in capturing conflict	Inconsistency, unrepeatability and sometimes inaccuracy in conflict reporting	[44, 73–82]
Virtual grid-based observation	Videos are overlaid with grids using video editors and temporal conflict indicators are defined by noting the time difference vehicles enter and exit a grid	Conflict indicators are objectively defined from the recorded videos	Time consuming and prone to error since manual observation is still needed	[83–95]

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Method	**Extraction of conflicts from data**	**Merits**	**Demerits**	**References**
Semi-automated trajectory approach	Vehicles are tracked manually using motion tracking software and conflict indicators are derived from the trajectories	Less prone to error while both proximity and evasive action-based conflict indicators can be defined	Tedious and prone to error due to misclicks	[43, 96–100]
Automated trajectory-based approach	Conflict indicators are derived from trajectories that are automatically extracted.	Automation enables conflict extraction for longer duration and real time safety assessment.	Limited to lane-based traffic and basic vehicle types common to homogenous traffic conditions.	[71, 72, 101–103]

Further, traffic conflict may also be simulated using a traffic microsimulation. The commercially available microsimulation software such as VISSIM, AIMSUN and PARAMICS have been mainly used in lane-based traffic [59]. In the reviewed literature, PTV VISSIM simulation software, along with SSAM (Surrogate Safety Assessment Model) developed by the FHWA (Federal Highway Administration), was utilized for microsimulation-based surrogate safety assessment [76, 87, 104–106]. Since the existing microsimulation software is unable to simulate crashes, traffic safety analysis based on microsimulation is less common. Further, limited application in developing countries may also be attributed to the cost of acquiring a license for a commercially available traffic simulator. As of now, open-source alternatives such as SUMO (Simulation of urban mobility) lack the features and capabilities to simulate non-lane-based heterogeneous traffic. Other technology-driven methods, such as the use of driving simulators and naturalistic driving studies, are limited in resource-constrained developing countries [107].

Sample size

To get a representative sample of the conflicts, appropriate duration and timings of data collection must be ensured. However, there were inconsistency in the duration of data collection for conflict measurement in the reviewed literature. Fig. 2.2 depicts the proportion different conflict extraction techniques and reported sample size of field conflict data in reviewed literature. Conflict data is generally collected for a few hours assuming it to be a representative sample of traffic interactions that lead to reported crashes. However, the traffic conditions prevailing during the survey may not fully capture the variation in traffic and weather conditions. In the reviewed literature, the effective sample size of the conflict survey was not estimated. Time of the day such as peak and off-peak hours, day and night time variation in traffic parameters may be considered for gathering a representative sample of conflict data.

2.3.2 Defining conflict in non-lane-based traffic

Conflict indicators are the metrics used to quantify near-miss situations or conflicts. Few researchers have reviewed these conflict indicators based on their origin, merit, demerits, and applicability for different conflict types, road users, and traffic facilities [20, 25, 54, 60].

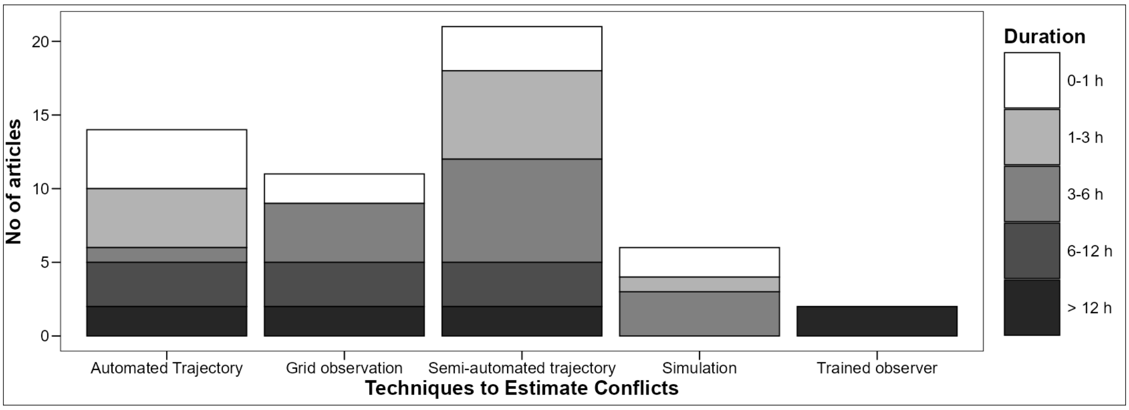

Fig. 2.2 Conflict data collection techniques and sample size

The review of conflict indicators used in selected articles is presented in this section. First, the most used conflict indicators are discussed, and then the suitability of conflict indicators based on conflict type and non-lane-based 2-D interaction are elaborated.

Single indicator to define conflicts

The most common conflict indicators (PET, TTC, MTTC, DRAC, TA) have been primarily based on temporal proximity. Since certain conflict indicators can capture a given type of conflict more appropriately, studies were reviewed based on the conflict types. In the reviewed literature, crossing and rear-end conflicts are investigated the most. PET and TTC are most common conflict indicators and are used for quantifying crossing, lane changing, and rear-end conflicts. Few studies have highlighted that few indicators are more appropriate for capturing specific conflict types. For instance, TTC is primarily defined and validated in various traffic conditions, assuming a car-following scenario where vehicles strictly maintain lane discipline. Similarly, PET is suitable for quantifying crossing conflicts [20]. These indicators are defined with the assumption that conflicting vehicles have their trajectory overlapping at least at a point. However, in non-lane-based traffic, it is apparent that vehicles move freely without maintaining any lane discipline Consequently, the assumptions of overlapping trajectories may not hold for non-lane-based traffic. Therefore, using any one of these indicators alone is inadequate to define conflict in non-lane-based traffic condition [43]. For more accurate conflict identification, few researchers have utilized trained observers to manually segregated the conflicts based on an observed evasive action and then quantified the conflicts using temporal indicators [76, 108, 109]. Table 2.3 summarizes the criteria used in the literature for selecting conflict indicators.

Table 2.3 Selection of conflict indicators

Approach	**Criteria for selection**	**Conflict indicator**	**References**
Single indicators	Type of conflict and high frequency of use in previous studies	TTC	[36, 110–112]
		PET	[85, 88, 113]
		MTTC (Modified TTC)	[114, 115]
Multiple Indicators	Incorporating multiple conflict type	PET and TTC	[106, 116]
		TTC, TA (Time-to-Accident) and DRAC (Deceleration Rate to Avoid Crash)	[117, 118]
		PET, Delta t and kinetic energy	[119]

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Approach	Criteria for selection	Conflict indicator	References
	Capturing conflicts associated with powered two wheelers	TTC, Yaw rate and Jerk	[108]
		TTC, Deceleration, Jerk and Yaw-rate	[120]
	Incorporating 2D conflicts	TTC and Centre spacing	[43]
		TTC and Lateral gap	[121]
		TTC and TDTC (Time difference to collision)	[122]
	To quantify the severity of conflicts	PET and CS (Conflicting speed)	[90, 92, 95, 123–125]
		TA and CS	[126–128]
		TTC and CS	[98]
		TTC and DRAC	[129–131]
		TTC, DRAC and CS	[132]
		Instantaneous perception time (IPT) and Headway	[133]

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Approach	**Criteria for selection**	**Conflict indicator**	**References**
Novel Indicators	Incorporating 2D conflicts	PSD (Proportion of stopping distance)	[134]
		Safety space	[86, 135]
		Extended TTC	[136, 137]
		Anticipated Collision Time (ACT)	[31]
		Instant Heeding Time (IHT)	[39]
		Modified PET	[138]
		Weight-incorporated risk level (WRL) and weight integrated risk level (WIRL)	[139]
		Receptiveness angle	[40]

Additionally, a few researchers have introduced conflict indicators based on evasive actions to define both conflict frequency and severity in non-lane traffic. These indicators are primarily based on acceleration, braking, and swerving and are used to quantify the change in speed or direction of road users. Few researchers [108, 120] compared the proximity and evasive action-based conflict indicators for the safety assessment of motorized two-wheelers in disordered traffic. Their findings indicated that evasive action-based indicators (e.g., deceleration, jerk, and yaw rate) are more effective in identifying conflicts in disordered traffic scenarios. However, application of evasive action-based indicators is less common.

Further, existing conflict measures are mostly defined using proximity between two vehicles. However, vehicular interaction in heterogeneous traffic is lane-free, leading to multiple vehicle interactions. These indicators do not quantify multiple vehicle conflicts. Fewer studies have focused on quantifying multivehicle conflicts. In such an attempt, Xu and Chen [140] utilized lateral and longitudinal acceleration to identify the evasive behavior of vehicles during single and multiple-vehicle conflicts.

Combination of multiple indicators

Depending on the conflict type, various conflict indicators capture different crash mechanisms and have their own merits and demerits [20]. Combining multiple conflict indicators is likely to capture the complex conflict events more appropriately.

Among the reviewed studies, multiple conflict indicators are mostly used in situation where more than one conflict types are investigated. For example, Paul et al. [106] utilized TTC and PET to quantify rear-end and crossing conflict, respectively. Further, researchers have combined two indicators for defining conflict in 2-dimensional vehicular interactions. Since most proximity-based conflict indicators are one-dimensional, it is more appropriate to utilize two indicators to define conflicts for 2-dimensional interactions. Das and Maurya [43] utilized TTC and center spacing to define conflicts for different leader-follower (L-F) pairs in disordered traffic conditions. The authors utilized TTC and centerline separation to capture longitudinal and lateral proximity respectively.

In the third approach of combining multiple indicators, researchers have integrated proximity indicators with vehicle speed. In heterogeneous traffic, drivers dynamically alter the headway and speed based on the vehicle's size and kinematic characteristics. Therefore, vehicle speed cannot be neglected in conflict analysis. Sometimes even with low values of PET or TTC, an interaction may not be a conflict if the speed of the vehicles is low [124, 125]. Researchers have utilized the Swedish traffic conflict technique by combining

Time-to-Accident (proximity) and conflicting speed to define conflict in heterogeneous traffic [126–128]. PET along with conflicting vehicle speed has also been used to define conflict [51, 90]. These researchers conclude that vehicle speed is important factor for quantifying the conflict severity.

Novel conflict indicators for non-lane-based traffic

Driver behavior in heterogeneous traffic is considerably dissimilar from homogenous traffic [3, 34]. The lane-free vehicular movement in heterogeneous traffic conditions leads to a 2-dimensional conflict scenario, which may lead to rear-end, side-swipe, angled, or head-on collision. In such traffic stream, using conflict indicators that have been defined primarily for one-dimensional vehicle interactions will not be appropriate. Few researchers have attempted to fill this research gap by proposing novel conflict indicators for non-lane-based traffic conditions. Nguyen et al. [34] proposed the concept of vehicle safety space which is an elliptical boundary maintained by motorized two-wheelers in a traffic stream. Chen et al. [86] extended the concept of vehicle safety space to cars. These studies were limited to car and powered two-wheelers traffic.

Further, TTC, the most common conflict indicator, is defined for one-dimensional vehicle interaction. Few researchers have attempted to modify TTC to a more general conflict indicator, suitable for lane-free traffic where vehicles trajectory does not overlap. Ward et al. [37] proposed an extended TTC to define conflict considering vehicles to be in unconstrained two-dimensional motion. In a similar attempt, Venthuruthiyil and Chunchu [31]) proposed a new conflict indicator namely Anticipated Collision Time (ACT). It is similar to TTC and is based on temporal proximity between two conflicting vehicles on a collision course. However, the author extended the definition of a strict lane-based one-dimensional collision course to a two-dimensional plane. Other researchers have also proposed novel conflict indicators in non-lane-based traffic as mentioned in Table 2.3.

2.3.3 Effect of vehicle and site-based heterogeneity

Vehicular heterogeneity refers to the difference in microscopic traffic parameters (space and time headway, lateral gap) resulting from differences in vehicle static and dynamic characteristics. This phenomenon is mostly observed in heterogeneous traffic conditions where the traffic stream comprises different types of vehicles. The effect of vehicular heterogeneity on various microscopic traffic parameters has been investigated by many researchers in the past decades [141–144]. The findings from these studies indicate the dependence of microscopic parameters on leading and following vehicles. Drivers tend to adopt longer headway when following heavy vehicles [145–147]. Further, Vehicle headway increases with an increase in heavy vehicle composition in the traffic stream [148]. While modeling minimum space and time headway in heterogeneous traffic, researchers have found similar results [2, 68, 143, 149]. Past studies highlight that microscopic traffic parameters significantly depend on vehicle type. Due to different sizes, swerving behavior, and breaking capacity, different vehicle types in heterogeneous traffic streams maintain different longitudinal gaps, speeds, and acceleration/deceleration. The findings of previous traffic modeling studies suggest that vehicle behavior heterogeneity can be included using vehicle types [146, 147].

However, most safety assessment studies [89, 119, 131, 150, 151] have not incorporated the effect of vehicle type while estimating crash risk using microscopic conflict indicators. Wong and Liao [152] examined conflict risk among different vehicle types in heterogeneous traffic conditions. They observed higher conflict and crash risk among motorized two-wheelers. In a recent study, Goyani et al. [89] investigated the effect of vehicle types on the crossing conflicts. Authors found that critical crossing conflict increases with an increase in motorized two and three-wheeler composition. In these studies, a pooled model that combines data from all vehicle types was utilized to assess crash risk. In complete pooled models, all the subgroups in the population are lumped (pooled) together, assuming that the population is homogeneous and a universal model is appropriate for all subgroups in the population. Previous studies have used a global threshold-based conflict technique for safety assessment, where a single (global) threshold was used to segregate conflicts for all vehicles. Minimum time and space headway and other microscopic conflict indicators such as TTC and post-encroachment time depend on the leader and follower (L-F) vehicle types [43, 153, 154]. Smaller vehicles (motorized two and three-wheelers) maintain smaller headway, while heavy vehicles (trucks and buses) tend to maintain bigger headway. Since the crash risk of every L-F pair is modeled with the same monolithic parameter, a pooled model fails to account for the behavior of different vehicle types and can produce misleading conclusions in heterogeneous traffic conditions [155, 156].

In another approach, to investigate the effect of vehicle type while crash risk assessment, studies have proposed to incorporate vehicle weight obtained from weight-in-motion sensors. Jo, Oh, and Kim [157] employed vehicle data from weight-in-motion sensors to study heavy vehicle rear-end crash risk. They observed that crash risk varied in different lanes on the freeway due to different vehicle types and compositions. In a similar study, Wang et al. [139] proposed a novel conflict indicator considering vehicle weight. The authors reported that the estimated crash risk, considering vehicle weight, was higher than the estimate based on traditional conflict indicators. Since crash risk varies with traffic flow level and vehicle composition, incorporating vehicle-related data will lead to more accurate crash risk assessment. To account for vehicular heterogeneity, few studies have proposed separate models for each L-F pair. In a conflict-based safety assessment study, Weng, Meng, and Yan [158] modeled four groups of leader and follower pairs separately. They found that crash risk for different groups varied, and car-truck pair had the largest crash risk in work zone traffic. In a similar study, Zhao and Lee [153] studied the rear end crash risk of car and heavy vehicles on freeways. They utilized deceleration of vehicle to avoid crashes (DRAC) as conflict metric. They reported different crash risk for different leader and follower vehicles. Hyun et al. [159] investigated the effect of vehicle type on crash risk using loop detector data. They divided vehicular interactions into three leader-follower pairs (truck-car, car-truck, and truck-truck pairs). They found that crash risk is significantly associated with the type of leader and follower vehicle, with a truck following a non-truck being at the highest risk. Although these studies divided the population into subgroups, conflict was obtained using the same threshold for all vehicles. In a recent study, Wang et al. [160] examined the effect of vehicle types on surrogate safety measures using simulated data. The authors found that vehicle headway increases with leader size, leading to a higher safety margin, time headway, and TTC. Further, they proposed to use different thresholds for conflict segregation based on vehicle type.

Also, researchers have considered multiple sites to minimize bias in data. For example, Paul et al. [94] investigated the crash risk associated with crossing conflicts in heterogeneous traffic. The authors utilized data from 14 three-legged and four-legged traffic intersections and fitted a negative binomial regression model by combining data from different sites. Goyani et al. [161] examined the effect of vehicular composition, traffic volume, and time of day on crossing conflicts by combining data from eight unsignalized intersections. Similarly, Hasain and Ahmed [116] performed safety assessment by incorporating data from three unsignalized intersections and two mid-block segments. While researchers have utilized data from multiple sites, site specific characteristics has not been incorporated into the model framework. Instead, a pooled modeling approach is adopted by most of the studies.

2.3.4 Segregating conflicts from normal traffic interactions

By definition, traffic conflicts are near-crash events that have the potential to become crashes if evasive action is not taken. In order to segregate conflicts from normal interactions, a proper threshold value of a conflict indicator must be used. Based on the reviewed literature in developing countries, three approaches namely, single, multiple and no threshold approach were used for segregating conflict in heterogeneous traffic scenarios.

Single threshold approaches

A range of threshold values have been applied across different traffic conditions and roadway facilities. For example, a TTC threshold of 1.5 s, 2 s, 3s, 4 s, and 5s was used in various studies [71, 87, 97, 132, 162]. Similarly, for PET, the threshold values from 1 to 6 s were utilized in different studies [69, 85, 88, 163]. Although literature suggests that traffic composition and vehicle types affect conflicts, most studies set a single threshold value for TTC, PET, and other conflict indicators.

Multiple threshold approaches

To address heterogeneity in traffic and study sites, multiple thresholds have been adopted based on conflict severity level, vehicle type, and different roadway geometry. For example, Jiang et al. [123] utilized two different sets of threshold values of PET for defining different levels of conflict severity in crossing and lane-changing conflicts. For lane changing conflict, the authors defined PET between 6 to 4 as low risk, 4 to 2.5 as moderate risk, and PET less than 2.5 sec as high risk. Similarly, for crossing conflicts, PET range from 6 to 1.9, 1.9 to 1, and less than 1 sec were utilized for defining low, moderate, and high severity of conflict respectively. Multiple thresholds were also adopted to account for speed variability in heterogeneous traffic [83, 91, 95, 125]. The threshold for proximity indicators such as TTC and PET was computed using speed of conflicting vehicles. Further, since minimum proximity between vehicles depends on the vehicle types, few researchers have proposed multiple thresholds based on vehicle types for more accurate safety assessment in heterogeneous traffic [164]. Another approach utilizing multiple thresholds was based on roadway geometry. Kar et al. [165] used different ACT threshold values (0.5 to 0.6 s) for 4-lane and 6-lane highways.

No threshold approaches

Some SSM-based safety assessment studies do not utilize any threshold values [113, 166]. For example, in a simulation-based study, Vedagiri and Killi [113] used summary statistics to compare the change in conflict indicators due to different countermeasures applied. In another simulation study, Yao et al. [69] developed a deep-learning model for simulating left-turning vehicle trajectories in heterogeneous traffic. They compared the distribution of actual PET derived from vehicle trajectories with PET derived using simulated left tuning trajectories. Adavikottu and Velaga [107] examined the relation between driver behavior and crash risk. They utilized a GLM to model the influence of aggressive driver behavior on TTC as dependent variable. Instead of utilizing a threshold, researchers in these studies have used the distribution of conflict indicators for relative safety assessment.

2.3.5 Methods to estimate thresholds

For segregation of conflicts from normal traffic interactions, a predefined threshold value for conflict measures is required. In this section, we summarize the common techniques that were used in the reviewed studies for identifying thresholds.

Threshold based on past studies

Setting a threshold based on literature is the most common approach found in the reviewed studies. Thresholds for most used indicators like TTC and PET are often selected based on previous literature. For example, Xia et al. [112] set a TTC threshold of 4 seconds based on Xing et al. [136]. Similarly, Wu and Lin [167] set a threshold of 3 seconds for TTC according to the recommendations reported in previous research.

Threshold based on quantiles

The second approach for selecting threshold is based on fixed quantiles. Conflicts are extreme traffic interactions that have the potential to be crash if required evasive action is not taken. Researchers have proposed to segregate traffic conflicts from normal traffic interactions based on a rule of thumb where some higher quantile is adopted as the threshold for the segregation of extremes. However, these quantiles are inconsistent across the reviewed studies. The values such as 15th, 50th and 85th quantile [115, 138], 20th and 60th quantiles [123], and 85th quantile [104, 109, 168] have been used. Other researchers have proposed to use two variances above the mean as the suitable threshold [169].

Threshold estimated using correlation method

Thresholds are also estimated using correlation analysis. In this approach, researchers have utilized crash-conflict correlation analysis for threshold selection. Several trial threshold values are used for comparisons, and the threshold resulting in the highest correlation between crash and conflict was selected. For example, Paul and Ghosh [88] proposed a rank correlation technique for estimating PET threshold values. Wang et al. [170] and Jiang et al. [171] utilized correlation between conflicts and crash rate, for setting a suitable threshold value for conflict indicators.

Threshold obtained from machine learning techniques

Few researchers have also utilized machine learning techniques such as K-mean clustering, an unsupervised machine learning technique, to classify the data into different conflict severity levels (Raju et al. 2019; Qu et al. 2020; Mohanty et al. 2021; Singh et al. 2023a). Also, supervised machine learning techniques such as support vector machine algorithms is also applied to classify conflicts (Chen et al. 2020b). Hu et al. (2022) utilized several machine learning techniques such as LightGBM algorithm, Random Forest, XGBoost, AdaBoost, Decision Tree, and K-nearest Neighbor for automated conflict detection using vehicle trajectory data. The authors proposed a LightGBM algorithm to discriminate traffic conflicts automatically. Although machine learning algorithms are capable of real-time conflict identification and safety assessment, the accuracy of these techniques depends upon the quality of training data.

Threshold estimated using extreme value theory

In SSM-based safety assessment literature, EVT has been extensively used to segregate and model extreme traffic events. EVT provides several visualization tools such as mean residual life plot, threshold stability plot, and spectral measure plot for estimation of suitable thresholds [172]. Although EVT based technique is extensively used in homogeneous traffic, its application in reviewed studies is less common [89, 165]. Kar et al. [165] utilized mean residual life plot and threshold stability plot for estimating suitable thresholds for ACT, a conflict indicator.

2.3.6 Modeling traffic conflicts

This section provides a concise overview of the diverse modeling approaches employed in the studies reviewed. Two main modeling approaches have been found across different conflict studies in developing countries: 1) the crash-conflict model, where researchers attempted to fit a relation between crash and conflict frequency, and 2) non-crash models, where conflict data alone is utilized for safety assessment at different traffic facilities. The summary of common modeling approaches is presented in Table 2.4.

Crash-conflict models

Traffic crashes are the primary measure of road safety, therefore, deriving a relation between conflicts and crashes is important. Tiwari et al. [44] utilized Spearman's rank correlation to check the validity of conflict-based safety assessment techniques in heterogeneous traffic. The author utilized 3 years of fatal crash data to correlate the observed traffic conflicts at 14 urban mid-block locations. They reported a poor correlation between observed conflict and fatal crashes. Further, Ge et al. [173] fitted linear regression models between conflict and crash count. The authors concluded that the proposed measure, WTTC showed higher coefficient of determination with crash count compared to TTC. Crash-conflict models are limited across developing countries due to the unavailability of reliable crash database.

Non-crash-based models

Due to unavailability of crash data, Purely conflict-based risk assessment models are frequently used among reviewed literature. Researchers have investigated how conflict indicators change with traffic parameters, roadway geometry, and road user characteristics [40, 75, 119, 174]. It is also common to develop safety performance functions using conflict data which models the relationship between conflict frequency and traffic parameters (headway, traffic volume, vehicle composition, speed, density), roadway geometry (road alignment, presence of minor access, segment length), vehicle type, and weather conditions. In this regard, GLM and its extensions such as Poisson regression model, fixed and random parameter Poisson models, Poisson-Tweedie regression, truncated negative binomial regression, and random-effect negative binomial regression models are most common [93, 94, 137, 152, 175].

The second most common approach is to first categorize conflicts into different severity levels and then fit a classification model with traffic parameters and roadway geometry [80, 96, 97, 115, 127, 128]. In this regard, mixed-effects logistic regression, binary logit, probit models, and ordered logit models are commonly used. In another approach, machine learning based conflict models are also applied by few researchers [151, 176]. Although, these models have capability for real time safety assessment, such studies are limited in heterogeneous traffic conditions.

The third most common modeling approach is based on EVT [172]. The EVT based model enables the prediction of unobserved extreme events (such as crashes) based on observed level of extreme events (such as traffic conflicts). Two common approaches are used to model extreme events namely, (1) Block maxima and (2) Peak-over threshold (POT) approach. Both of these approaches have been utilized for crash risk assessment in developing countries. In the BM approach, the dataset is binned into blocks of certain width, and the largest value in each block is utilized for fitting a generalized extreme value distribution. Kar et al. [177] used the BM approach for modeling vehicular conflicts at 4-lane and 6-lane divided highways and pointed out the problems associated with selecting the size of the blocks. The same block size may not contain extreme events for all vehicle types in heterogeneous traffic. Also, selecting a single observation from each block may discard other extreme observations within the same block. Researchers suggest the POT approach for modeling conflicts as it selects extreme observation more efficiently. In contrast to BM, in the POT method, observations over a pre-specified threshold are selected to fit the generalized Pareto distribution. As shown in Table 2.4, various conflict modeling approaches have been used in the reviewed literature.

Table 2.4 Summary of Conflict modeling approaches in reviewed literature

Modeling Approaches	**Model type**	**Model specification**	**References**
Crash-Conflict Models	Correlation model	Pearson or Spearman correlation	[44, 73, 114, 171]
	Generalized linear models with crash as response	Linear and multiple regression	Ge et al. (2019)
Non-crash Models	Conflict frequency model	Linear and multiple regression, Poisson regression, Negative binomial models, Poisson-Tweedie regression, Fixed and random parameter Poisson models	[59, 87, 140, 161, 178, 179]
	Conflict severity model	Logistic regression; Ordered logit and probit models; Hierarchical clustering methods; Machine learning models (K-mean clustering, support vector machine, and deep learning)	[90, 95, 115, 126, 128, 151, 162, 176]

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Table 2.4 continued from previous page

Modeling Approaches	Model type	Model specification	References
	Crash prediction model	Univariate and bivariate stationary EVT models; Non-stationary EVT models; Bayesian Hierarchical EVT models	[165, 177, 180]

2.4 Research Gaps

Surrogate safety measures (SSMs) are widely used for proactive road safety assessment that circumvent the dependence on crash data. However, despite its potential utility amid escalating road fatalities and lack of good-quality crash data in developing countries, its applications have been limited. The application of SSMs is more common in developed countries where the traffic stream has homogeneous vehicle types and follows a strict lane discipline. In contrast, traffic in many developing countries (e.g., China and India), is characterized by vehicular heterogeneity and multi-vehicle interactions resulting from non-lane-based vehicular movement. Due to resource constraints and a lack of standard methods of archiving data, it is challenging to maintain reliable and unbiased crash records in these countries. Therefore, developing safety performance measures that do not require extensive crash data is needed. Literature suggests that SSM is a useful tool for quantifying road safety in the absence of reliable crash data. This chapter reviews existing literature and outlines potential challenges associated with SSMs-based safety assessment in developing countries.

Firstly, the challenges in data collection are highlighted. Due to the lack of robust algorithms that automate vehicle tracking and conflict detection with high accuracy, the semi-automated method has been commonly used. For efficient and accurate safety assessment, an automated conflict detection method is required.

Secondly, conflict indicators defined for one-dimensional vehicular interactions are commonly utilized for non-lane-based traffic where interactions are two-dimensional. Although multiple conflict indicators are proposed by many researchers, there has been limited use of appropriate multivariate models to aggregate these indicators. Further, researchers have proposed novel conflict indicators such as extended TTC and ACT for defining conflict in two-dimensional non-lane-based vehicular interactions. Application and validation of such indicators in different traffic scenarios are required.

Thirdly, the segregation of conflict is inconsistent. The review highlights three different approaches for conflict segregation namely (1) Single threshold, (2) Multiple thresholds, and (3) No threshold approach. The multiple threshold approach is more appropriate for conflict segregation as different threshold values are applicable based on vehicle type, conflict severity, and roadway geometry.

The fourth challenge is to appropriately select a threshold. Several techniques have been adopted for the selection of suitable thresholds. These include fixed quantile method, correlation method, machine learning techniques, and EVT-based techniques. Although EVT-based methods and machine learning techniques have been used recently by many researchers, these need further validation.

The non-availability of reliable crash data in developing countries is a major limitation. The crash-conflict modeling approaches are very limited in the studies reviewed in this thesis. Although conflict-based models have been proposed for safety assessment in different traffic conditions, validating these models in the absence of reliable crash data is challenging. This aspect limits the credibility of conflict analysis in heterogeneous traffic conditions. In the absence of crash data, micro-simulation and driver simulator-based studies may be utilized for model validation.

This chapter highlights several demerits and challenges of existing surrogate safety measures applied in literature across developing countries. This literature review provides valuable insight into efficient conflict-based safety assessment for traffic streams characterized by vehicular heterogeneity and non-lane-based movements.