

# Comparison of Various Time-to-Collision Prediction and Aggregation Methods for Surrogate Safety Analysis

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## **ABSTRACT**

Surrogate safety analysis is the practice of diagnosing road safety by observation of ordinary traffic behaviour instead of rare traffic accidents. While this proactive approach was first proposed in the 60's, issues of subjectivity, transferability, and validity impeded the technique's maturity. However, it has recently gained some renewed traction with the advent of sophisticated, large-scale, microscopic data acquisition techniques solving some of the issues of objectivity, though the tasks of improving model transferability and validity remain, with the exception of speed indicators, which benefit from a large body of evidence linking them to road safety, especially collision severity. While trajectory measurement techniques have improved, the interpretation and definition of dangerous traffic events still lags. Various competing safety indicators have been proposed and tried, some more precise, objective, or context-sensitive than others.

This paper examines and reviews the definition and interpretations of time-to-collision, one of the most ubiquitous and least context-specific surrogate safety indicators, for its suitability as an indicator of dangerous traffic events. An important emphasis is put on motion prediction methodology when defining time-to-collision, as well as aggregation methods of instantaneous time-to-collision exposure. This analysis is performed using one of the largest trajectory data sets collected to date for the purpose of surrogate safety analysis.

The study recommends the aggregation of instantaneous time-to-collision indicators by 15th percentile over the use of minimum values, highlights the context-dependency of constant velocity motion prediction (particularly regarding car-following), recommends the use of motion pattern prediction using trajectory learning, and examines sensitivity to traffic event ranking by collision probability threshold.

## INTRODUCTION

Traditional methods of road safety analysis rely on direct road accident observations, data sources which are rare and expensive to collect and which also carry the social cost of placing citizens at risk of unknown danger. Surrogate safety analysis is a growing discipline in the field of road safety analysis that promises a more pro-active approach to road safety diagnosis. This methodology uses non-crash traffic events and measures thereof as predictors of collision probability and severity (1) as they are significantly more frequent, cheaper to collect, and have no social impact.

Time-to-collision (TTC) is an example of an indicator that indicates collision probability primarily: the smaller the TTC, the less likely drivers have time to perceive and react before a collision, and thus the higher the probability of a collision outcome. Relative positions and velocities between road users or between a user and obstacles can be characterised by a collision course and the corresponding TTC. Meanwhile, driving speed (absolute speed) is an example of an indicator that measures primarily collision severity. The higher the travelling speed, the more stored kinetic energy is dissipated during a collision impact (2, 3). Similarly, large speed differentials between road users or with stationary obstacles may also contribute to collision severity, though the TTC depends on relative distance as well. Driving speed is used extensively in stopping-sight distance models (4), some even suggesting that drivers modulate their emergency braking in response to travel speed (5). Others contend that there is little empirical evidence of a relationship between speed and collision probability (6).

Many surrogate safety methods have been used in the literature, especially recently with the renewal of automated data collection methods, but consistency in the definitions of traffic events and indicators, in their interpretation, and in the transferability of results is still lacking. While a wide diversity of models demonstrates that research in the field is thriving, there remains a need of comparison of the methods and even a methodology for comparison in order to make surrogate safety practical for practitioners. For example, time-to-collision measures collision course events, but the definition of a collision course lacks rigour in the literature. Also lacking is some systematic validation of the different techniques. Some early attempts have been made with the Swedish Traffic Conflict Technique (7) using trained observers, though more recent attempts across different methodologies, preferably automated and objectively-defined measures, are still needed. Ideally, this would be done with respect to crash data and crash-based safety diagnosis. The second best method is to compare the characteristics of all the methods and their results on the same data set, but public benchmark data is also very limited despite recent efforts (8).

The objectives of this paper are to review the definition and interpretation of one of the most ubiquitous and least context-sensitive surrogate safety indicators, namely time-to-collision, for surrogate safety analysis using i) consistent, recent, and, most importantly, objective definitions of surrogate safety indicators, ii) a very large data set across numerous sites, and iii) the latest developments in automated analysis. This work examines the use of various motion prediction methods, constant velocity, normal adaptation and observed motion patterns, for the TTC safety indicator (for its properties of transferability), and space and time aggregation methods for continuous surrogate safety indicators. This represents an application of surrogate safety analysis to one of the largest data sets to date.

## LITERATURE REVIEW

### Earliest Methods

The earliest attempt to implement surrogate safety analysis was manifested in the traffic conflict technique (TCT). The TCT was conceived at General Motors in the 60's (9) and was adapted soon after in many different countries, particularly England (10, 11), Sweden (12), Israel (13), and Canada in the 70's and 80's. The TCTs provide conceptual and operational definitions of traffic events and safety indicators and methods to interpret the field observations for safety diagnosis. TCTs allow to categorize traffic events by risk of collision according to a set of guidelines developed to train observers for field manual data collection. Unfortunately, these efforts have not fully matured as several problems have persisted with reproducibility, non-transferability, subjectivity of observations, and data collection cost (14, 15, 16, 17).

There has been some resurgence in the field lately (18), with efforts to modernize the technique by automating the data collection and analysis, particularly using video data and computer vision (19). A variety of indicators and analysis methods have been proposed, however the field faces the same problems of non-transferability of results without some level of reliability testing (1, 20).

### Safety Indicator Types

There is a wide variety of safety indicators presented in the literature (1). Too many, in fact, for many of these indicators are often study-specific or site-specific and as such suffer from the same problems of non-transferability and non-reproducibility as the TCTs. Instead, the following indicators are proposed for their ubiquity in the literature and generalizable properties related to all types of traffic behaviour in any traffic safety study of any type of road infrastructure:

- **Speed** requires no introduction as a behaviour measure as its effects on collision severity are already well established and well researched in the literature (2, 3). However, its usefulness as a predictor of collision probability is still questionable, with some in favour (2, 3) and others against (6), and does not offer perfect transferability as geometric factors and exposure come into play. We know that accident rates do not always scale linearly with speed (3), e.g. when comparing highways and intersections.
- **Time-to-collision (TTC)**, first proposed by (21), is an indicator describing the time remaining for two road users (or a road user and an obstacle) on a collision course to collide. It relies on a motion prediction method. TTC is measured continuously and can evolve over time if road users take evasive action and change collision course. The dimension of TTC is time and it decreases over time at a one-to-one ratio if the initial conditions of the collision course remain unchanged for lack of driver action or reaction. As such, it is generally accepted in the literature as a potential substitute for collisions resulting from driver errors and is typically proposed as a trigger for collision-avoidance systems (22). Its interpretation is that lower TTCs are more likely to be associated with a probability of collisions. In fact, a TTC of exactly 0 is a collision by definition. TTCs can manifest themselves in virtually every type of driving scenario and as such are the ideal candidates for transferability.
- **Post-encroachment time (PET)** is the time between successive arrivals at the same point in space by two road users (23, 24). Interactions with a measurable PET are very common

at intersections, but not necessarily in other environments (notably highways (25)), which could make comparisons difficult between different classes of road infrastructure. While PET is computed once for a pair of road users from observed trajectory data, predicted PET is computed continuously based on motion prediction. As they share the same dimension of time, PET has the same interpretation of safety as TTC, although possibly not the same magnitude of impact.

### **Motion-Prediction Methods**

TTC depends on robust motion prediction methods, i.e. the ability to predict possible future positions of moving objects according to a set of consistent, context-aware, and rigorous definitions of natural motion. They typically explore situations, large and small, in which road users find themselves on potential collision courses with others or obstacles, and measure the expected time of arrival at the potential collision point. In the strictest sense, the collision of two moving bodies predicted 10 or even 60 seconds into the future constitutes a collision course, however, such times are so large that i) the prediction model is probably inaccurate, and ii) road users are more than capable of correcting their course in this time.

A number of methods are employed in robotics, computer vision, and transportation applications to predict natural motion with various criteria such as accuracy, performance, effective time horizon (26), but a few stand out for their suitability for surrogate safety modelling and recent applications:

- **Constant velocity** is the most simple motion prediction model, wherein vehicles are projected along straight paths at a constant speed and heading using the velocity vector at that moment in time. This models simple Newtonian motion where no driver action is applied to the motion of the bodies in reaction to some event or navigational decision making.

This model is the simplest and most commonly used, often implicitly and without justification, but it also makes the most assumptions: only one movement is predicted at every instant (dependant on velocity vector), it does not depend on the context (road geometry or traffic), and driver actions are assumed to be the only sources of forces acting on a moving object (it does not account for friction or wheels already engaged in a rotation). These assumptions may be adequate for specific applications of the methodology, e.g. highways (25), but not all. The current implementation is based on (24).

- **Normal adaptation** uses the initial velocity vector at the prediction moment to project trajectories, but modifies the velocity vector to account for normal driver variation iteratively from that initial velocity. This model is probabilistic and benefits from a wider range of possible outcome velocity vectors, but otherwise suffers from dependency on many of the same assumptions as the constant velocity prediction method. The implementation of normal adaptation studied is based on (27).
- **Motion patterns** are a family of models which use machine learning techniques to calculate future position likelihoods from past behaviour (26, 28, 29). This type of model is the most promising, as motion prediction is probabilistic in nature and inherently models naturalistic behaviour. However, motion patterns are also more complex to implement

and expensive to process, requiring training data encompassing the space where all collision courses may occur. The type of motion pattern being studied for implementation is a simple, supervised, discretized probability motion pattern matrix (30).

The source code for the calculation of all of these indicators is (or will be) available in the open-source project “Traffic Intelligence” (31).

It should also be noted that motion prediction methods that take into account several paths that may lead road users to collide also model collision probability (motion patterns particularly and normal adaptation to a much lesser extent) and inherently make fewer assumptions. The interpretation of the indicators based on these prediction methods is thus expected to shift away from prediction accuracy and towards reaction probability and related mechanics.

### **Analysis Methods**

While indicators are relatively straightforward to generate and some are highly generic, several interpretation approaches have been proposed for safety analysis. This section highlights some of the major ones.

#### *Number of Traffic Events based on Thresholds*

The core approach of the TCT is to count the number of most severe traffic event observations defined in some capacity. Originally this was done with trained observers. Results were mixed and not without some criticism (14, 15). Hyden performed some reliability tests of observers in different cities and found positive results (7, 32), while others ran into difficulties (15). Some efforts have been undertaken, with moderate success, to link dangerous traffic events with accident rates. Some conversion factors for traffic event rates and accident rates have also been produced (7, 32, 33, 34) but little research has been done about their transferability.

The approach applies a trigger threshold on one or more objectively measured safety indicators. The literature frequently recommends a value of 1.5 seconds on temporal indicators, in particular TTC (7, 35), as a surrogate for typical reaction times, although some have suggested using values as high as 5.0 seconds for TTC and 12.0 seconds for PET (36). Some recent efforts have attempted to choose a threshold to fit a distribution model, notably the use of a shifted gamma-generalized pareto distribution as in (37).

#### *Analysis of Indicator Distributions*

Instead of categorizing traffic events as either dangerous or not dangerous according to some threshold, this approach presumes that all indicator values produce different degrees of risk throughout the safety continuum (38, 39, 40). This approach can be based on the distribution of the number of events per unit of time for each level of the indicator, or its normalized density. It looks at shifts in distributions in cross-sectional or before-after approaches: without some degree of quantification, it can only offer conclusive results in some cases. If using the number of events or the density function, it is conclusive where there is a systematically higher number of events for all indicator values (39) or where "high risk" indicators clearly outweigh "low risk" indicators (25, 30) respectively. This is a visual approach, unless some non-parametric statistical tests, such as the Kolmogorov–Smirnov test, are performed in conjunction with the latter case.

### *Time-Series Analysis*

Time-series analysis looks at road-user interactions microscopically for evolutions of indicators such as TTC, but also descriptive kinematic indicators such as distance and speed differential, over the course of the interaction. This approach has been developed in (41) and aims at finding similarities between interactions with and without a collision: the goal is to better understand collision processes and identify interactions without a collision with a strong safety predictive power.

## **METHODOLOGY**

### **The Interaction Definition**

How is an interaction defined? In the simplest definition, it is a pair of two road users existing simultaneously and closely in space. To illustrate the constraints, a time snapshot of a series of road users interacting at a roundabout merging zone (the scene) is presented in Figure 1. In this example, road user *B* is physically separated from and cannot reach or be reached by all others, except for *A* who may or may not exit the roundabout at this point in time. In addition, road user *B* does not even cross the merging zone and is therefore not analyzed at all. *A* might cross the merging zone while *C*, *D*, and *E* are or will be crossing it. However, *A*, *D*, and *E* lie outside the motion prediction time horizon, so only interactions between *A* and *C*, *C* and *D*, and *C* and *E* are considered at this time. The time horizon is calculated using the motion prediction employed.

The above example illustrates the methodology at an instant in time and describes interaction instants. These road users are in fact interacting over several time steps, termed “user pair” or simply “interaction”. Analysis of the evolution of indicators over these time steps is time-series analysis.

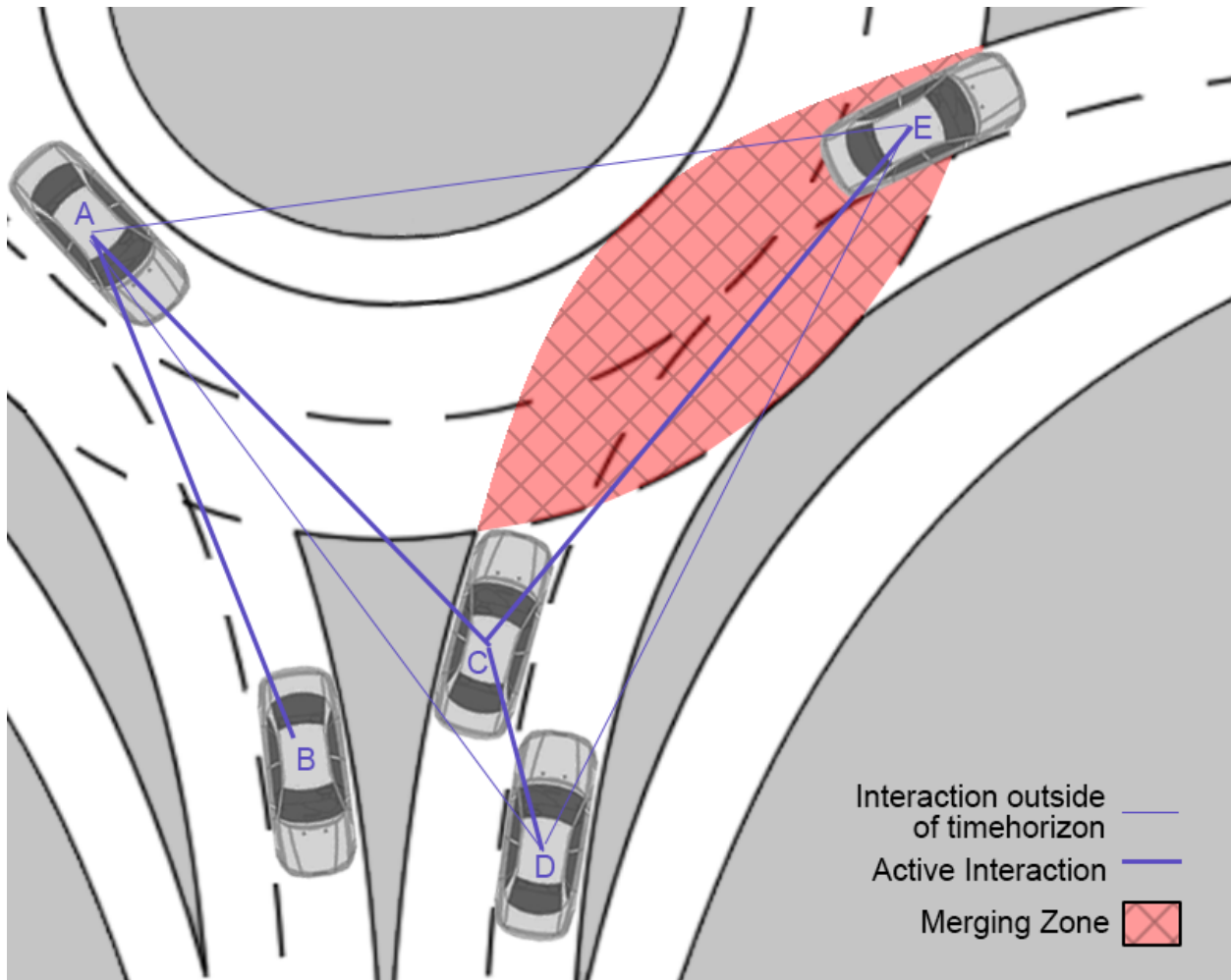
Some other points should be mentioned:

- visual obstructions or distractions could affect the outcomes of indicators, by adding noise or preventing road users from being partially or completely tracked.
- the region of analysis (i.e. camera space if obtained from video data) can have a bounding effect on indicators. Because indicators are predictions, it is important that the analysis area be completely enclosed by the camera space and that sufficient upstream distance be provided for indicators to be generated at the merging zone.
- it is possible for *C* to obstruct the movement of *D* in relation to *A*. These are special cases involving interactions with more than two road users that will have to be handled in the future, when the methodology matures with more sophisticated prediction methods.

### **Indicator Calculation**

The time-to-collision calculations for constant velocity (24) and motion patterns (30) are performed with no need for additional constants or parameters. For normal adaptation, the empirical constants used in (27) are re-used, namely triangular distributions for acceleration and steering with an acceleration range  $\alpha$  of  $\pm 2$  m/s<sup>2</sup> and a maximum steering range  $\sigma$  of  $\pm 0.2$  rad/s (these ranges are empirical (27)).

In all cases of motion prediction, predictions are performed into the future no more than a chosen time horizon. Indicators derived from motion prediction using time horizons above 10



**FIGURE 1** Spatial relationships for instantaneous interactions between five different road users (seven user pairs) at a roundabout merging zone at a given instant in time.

seconds are generally ignored in the literature for two reasons: i) they produce indicators corresponding to mostly uniform noise, and ii) are significantly larger than reaction times of all drivers and so are of little value. Also, because motion-pattern prediction is based on observed behaviour, it can only predict motion that falls within the space of observed behaviour. This adds a practical time horizon constraint.

### Indicator Aggregation

Indicators computed continuously for all interaction instants may be aggregated in various ways at the user-pair level (over all interaction instants).

- The **all indicators** method treats every single instantaneous observation as an indicator of safety. It has the advantage of generating large datasets and capturing continuous behaviour to reduce errors from noise, but suffers from sampling bias and issues interpreting conditional probability. The sampling bias stems from oversampling of objects



moving at slower speeds.

- The **minimum unique** method uses the most severe observation in the time series of indicators, usually the lowest for temporal indicators. This approach solves the problems with the previous approach, but assumes that dangerous traffic events occur only once per user pair and is prone to outlier effects from noisy data and instantaneous tracking errors. This technique is identical to the principle of  $TTC_{min}$  commonly used in the literature (21, 42).
- The **15<sup>th</sup> centile unique** method is identical to the minimum unique method but proposes using a centile of the indicator values over time instead of a minimum in order to be more robust to the effects of noise and instantaneous tracking errors.

### Indicator Thresholds

The classic TCT method is examined by comparing consistency of site risk ranking of traffic events corresponding to threshold criteria for various motion prediction and indicator aggregation methods.

The criteria examined in this paper are based on the traditional time-to-collision interpretation of the 1.5 s human reaction time (7). In addition to indicator aggregation, events can be reported by probability

$$P(U_{i,j,ind_{agg} < ind_{threshold}}) = \frac{\sum[U_{i,j,ind_{agg} < ind_{threshold}}]}{\sum[U_{i,j}]} \quad (1)$$

where  $U_{i,j}$  is a time series of interaction instants between the same two road users  $i$  and  $j$ ,  $ind_{agg}$  is the representative indicator ( $TTC_{min}$  or  $TTC_{15th}$  in this case) of the user pair's time series according to the chosen indicator aggregation method and  $ind_{threshold}$  is a chosen maximum indicator criterion, in this case  $ind_{threshold} = 1.5$  s. This may be useful for comparison with accident rates. Events may also be reported simply by hourly counts. This approach is sensitive to exposure, and may be a better predictor of expected accidents over time.

A secondary constraint for motion-pattern prediction is also put in place during modelling. Motion pattern prediction creates a probabilistic spectrum of collision events. The indicator alone isn't sufficient to describe the event. The event criteria need to be expanded to take into account the modelled collision probability criteria because motion patterns will generate many more collision points than constant velocity motion prediction, only with smaller collision probabilities. Equation 2 is adapted accordingly for motion prediction using a prediction continuum:

$$P(U_{i,j,ind_{agg} < ind_{threshold}}) = \frac{\sum[U_{i,j,ind_{agg} < ind_{threshold} \cap P(collision) > p_{threshold}}]}{\sum[U_{i,j}]} \quad (2)$$

where  $P(collision)$  is the total probability of predicted collision at the indicator's instant determined by the aggregation method and where  $p_{threshold}$  is the desired minimum probability of collision at that instant in time. For this work, we choose  $p_{threshold} = 0.001$  as a control case arbitrarily and compare its performance with  $p_{threshold} = 0.01$ . An attempt at accident-rate modelling should calibrate this parameter accordingly or remove it entirely by incorporating a calibrated collision prediction.

### Indicator Distributions

Assuming some association between TTC and collision probability, qualitative safety comparisons can be made between density functions of indicators when the direction of shift in weight (safety impact) of a density function cannot be governed by the individual weight (safety impact) of that indicator (e.g. TTC). This occurs when probability density functions intersect exactly once, or their corresponding cumulative distribution functions do not intersect at all. For example, if TTC follows a gamma distribution, this occurs when either the scale or the shape parameters are conserved.

The principle of this analysis is demonstrated in Figure 2. Two different control cases for two options are presented, each with their corresponding probability and cumulative distribution functions. In the first case, all high-risk behaviour (low TTCs) is shifted towards low-risk behaviour (high TTCs), resulting in a non-ambiguous gain in safety for one of the two options, assuming TTC is associated with safety. The gain is however not quantified. In the second control case, some high-risk behaviour (low TTCs) and low-risk behaviour (high TTCs) is shifted towards the middle. Results are therefore inconclusive without quantifying collision probability of individual TTC observations.

## EXPERIMENTAL RESULTS

### Data Source and Size

Video data was collected at 1 to 3 merging zones at 20 different roundabouts of varying land use across the province of Québec for a total of 37 different sites. Video was shot using a purpose-built mobile video data collection system designed for temporary, high-angle video data collection, with tamper-proof, weather-proof, self-contained cameras mounted at a height of 3.5 to 10.5 metres (31). Vehicle trajectories are extracted frame by frame (position and speed 15 times per second or more) using established computer vision techniques applied to traffic analysis (26, 43), available in the opensource “Traffic Intelligence” project (31).

In addition to regional variation among the 20 roundabouts, each of the 37 merging zones varied by lane configuration, geometry, traffic volumes, and flow ratios. The merging zone of the roundabout is defined as the portion of the roundabout ring intersected by an approach and the following exit, and the area proper is the area where the approach and exit lanes overlap with the ring. There is generally one merging zone between every pair of adjacent branches, unless one of these branches does not have an approach (these cases are rare and not included in the study). The flow ratio is defined as

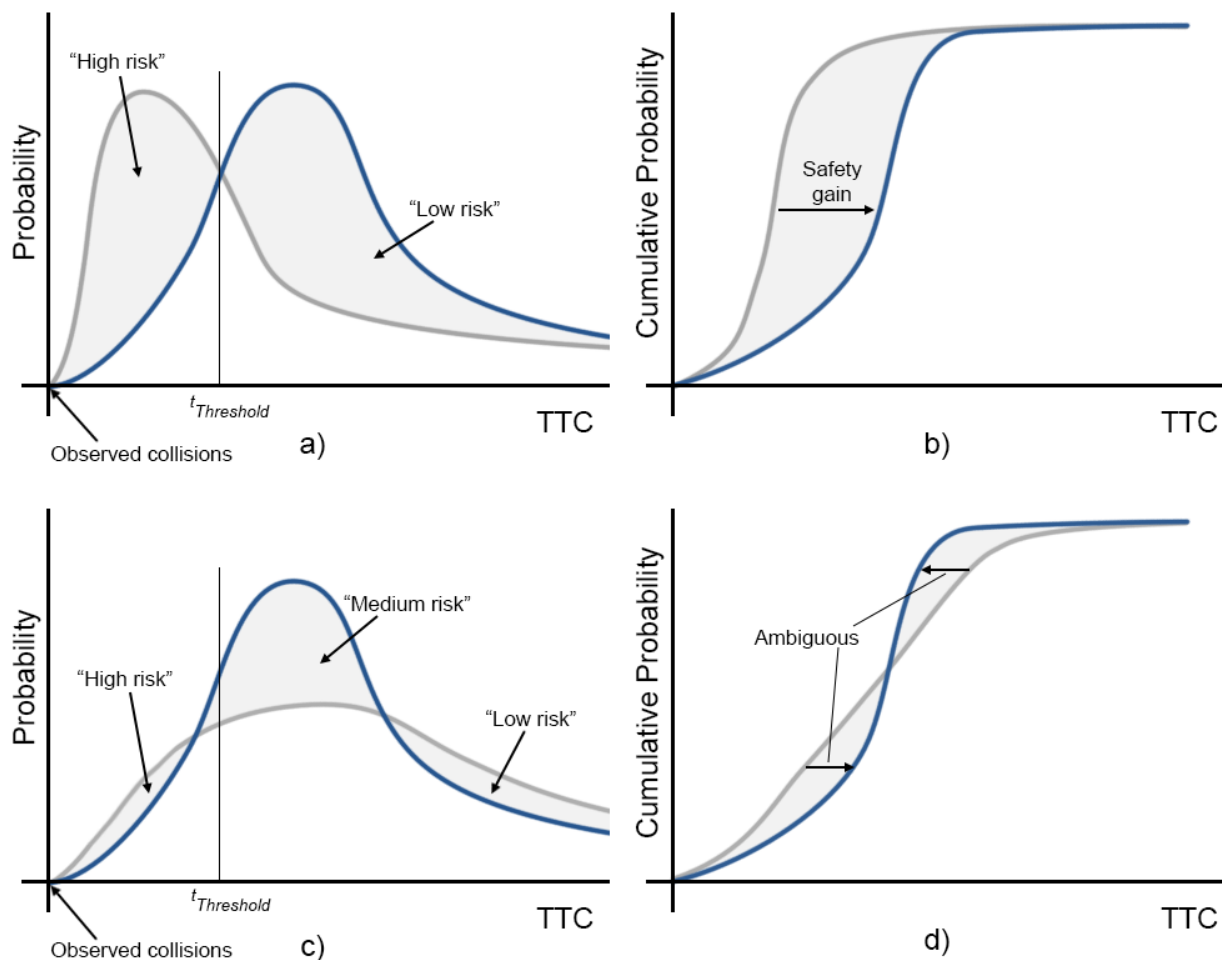
$$Flowratio = \frac{Q_{app} - Q_{in}}{Q_{app} + Q_{in}} \quad (3)$$

where  $Q_{app}$  is the total flow rate at the approach and  $Q_{in}$  is the total flow in the roundabout lanes at the beginning of the merging zone. Video data at each site was taken on a mild summer workday from 6 AM to 7 PM or 10 PM, which captures both peak traffic hours (25). In total, the dataset analyzed in this paper constitutes 359.5 hours of data comprising 79,432 vehicles driving a combined distance of 9505.97 veh-km. It follows that the amount of user pairs generated at each site are highly dependant on overall flow ratio (traffic mixing) and absolute traffic volumes (Poisson arrivals). See Table 1 for details.

TTCs are computed for all pairs of road users using constant velocity, normal adaptation, and motion pattern motion prediction methods.

**TABLE 1 Data details**

<b>Rank</b>	<b>Duration (h)</b>	<b>Flow (veh/h/ln)</b>	<b>User Pairs hour (up/h)</b>	<b>per</b>	<b>Total vehicle kilo- metres per hour</b>	<b>Flow Ratio</b>
1	9.5	372	501		20.3	-0.67
2	6.0	309	472		15.1	0.30
3	10.2	446	702		29.2	0.20
4	10.7	354	817		29.0	-0.15
5	10.6	186	216		11.6	-0.20
6	13.2	132	264		17.7	-0.02
7	10.4	89	28		5.0	0.95
8	7.9	263	578		54.3	-0.37
9	10.5	132	205		13.8	0.00
10	10.6	103	226		17.4	0.26
11	10.0	116	286		14.3	0.08
12	10.6	345	685		44.0	-0.38
13	3.0	177	5549		14.3	0.92
14	5.6	78	170		6.6	0.58
15	14.8	95	468		42.3	0.62
16	9.4	91	42		4.2	-0.83
17	9.7	131	98		8.6	0.59
18	6.5	453	1417		35.3	-0.36
19	5.0	137	1653		61.1	0.84
20	2.9	151	480		21.2	-0.55
21	6.0	534	1954		43.8	-0.25
22	8.2	263	356		14.3	-0.21
23	11.1	75	441		7.3	0.72
24	11.8	153	4971		39.7	0.82
25	10.4	193	706		18.1	0.57
26	10.8	359	2222		22.1	-0.49
27	13.9	125	743		25.1	0.71
28	14.0	246	1852		67.4	-0.22
29	9.4	138	456		20.2	-0.22
30	13.6	101	963		8.0	-0.41
31	12.8	182	358		12.1	0.60
32	10.5	225	447		15.4	0.38
33	3.8	53	24		2.0	0.65
34	10.5	68	57		4.3	0.07
35	13.0	51	10		2.3	0.76
36	10.5	51	27		3.2	-0.15
37	12.1	53	95		7.0	0.27



**FIGURE 2** Density function comparisons for two different control cases. In figures (a) and (b), probability and cumulative distribution functions respectively, for a case study between two options, one of the options demonstrates a shift to safer behaviour. In the second control case, illustrated in the probability and cumulative distribution functions of (c) and (d) respectively, the benefits of one of the options are more ambiguous without quantitative knowledge of the impact of TTC on collision probability.

### Comparison of Traffic Events by Threshold

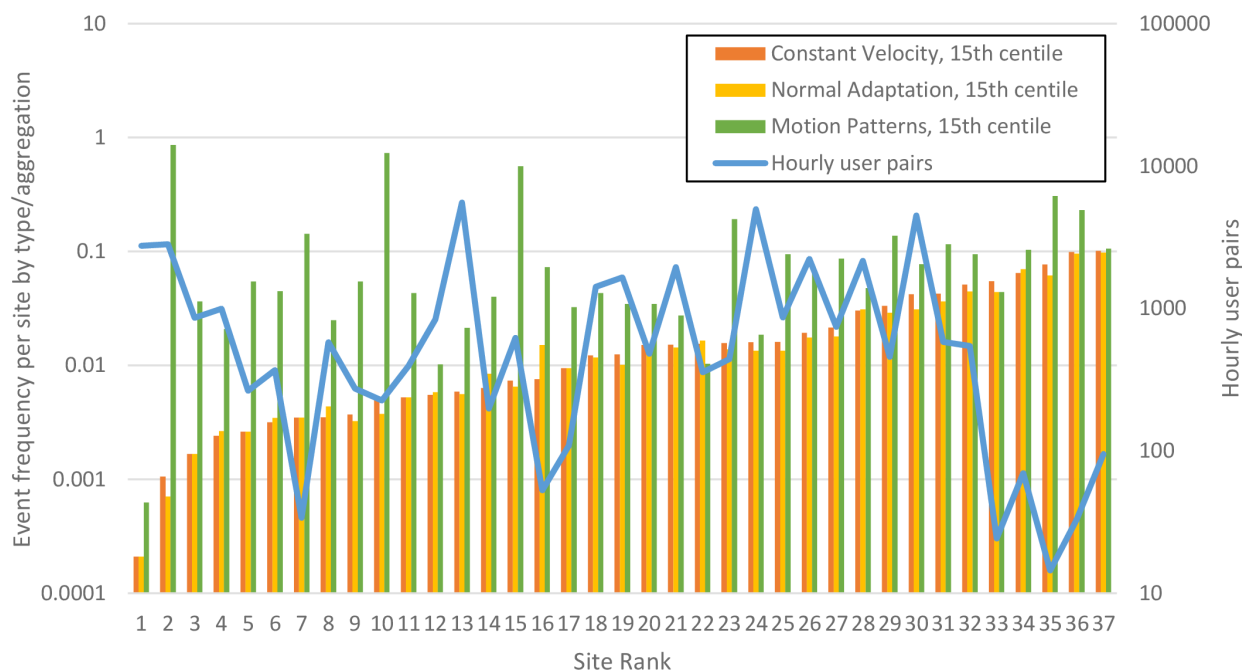
Sites are ranked for comparison using the Traffic Events Threshold analysis, as is demonstrated in the event frequencies of Figure 3. In this case,  $p_{threshold} = 0.001$  and  $t_{Threshold} = 1.5$  s, while sites are ranked according to constant velocity motion prediction, with a TTC indicator aggregated by unique 15th percentile. Sites ranked with the highest event frequencies are indicative of the most danger for drivers.

Aggregating TTC indicators by unique minimum was also attempted, but it yielded essentially similar results for all motion-prediction models. Unique minimum was consistently 10 % larger, and more sensitive to outliers, and is not shown for the sake of figure clarity. Constant velocity and normal adaptation prediction methods yield essentially similar rates and similar rank-

ings, but motion patterns do not appear to follow this ranking. In six of the cases, motion-pattern prediction yields results similar to the other motion prediction methods, but, for the remaining sites, it generates significantly more events in the 0.01-0.1 range. Sites # 2, 10, and 15 have abnormally high event frequencies (close to 1.0). The only common factor among these sites is that they are subject to large speed differentials between mixing flows, which may explain the observation. It remains to be seen if this correlates with increased real collision probability.

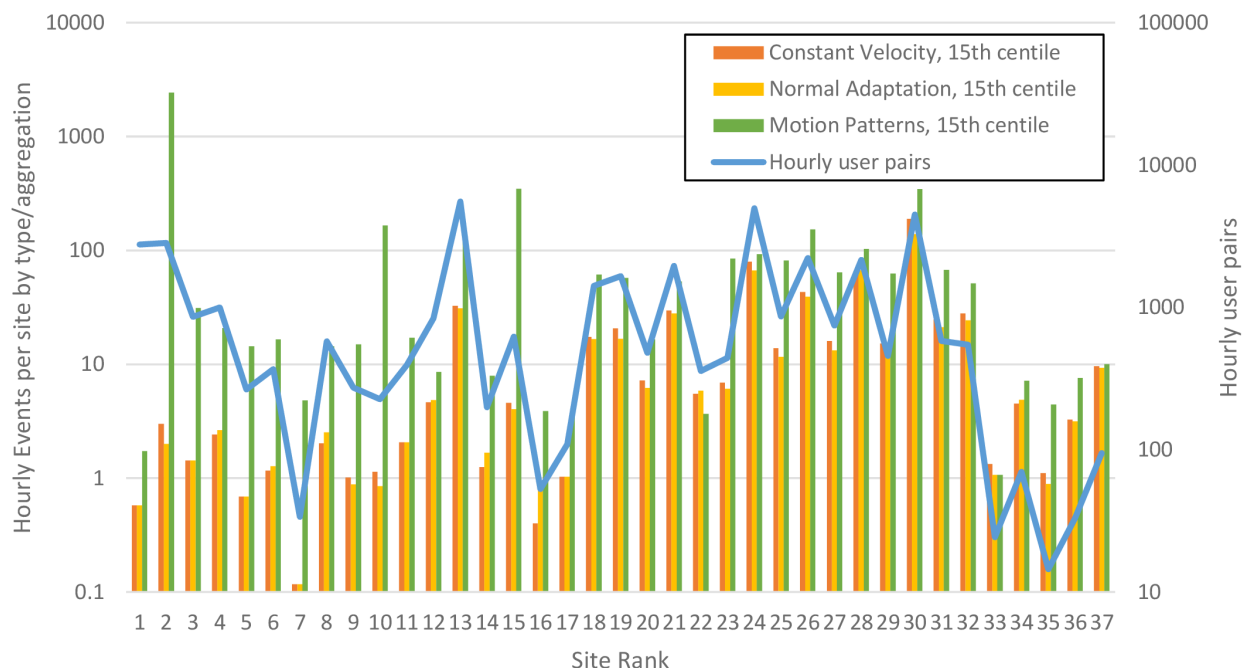
Overall, the average and median dangerous event generation rates are about 2.1 % and 1.3 %, respectively, for constant velocity, while the average and median dangerous event generation rates for motion patterns are 0.125 and 0.054, respectively. Some validation will be necessary to see if motion patterns are more sensitive to real collision potential or if the prediction method is a little too aggressive. Overall, variation in event frequencies varies by three orders of magnitude. Some of the higher constant velocity and normal adaptation rates may be under-sampled, generating less than 100 user pairs of interactions. This is common in roundabouts situated in low-density residential areas where flows are low, but approach speeds are high as users may become accustomed to not yielding.

In comparison, Figure 4 plots the hourly traffic events in relation to the hourly user pairs. Traffic events and user pairs are between one and two orders of magnitude apart (at the high end and low end respectively). Site ranking persists in this figure as the discrepancy between hourly events and user pairs.



**FIGURE 3** Log plot of traffic event frequency compared with hourly user pairs as defined by the event threshold criteria. Sites are ranked by constant velocity event frequency.

A comparison of collision probability threshold is also performed on motion patterns and demonstrated in Figure 5. Constant velocity yields a consistent, though relatively rare, colli-



**FIGURE 4** Log plot of hourly traffic events compared with hourly user pairs as defined by the event threshold criteria. The site ranking is consistent with the previous ranking.

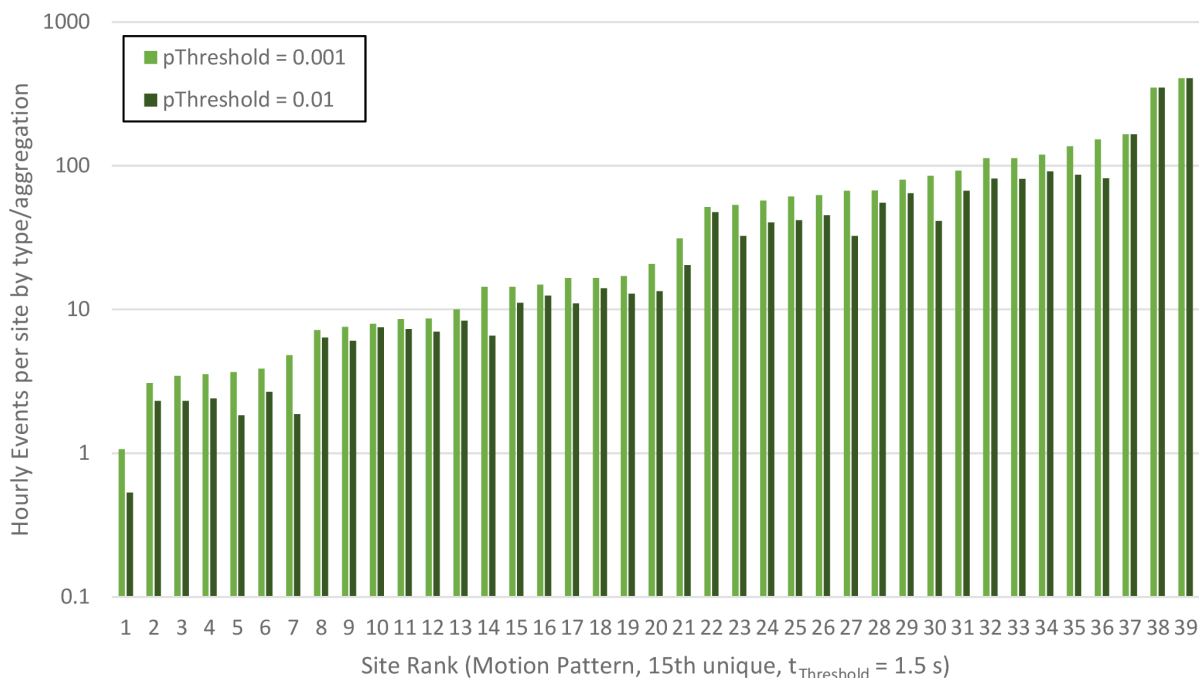
sion probability of exactly 1.0 (a single collision point), while normal adaptation yields anywhere between 1 to 100 collision points with sum of probability of collision of 1.00. They are both therefore ignored. For clarity of comparison, the sites have been reordered by motion pattern, using the unique 15th percentile indicator aggregation and thresholds  $p_{threshold} = 0.001$  and  $i_{Threshold} = 1.5$  s. In comparison, a  $p_{threshold} = 0.01$  yields important decreases in the number of hourly events reported, and, more importantly, changes site ranks.

### Comparison of Cumulative Distributions of Indicators

As depicted in Figure 6, unique minimum values have the problem of over-representation of low-TTC outliers (especially in the the 0-0.25 s TTC range) due to data noise and possibly instantaneous tracking errors. The effect seems slightly worse for motion pattern prediction, which does add a second layer of discretization to the analysis. Unique 15th percentile generally corrects this error.

Overall, normal adaptation offers little benefit over constant velocity. Meanwhile, the increase in low TTC detection can be seen for all indicator aggregation methods.

Finally, sites are clustered by geometric and built-environment similarity in Figure 7 to illustrate some minor discrepancies in interpretation, although not nearly as prominent as in the case of site ranking by event thresholds. Most prominently, following the methodology outlined in 4.5, interpretation of cluster `_cl_1` changes significantly between aggregation and prediction methods, while the interpretation of cluster `_cl_5` changes according to the prediction method. The interpretation of the other clusters are mostly unaffected.



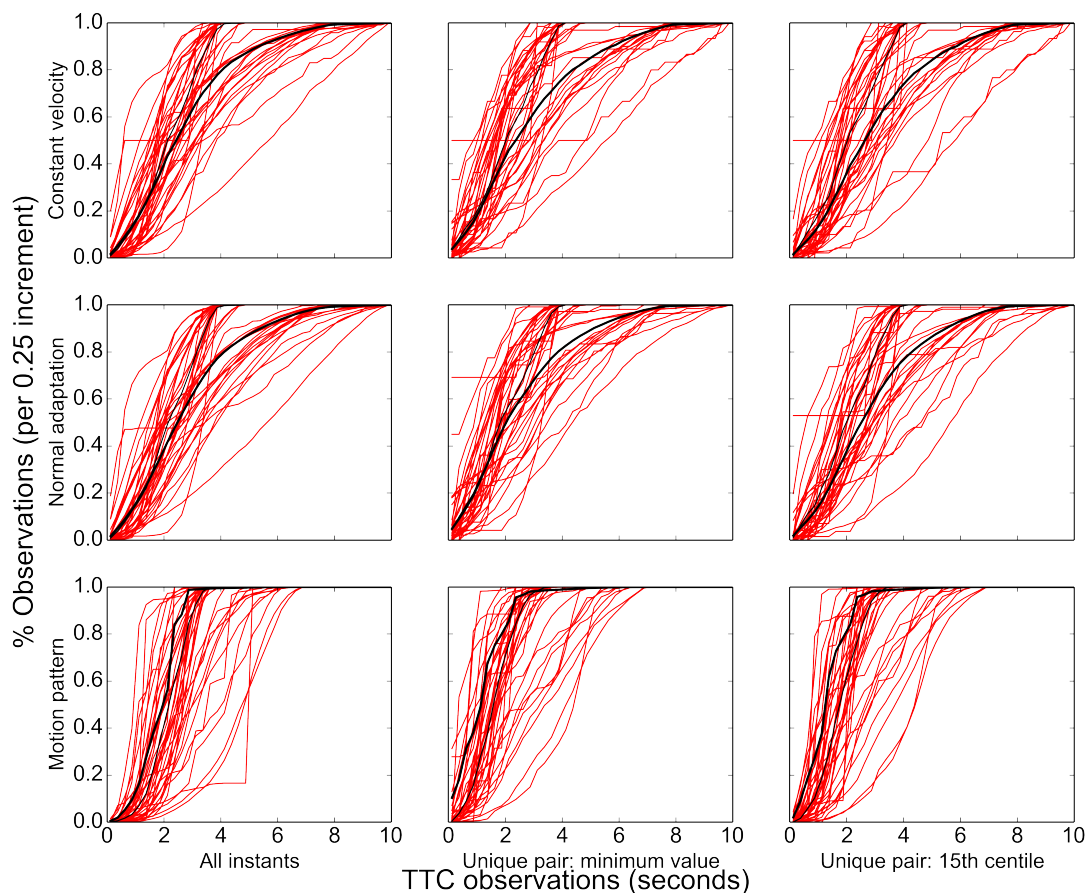
**FIGURE 5** Log plot of hourly traffic for motion patterns at each site comparing different  $p_{threshold}$ .

## CONCLUSION

Overall, this paper discusses and demonstrates the sensitivity of different surrogate safety analysis models and the importance of strong and objective definitions. While this paper did not tackle the issue of validation using accident data, nor did it compare indicators across different types of road infrastructure, it takes the first step in the direction of suggesting improvements to surrogate safety analysis by comparing and contrasting several different models and analysis techniques on one of the largest datasets to date. More importantly, the site rankings show how results are sensitive to small differences in indicator reporting and analysis methodologies, particularly spatial and temporal aggregation, and thus the importance of robust, consistent, and well documented use of indicator measurement and analysis. This is somewhat less the case for clustered analysis by geometric factors.

Normal adaptation does not seem to add significant benefits over constant velocity, at least for roundabout site diagnosis. Less context-dependent motion prediction techniques such as motion patterns are recommended overall—these should be more feasible as computing power and data collection equipment (high-quality cameras in particular) become more accessible. The intrinsic properties of motion patterns (i.e. better adapted for turning movements and fewer assumptions about driving behaviour) lend themselves better to transferability over methods based off of constant velocity, but remain to be fully validated as a predictor of collision probability.

To further transferability of safety indicators, future work must compare results across data sets of multiple types of road infrastructures, not just roundabouts: urban and rural highways, interchanges, intersections, collector roads, etc. For the immediate future however, validation is



**FIGURE 6** TTC cumulative distributions aggregation and prediction method comparisons.

the next step.

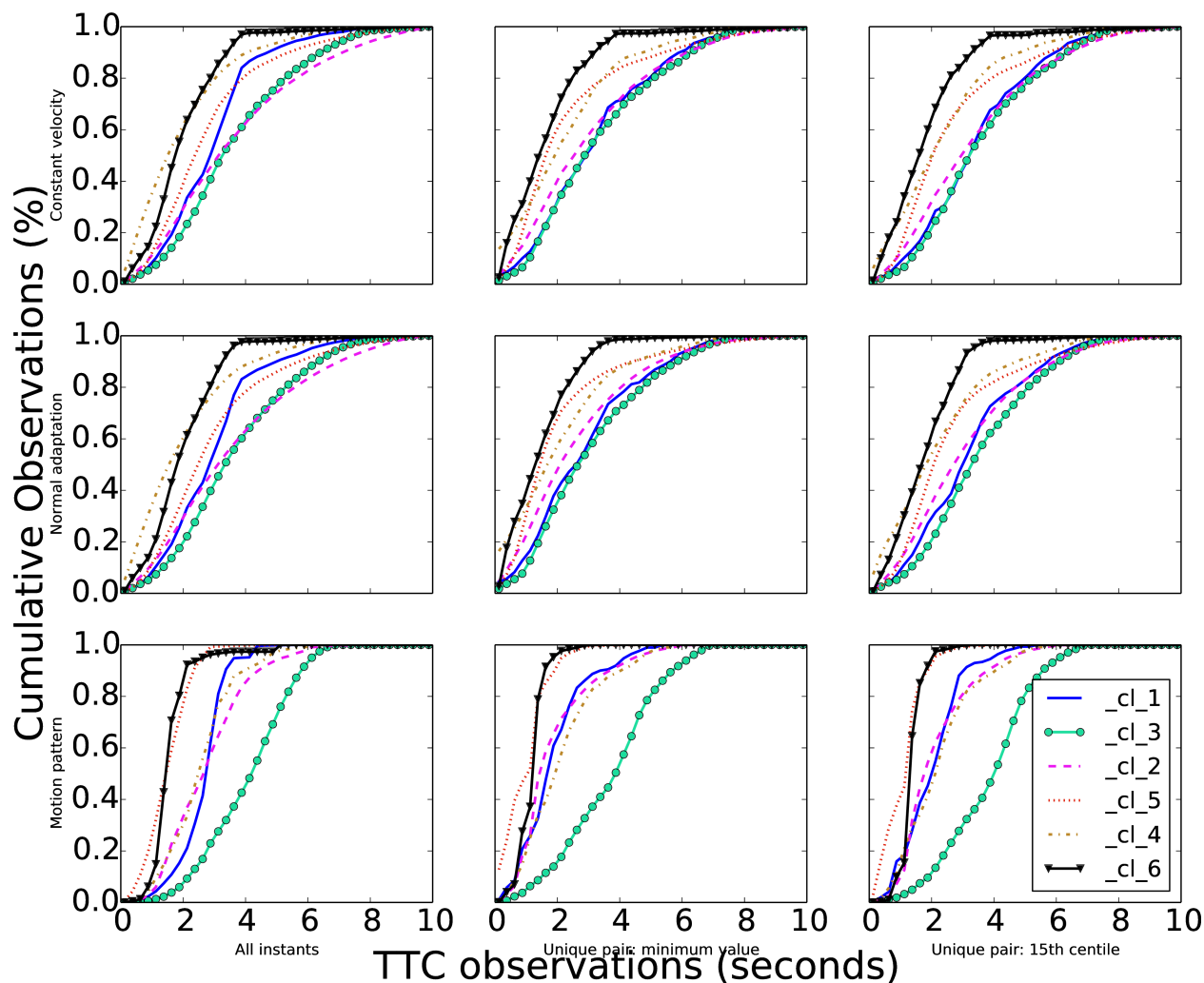
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**FIGURE 7** TTC cumulative distribution clustering comparison.

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