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Exploring the effects of critical driving situations on driver perception time (PT) using SHRP2 naturalistic driving study data

Kun-Feng Wu*, Ya-Jin Lin

Department of Transportation and Logistics Management, National Chiao Tung University, 1001 University Road, Hsinchu, 300, Taiwan, ROC

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ABSTRACT

Driver PT is critical when a driver faces an imminent crash risk and needs to determine what evasive maneuvers to execute. Therefore, it is of utmost importance to study how PT varies across different critical driving situations. PT refers to the time drivers need to recognize the nature and significance of external stimuli. Driver PT is critical when he or she faces a potentially hazardous driving situation, and must determine what action(s) or evasive maneuver(s) to execute. Although past research has identified many factors associated with PT, little research has been done on the effects of critical driving situations on PT, let alone in a real-world driving environment. Naturalistic driving study (NDS) data provides an unprecedented opportunity to look into PT prior to the occurrence of safety-related events. This study seeks to shed light on how critical driving situations influence driver PT, as well as how the driving environment and driver behavior affect PT during real-world driving by utilizing the Second Strategic Highway Research Program (SHRP2) NDS data. An NDS consists of two primary features that distinguish it from retrospective approaches: vehicles are equipped with video camera technologies that observe the driver and the road ahead of the vehicle continuously while driving, and drivers are asked to drive as they normally would. To best study PT while minimizing the effects of confounding factors, this study focused on a total of 1417 rear-end crashes and near crashes. It was found that critical driving situations, the driving environment, and driver behavior are all influential factors in explaining the variation of PT among different drivers. The longest PTs are during critical driving situations where the vehicle ahead is stop-and-go, which can be as long as 2.84 s while controlling for the effects of driving environment and driver behavior factors, compared to other types of driving situations such as a vehicle ahead decelerating or lane changing.

1. Introduction

A driver's PT is critical when a driver faces an imminent crash risk and needs to determine what evasive maneuver(s) to execute. PT has been identified as one of the factors which significantly contributes to crash occurrence. A driver's PT is an important variable when determining a driver's ability to respond to precipitating events in a safe and timely manner. Theoretically, the longer the PT, the less time for drivers to contemplate an appropriate reaction, and hence the longer the stopping distance and the higher the crash probability. As such, it is critical to better understand the role of PT in crash occurrence; in particular, how much time is needed for drivers in different critical driving situations to calculate the most appropriate response. Although extensive research has been conducted in this area in the past, it is still limited by the lack of avaliablity of real-world driving data, especially those events involving crashes or near crashes.

1.1. Brake-Reaction Time (BRT) and Driver Perception Time (PT)

McGee et al. (1983) suggested that a driver's information process involves three stages: perception (latency, eye movement, eye fixation, and perception), decision, and brake reaction, referred to as brake-reaction time. BRT is highly variable since it varies across different drivers and it is affected by various driving behaviors, driving environments, and driving situations. BRT can be as short as less than 0.5 s under optimal lab conditions, and it can be greater than 3 or even 5 s in real-world driving (e.g. McGee et al., 1983; Chapter 5 in Shinar, 2017). The variability of BRT remains under-studied as BRT depends on many factors (e.g. McGee et al., 1983; Chapter 5 in Shinar, 2017).

PT has been identified as one of the factors significantly contributing to the variability of BRT, and it consists of the time required for latency, eye movement, fixation, and recognition. PT refers to the time drivers need to recognize the significance of a given stimulus, and

* Corresponding author.
E-mail addresses: kfwu@nctu.edu.tw (K.-F. Wu), aggie801031@gmail.com (Y.-J. Lin).

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it can be further decomposed into the physiological latency of the nerve conduction of the stimulus, the redirection of the eyes to fixate on it, the fixation duration required to absorb the information, and the time it takes to recognize the meaning of the stimulus (McGee et al., 1983). The length of PT not only involves driver hazard perception and situational awareness (Endsley, 1995), but also what evasive maneuvers are possible in the time remaining (the longer the PT, the longer the BRT, and hence the less time remaining for drivers to avoid imminent collision risk). Without doubt, PT is critical to safe driving. Not surprisingly, it also helps explain why experienced drivers or drivers who undertake hazard perception training generally have a lower crash risk, as these drivers can generally identify potential hazards earlier and have shorter PT (Shinar, 2017).

Past research has identified many factors associated with PT, and they are mainly driver and driving environment factors. Green (2000) reviewed extensive research on PT and concluded that one of the most critical variables in terms of PT is "driver expectation." Other research has reported that impairment and distraction (e.g. cellphone usage) increases PT Wickens (1992) Strayer and Johnston, 2001; Consiglio et al., 2003; Horberry et al., 2006; McKnight and McKnight, 1993; Brookhuis et al., 1994; Alm and Nilsson, 1995; Lamble et al., 1999; Philip et al., 2005). Furthermore, driving environment factors associated with PT include the weather (Morris et al., 1977; Bhise et al., 1981; Ivey et al., 1984), lighting (Dewar and Olson, 2007), traffic flow (Del Castillo et al., 1994), and roadway geometry (Green, 2000).

One of the major goals of studying PT is to better understand its role in crash occurrence. As shown in Fig. 1, when a normal driving situation progresses to a critical driving situation, and drivers have to respond to the driving tasks required from the driving environment and/or other road users' maneuvers (e.g. sudden vehicle deceleration), drivers need some time to perceive the situation (PT) before reacting. The PT needed then essentially determines the options and time drivers have available in response to the critical driving situations. Critical driving situations are refered to as precipitating events (InSight, 2018) or pre-accident situations (Van Elslande et al., 2008), and have been considered one of the keys to better understand the kinds of difficulties encountered by drivers (Van Elslande et al., 2008).

1.2. PT and naturalistic driving study (NDS) data

Understanding drivers' PTs in safety-related events such as crashes and near-crashes is important as critical driving situations are related to driver situational awareness, involving drivers' comprehension and hazard perceptions (Endsley, 1995). Although driver PT is critical to safety, it involves many subtle steps that are not easily measured. For example, McGee et al. (1983) argued that perception includes latency, eye movement, eye fixation, and recognition, and Boff and Lincoln (1988) considered that perception indicates a process in which humans respond to a sensory input that involves mental processing time.

Past research on PT was conducted mainly through use of driving simulators, test track studies, and on-the-road experiments (e.g. see Chapter 5 in Shinar, 2017). However, there is still much to learn about how the interactions of driver, event attributes, and the driving environment itself impact PT in real-world driving. For example, although the effects of driver expectancy, impairment, and distraction on PT have been studied extensively, such effects have been shown to vary considerably across different driving environments, and there remains insufficient information on the precise interactions of these factors with the real-world driving environment (McGee et al., 1983; Green, 2000). Evidently, such information would be of great value in clarifying the relationship between PT and actual crash occurrence.

To better understand the effects of driving situations on PT, and the role of PT on crash occurrence, the information on the pre-crash stage is critical (Green, 2000). This type of data was rarely complete and available for traffic safety research until recently, with the growing number of NDS studies. Naturalistic driving study (NDS) data provides an unprecedented opportunity to look into PT, and in particular, PTs in safety-related events (crashes and near crashes). An NDS consists of two primary features that distinguish it from retrospective approaches (Dingus et al., 2005; SHRP2 NDS; Jovanis et al., 2011):

1 Vehicles are equipped with video camera technologies that observe the driver and the road ahead of the vehicle continuously while driving. In addition to the video, other onboard sensors continuously record vehicle accelerations in three dimensions as well as rotational motion along the same axes. Radars are often present to record proximity to other vehicles and potential obstacles on the roadway or roadside.
2 Drivers are asked to drive as they normally would (i.e., without specific experimental or operational protocols and not in a simulator or test track). The period of observation can vary from several weeks to a year or more.

Many studies have utilized NDS data for safety analysis, for example driver distraction (Stutts et al., 2005; Olson et al., 2009; Klauer et al., 2014); crash surrogate analysis (Guo et al., 2010; 2013; Guo and Fang (2013); Hallmark et al., 2011; Simons-Morton et al., 2012; Gordon et al., 2013; Wu et al., 2014); driver fatigue (Hanowski et al., 2007a, b), and recently, crash sequence (Lee, 2014; Wu and Thor, 2015). The basic NDS structure has more recently been used to study specific user populations such as younger drivers (Simons-Morton et al., 2012), vulnerable road users (e.g. Barnard et al., 2016) and motorcycles (VTTI, 2016). Victor et al. (2015) used the NDS data to analyze the relationship between glances, inattention and crash risk and especially pointed out that off-path glances of between 1 s and 3 s before a crash or time to collision will result in higher risk.

1.3. Research objectives

Although there has been a significant amount of research examining PT in the past, there is a need for analyzing PT using real-world data, the PT needed under different critical driving situations in particular. As such, the research objective is to analyze the effects of critical driving situations on a driver's PT during real-world driving. It is hoped the results of this research could provide useful information for driving education and training programs, and the development of an advanced

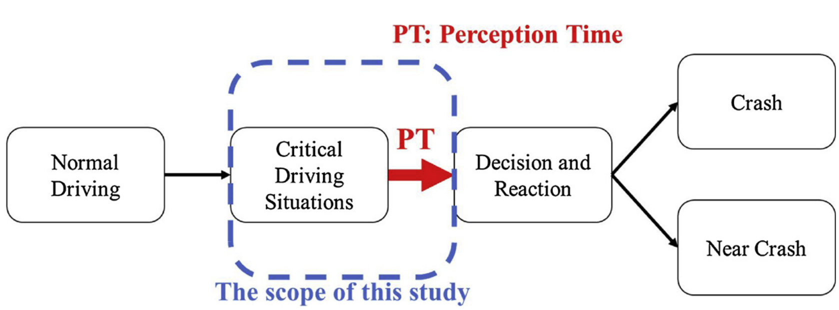


Fig. 1. The role of PT in affecting crash occurrence and the scope of this study.

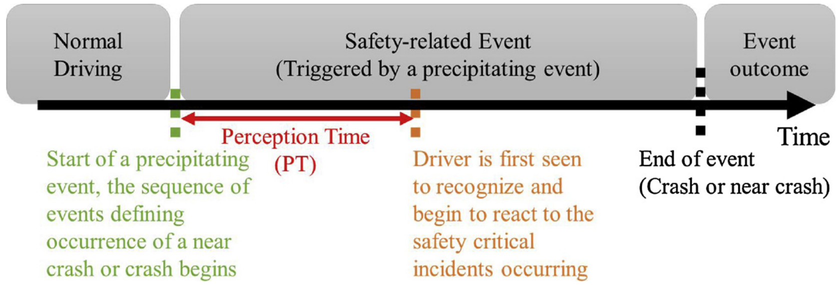


Fig. 2. The definition of PT using SHRP2 NDS.

driver assistance system.

2. The data and analysis method

This section first introduces the data collected in SHRP2 NDS data, and then discusses how PT was measured using SHRP2 data and the data included in this study. The last subsection discusses the statistical model applied for modeling the effects of critical driving situations on PT.

2.1. The SHRP2 NDS data

The data utilized in this study is the NDS dataset collected in the SHRP2 Program, which supported one of the most comprehensive NDS data collection efforts ever conducted. The SHRP2 NDS is the largest-scale NDS data collection program. The NDS data provides comprehensive information regarding how a driver interacts with other surrounding vehicles, road users, and the driving environment (Campbell, 2012);(InSight, 2018). This included the collection of multiple petabytes of data from over 3000 volunteer drivers over a three-year period. The on-board instrumentation included cameras, radar, and GPS tracking. Additionally, a complementary RID collected detailed roadway and roadside information over 12,000 centerline miles of data for the routes most traveled by the SHRP2 NDS study participants (InSight, 2018). The RID includes roadway geometric information, photo logs, as well as other supplemental datasets.

A typical NDS data set contains four major data types: time series, driver, video, and a roadway information database (RID) data (InSight, 2018). Time series data include a set of variables collected from vehicles by the on-board Data Acquisition System (DAS) at typically 10 or 20 Hz. The time series data normally contains more than one hundred variables, ranging from vehicle locations, speed, longitudinal and lateral acceleration, pedal and brake positions, lane position, range to forward radar targets measured longitudinally and laterally from the radar. The time series data can also be used to provide information about the types of trips (e.g., trip duration, day of week, time of day, maximum speed, etc.). All these data are recorded and stored within a DAS for eventual assembly into an analyzable database. A typical DAS may include data from cameras for video recording, kinematic sensors, radar, lane tracking devices, and a hard drive for data storage.

The driver data comprises drivers' physical and physiological conditions based on a series of tests and questionnaires, which might include a driver behavior questionnaire, driving history questionnaire, driving knowledge survey, visual and cognitive tests, risk perception, sensation seeking scale survey, medical conditions and medications data, physical strength tests, and sleep habits (InSight, 2018). Video data records image information both within and outside participants' vehicle through cameras, including front, driver-face, dashboard, and rear views. The roadway data can be collected from both state roadway inventory data (existing data) and mobile data using an instrumented van. The variables may include latitude and longitude, curvature length and radius, curve direction, points of curvature and tangency (PC/PT) in terms of latitude and longitude, grade and cross slope/super elevation, lane width/type, paved shoulder width/type, speed limit, presence of lighting/medians/rumble strips, types of median, intersection information, roadside information (roadside slope, presence of utility pole, tree, or guardrail), presence of traffic signal, presence of center-turning lane, and presence of access point except for driveway.

2.2. How PT was measured using SHRP2 data

Although the NDS data allows for observing a driver's reaction when a precipitating event is triggered, there is limited consensus regarding how best to define driver PT, the focus of this study. In driving simulators, test track studies, and on-the-road experiments, PT is typically measured as the time from the onset of the brake light until the initial release of the accelerator pedal. But in real-world driving, it remains challenging how best to define driver PT due to the complexity of the

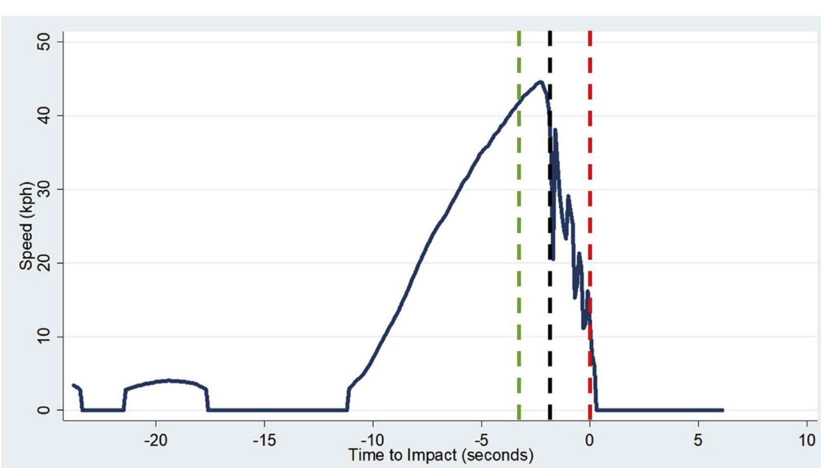


Fig. 3. An example from SHRP2 NDS: a critical driving situation (the green dashed line) occurred 3.8 s prior to a crash (the red line), where a vehicle ahead was decelerating, and the driver was first seen to recognize the imminent crash risk based on his facial expression, not shown here, 2.3 s before the crash (the black dashed line). Therefore, in this event, the PT is considered as 1.5 s. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

driving environment and drivers' reactions and responses.

As shown in Figs. 2 and 3, the PT is defined as the time duration between when a hazard materializes (the event start), and when the driver involved perceives the hazard (InSight, 2018). To measure PT in safety-related events, two anchors are used: first, the time when a critical driving situation starts; and secondly, the moment drivers can be seen to begin to react to the triggering event. The onset of an event (event start) is defined as the point when the sequence of events defining the occurrence of the incident, near-crash, or crash begins. The PT is defined as the time duration between the event start and the point when the driver is first seen to recognize and begin to react to the safety-critical incidents occurring (defined as the first change in facial expression to one of alarm or surprise or the first movement of a body part in a way that indicates awareness and/or the start of an evasive maneuver, whichever occurs first). As such, PT is defined as the time duration between when an event starts and when a driver is seen to recognize the occurrence of a precipitating event.

It should be noted that although we were interested in the entire perception and decision times initially, it was found that in some cases a driver did not brake or execute any other obvious evasive maneuvers, so in those instances decision times are difficult to observe or measure. Sometimes, drivers choose to have longer reaction times simply because they don't think the situation is dangerous enough for them to react.

Therefore, one may be legitimately concerned that the way in which PT is measured and defined in this study, based as it is on facial expressions, is likely to result in measurement error, and hence biased estimates. Since this study is focused on exploring how differing contexts and/or driving environments affect a driver's PT, as long as random measurement errors do not change the average values of a variable or the average values for subsets of individuals, the random error in the dependent variable will not bias regression estimates, and hence the results reported in this study should not be subject to potential measurement error (as discussed in the previous section).

2.3. The data included in this study

To minimize the effects of confounding factors on PT, this study only included rear-end events, as other types of events may invovle many other contributing factors which are difficult to control for. In this study, a total of 1417 rear-end safety-related events, including 92 crashes and 1325 near-crashes, are included and analyzed. Table 1 and Fig. 4 show the descriptive statistics analysis and histograms of PT in seconds. For the events included in this study, the average PT is 1.95, and Fig. 4 shows the histogram of PT in crash and near-crash events, respectively. Although the average PT for crash events are 0.6 s longer than those for near-crash events, the difference is not statistically significant. Nevertheless, one can still see that the shapes of the distributions are slightly different. After merging with driver attribute data, a total of 1058 rear-end events were included in the modeling for comparison, involving 542 drivers and 18 different types of critical driving situations.

In SHRP2 NDS data, critical driving situations are referred to as precipitating events, in which the "environmental state or action by the subject vehicle, another vehicle, person, animal, or non-fixed object that was critical to this vehicle becoming involved in the crash or near-crash" (InSight, 2018). There are a total of 76 types of precipitating events defined in SHRP2 NDS data, but as this study focused on rear-end events only, there are only 22 types of precipitating events involved. They are also referred to as triggering events, which indicate "an unexpected event that triggers or interrupts the driving situation by upsetting its balance and thus endangering the system" (Van Elslande et al., 2008).

Table 1
Driver's PT descriptive statistics.

	Number of obs.	Mean	Std. Dev.	Min	Max
Crash	92	2.51	1.57	0.025	8.5
Near crash	1,325	1.91	1.59	0.001	14.70
All	1,417	1.95	1.60	0.001	14.70

One of the research questions in this study is to explore the effects of critical driving situations on PT. For the rear-end crashes and near crashes included in this study, a total of 22 types of critical driving situations were involved. To simplify, we categorized them into five major critical driving situations: other vehicles ahead is stop-and-go, other vehicles ahead decelerating, other vehicles lane changing – from left, other vehicle lane changing – from right, and others, e.g. subject lane change. From Fig. 5, it is apparent that PTs vary across different critical driving situations. Nevertheless, it should be noted that these variations are likely due to the effects of other driving environments or driver behavior. Two real and typical examples of driving situations relating to other vehicles ahead stop-and-go, and other vehicles ahead decelerating, in terms of subject vehicle's speed changes over time can also be seen in Fig. 6. The situations relating to other vehicles ahead stop-and-go were usually observed at intersections with lower traveling speeds; whereas situations relating to other vehicles ahead decelerating were usually observed on roadway segments.

2.4. Analysis method

This subsection discusses the use of mixed-effects models employed for analyzing the effects of critical driving situations on PT. Because PT is difficult to measure accurately, the way PT is measured may be subject to possible measurement errors. In this section, we will first prove that despite this, the validity of the statistical modeling carried out in this study remains unbiased.

First, the PT is modeled as a dependent variable in a regression model, the y_i in Eq. (1)

$$y_i = \alpha + \beta X_i + \varepsilon_i \tag{1}$$

To prove possible measurement errors in PT would not affect the lack of bias of β, the effects of driving environment X_i on PT. Instead of the true y_i, we assume it is measured with some error, so that we only observe $\tilde{y}_i$, and,

$$\tilde{y}_i = y_i + v_i \tag{2}$$

Therefore, the estimated $\tilde{\beta}$ based on $\tilde{y}_i$ can be written as:

$$\tilde{\beta} = \frac{Cov(\tilde{y}_i, X_i)}{Var(X_i)} = \frac{Cov(y_i + v_i, X_i)}{Var(X_i)} = \frac{Cov(\alpha + \beta X_i + \varepsilon_i + v_i, X_i)}{Var(X_i)}$$
$$= \frac{Cov(\alpha, X_i)}{Var(X_i)} + \beta\frac{Cov(X_i, X_i)}{Var(X_i)} + \frac{Cov(\varepsilon_i, X_i)}{Var(X_i)} + \frac{Cov(v_i, X_i)}{Var(X_i)} = \beta \tag{3}$$

In addition to the assumptions for a typical regression model, as long as the covariance between v_i, the measurement errors, and X_i is zero, the coefficient of $\tilde{\beta}$ is still consistently estimated. The additional term in the error, v_i, is likely to reduce the power of statistical tests. In other words, such a measurement error in the dependent variable may result in a would-have-been significant effect found to be insignificant, even though it might be there in reality.

As multiple observations for each precipitating event are obtained, this study considers a panel data analysis regression model to take advantage of the between and within-subject variation to enhance modeling precision, and hence a mixed-effects model is employed (Wooldridge, 2015). As this study seeks to utilize the panel data structure to simultaneously examine the effects of driving situation and driver difference on driver's PT, a ME model is specified, i.e. multiple events belonged to different driving situations (for instance, a student can only belong to one class). A ME model was therefore constructed as follows (Baltagi, 2013).

$$y_{ij} = \alpha + \zeta_{1i} + \varepsilon_{ij} \tag{4}$$

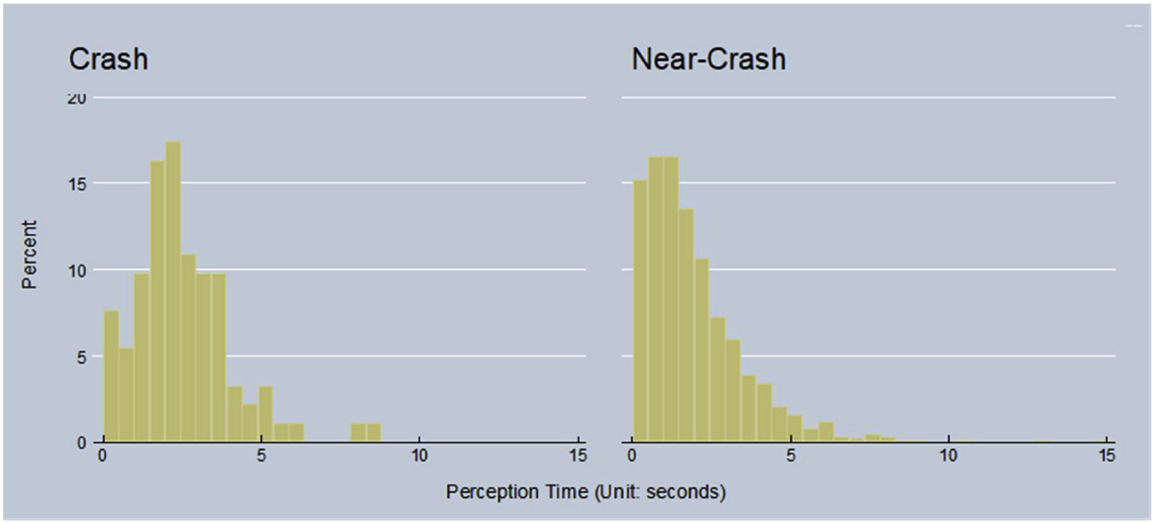
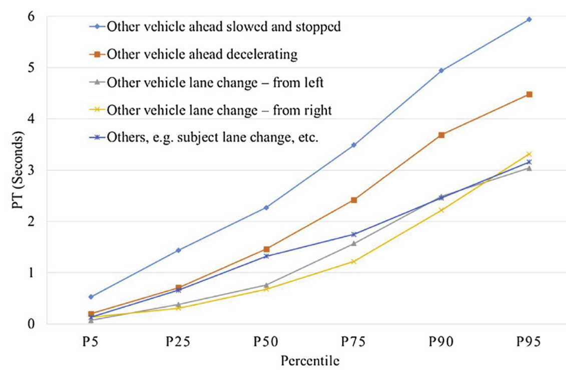


Fig. 4. Distributions of PT for crashes and near-crashes.



Critical Driving Situations	N	mean	p5	p25	p50	p75	p90	p95
Other vehicle ahead stop-and-go	424	2.66	0.53	1.44	2.27	3.49	4.94	5.94
Other vehicle ahead decelerating	797	1.78	0.20	0.71	1.46	2.42	3.69	4.48
Other vehicle lane change – from left	71	1.15	0.07	0.38	0.76	1.57	2.49	3.04
Other vehicle lane change – from right	99	1.01	0.13	0.31	0.68	1.22	2.22	3.31
Others, e.g. subject lane change, etc.	26	1.32	0.13	0.66	1.32	1.75	2.46	3.16

Fig. 5. PT vary across different critical driving situations in rear-end crashes and near crashes.
Other vehicle ahead stop-and-go:
Other vehicle ahead decelerating:

Here ζ_{1i} is random intercepts for driving situation or driver i and event j, and ε_{ij} is a residual error term. ζ_{1i} has variance ψ_1. The residual ε_{ij} has zero mean and variance θ. It follows from the assumption that the variance of PT given the covariates becomes:

$$Var(y_{ij}) = \psi_1 + \theta \tag{5}$$

As such, the corresponding infraclass correlations can be computed to compare the magnitudes of driving situation or driver effects. The higher the interclass correlation, the greater the difference of the effects of driving situation or driver on PT. The infraclass correlations for driving situations is:

$$\rho(driving\ situation) \equiv \frac{\psi_1}{\psi_1 + \theta} \tag{6}$$

To quantify the effects of critical driving situations on PT, Eq. (4) will need to be adjusted to consider driving situations as fixed effects instead of random effects, i.e. specify ζ_{2j} as $\boldsymbol{X}_{ij}\boldsymbol{\beta}$ as and nested by drivers (ζ_{1i}), as shown in Eq. (7).

$$y_{ij} = \alpha + \zeta_{1i} + \boldsymbol{X}_{ij}\boldsymbol{\beta} + \varepsilon_{ij} \tag{7}$$

Eq. (7) can be extended to incude driver-level predictors, rewritten as Eq. (8), and ζ_{1i} and $\boldsymbol{\zeta}_2$ obey a $(k+1)$ multivariate normal distribution.

$$y_{ij} = (\alpha + \zeta_{1i}) + \boldsymbol{X}_{ij}(\boldsymbol{\beta} + \boldsymbol{\zeta}_{2\boldsymbol{k}}) + \varepsilon_{it} \tag{8}$$

To better compare the effects of critical driving situations on PTs in terms of different modeling formulation (Eqs. (4) and (8)), a reference model which does not include any predictors and random intercepts are present at the critical driving situation level (Eq. (4)) will be first constructed. ME models will then be constructed to include driving environment and driver behavior, and random intercepts and slopes are present at driver level (Eq. (8)).

3. Data analyses

Three models based on Eqs. (4) and (8) were reported in Table 2. All three models yield stable and consistent results in terms of the sign and magnitude of the independent variables. The difference between Models 2 and 3 is whether or not driver age was included.

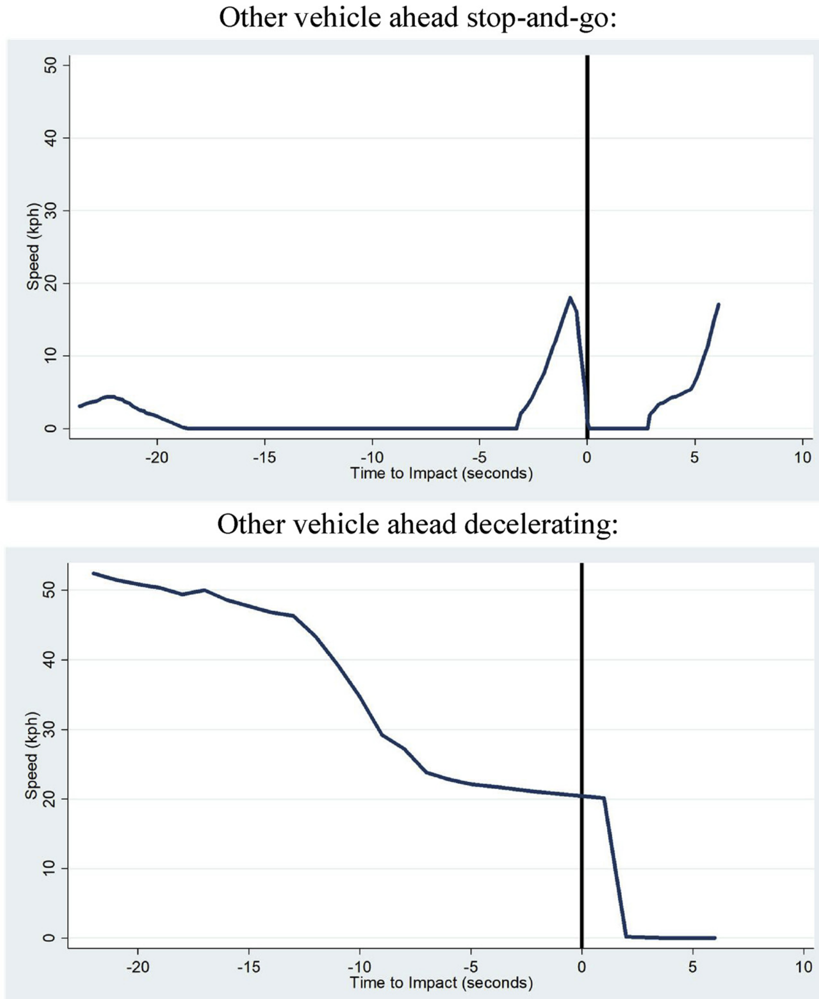


Fig. 6. Two real and typical examples of driving situations relating to other vehicles ahead stopping and going (upper) and other vehicles ahead decelerating (lower) in terms of the subject vehicle's speed changes over time.

3.1. The effects of critical driving situations on PT

As a reference, no predictors were included in Model 1. Model 1 was based on the model constructed in Eq. (4). The overall average of PT for all 1058 crashes and near crashes included in this study is 1.685 s. But it should be noted that Model 1 did not account for any factors related to driving environment or driver behavior. An intraclass correlation was reported in Model 1 for this critical driving situations nested model. The residual interclass correlation for critical driving situations, the correlation among PTs for the same driving situation, was estimated as 0.15 ($0.15 = 0.61^2/(0.61^2 + 1.5^2)$, Eq.(6)), and is statistically significant (p-value < 0.001). As a comparison, the intraclass correlation when specifying the driver as a level-two variable is 0.06 (p-value = 0.02), suggesting the correlation over events within critical driving situations is greater than that within drivers, i.e. critical driving situations result in greater variations than driver differences.

To quantify the effects of critical driving situations on PT, 18 types of critical driving situations were grouped into five groups in this study, and a driving situation where vehicles ahead are stopping and going was used as the baseline. It was found that the other four categories have significantly shorter PTs than the baseline, as shown in Table 2 and Fig. 5. In particular, a series of statistical tests was conducted, and it was found that the longest PT needed was for situations where other vehicles ahead stop-and-go, and the second longest for situations where other vehicles ahead decelerated (please also see Fig. 6 for examples of these two types of driving situations). The PT for the other three types of driving situations, where other vehicles change lanes from left and right; other vehicles change lanes from right to left; and where the subject changes lanes are significantly shorter than the other two, and the difference between these three types is not significant.

To compare the effects of different critical driving situations on PT, Model 3 shows that drivers' PT is 0.97 s shorter on average for situations where a vehicle ahead decelerates than for situations where a vehicle ahead stop-and-go (the baseline), while controlling for the effects of driving environment and driving behaviors. The PTs for other vehicles ahead changing lanes from left or right are both 1.48 and 1.6 s faster than the baseline situation, respectively. Taken as a whole, the longest PT is for critical driving situations where the vehicle ahead is stop-and-go, compared to other types of critical driving situations such as when the vehicle ahead is decelerating or changing lanes from left or right.

Accounting for the effects of the driving environment and driver behavior can help better explain the effects of critical driving situations. As shown in Fig. 5, the difference in PT between the 5th percentile and 95th percentile is calculated to be 5.4 s initially for driving situations where other vehicles ahead stop-and-go. This variation was reduced by applying a ME model which controls for the effects of between-driver difference, driving environment, and driver behavior. This difference was reduced to 0.6 s. The 0.6 s difference was obtained by calculating the difference between the 5th percentile and 95th percentile of the random parameters of driving situation where other vehicles ahead stop-and-go (ζ_{2k} in Eq. (8)). Altogether, between-driver difference,

Table 2
Driver's PT model summary.

Dependent variable: PT (in seconds)	Model 1 Eq.(4)	Model 2 Eq.(8)	Model 3 Eq.(8)
Critical Driving Situations, baseline: other vehicle ahead stop-and-go			
Other vehicle ahead decelerating	NA	−0.97	−0.97
S.E.		0.11	0.11
P-value		< 0.01	< 0.01
Other vehicle lane change – from left		−1.48	−1.48
S.E.		0.21	0.21
P-value		< 0.01	< 0.01
Other vehicle lane change – from right		−1.60	−1.60
S.E.		0.20	0.20
P-value		< 0.01	< 0.01
Others, e.g. subject lane change, etc.		−1.37	−1.38
S.E.		0.33	0.33
P-value		< 0.01	< 0.01
Sleepy (not sleepy)		0.19	0.19
S.E.		0.24	0.24
P-value		0.41	0.42
Non-daylight (Daylight)		0.33	0.32
S.E.		0.12	0.12
P-value		< 0.01	< 0.01
Rural/High speed (Urban/ Business)		−0.14	−0.14
S.E.		0.11	0.11
P-value		0.20	0.19
More pedestrians (Urban/ Business)		0.31	0.32
S.E.		0.16	0.16
P-value		0.04	0.04
Intersection (Non-junction)		−0.50	−0.50
S.E.		0.12	0.12
P-value		< 0.01	< 0.01
Others (Non-junction)		−0.14	−0.14
S.E.		0.11	0.11
P-value		0.19	0.19
Constant	1.68	2.84	2.84
S.E.	0.217	0.11	0.11
P-value	< 0.01	< 0.01	< 0.01
LL	−1930.38	−1900.62	−1900.75
Level 2 (see Eq.(4) and Eq.(8))			
sd(Driving situations), ζ_{1i} (Eq.(4))	0.61	NA	NA
sd(Residuals), ε_{ijk} (Eq.(4))	1.482	1.42	1.42
sd(Drivers), ζ_{1i} (Eq.(4))	NA	0.15	0.18
sd(Other vehicle ahead slowed and stopped), ζ_{2k} (Eq.(8))	NA	0.49	0.5
sd(age group), ζ_{2k} (Eq.(8))	NA	0.03	NA

(): words in parentheses means baseline category.

driving environment, and driver behavior were found to be influential factors in explaining the variation of PT among drivers.

3.2. The effects of driving environment and driver behavior on PT

As the inclusion of driver age was not found to significantly improve model goodness-of-fit in terms of log-likelihood, the interpretation of the results in the rest of the paper will be based primarily on Model 3 even though Models 2 and 3 are almost identical. The results of the effects of driving environment and driver behavior-related variables based on Model 3 are discussed below. The results are summarized as shown in Fig. 8.

Environment-related variables include lighting conditions and the locations of the safety-related events. Driving in a non-daylight environment increases drivers' PTs by 0.32 s while controlling for the other predictors. In other words, the average of drivers' PTs is 2.52 s when driving in a daylight environment (2.84 - 0.32 = 2.52). The PTs for events in rural/high speed areas are 0.5 s faster than in urban and business areas, but the PTs in playground and school areas are 0.32 s longer. For roadway attribute variables, the effect of the variable "relation to junction" is statistically significant as it involves driver expectation (Green, 2000). Driver PTs at intersections are 0.5 s faster than those on other road segments, i.e., the average PT of drivers is 2.34 s when approaching or driving through intersections.

It should be noted that although the driving environment factors were discussed separately above, their combined effects would be more realistic. Take the crash discussed in Fig. 3 as an example, the critical driving situation is vehicle ahead decelerating (-0.97), daylight (-0.32), and at an intersection (-0.5), and there is no apparent sign of sleepiness (0). Hence, the PT of this crash is predicted to be 1.05 s (2.84 – 0.97 – 0.32 – 0.5 + 0 = 1.05), which is observed to be 1.0 s in reality.

Driver behavior-related variables mainly include driver sleepiness, as shown in Fig. 7. This variable was coded based on reviewing driver face-view camera done by researchers at (VTTI, 2016) where "subject vehicle driver exhibits obvious signs of being asleep or tired, or is actually asleep while driving, degrading performance of the driving task. This should also be coded as drowsy, sleepy, asleep, fatigued under driver impairment." It should be noted that in this study we combined all drowsy, sleepy, asleep, fatigued under driver impairment as sleepiness due to sample size issue.

The presence of driver drowsiness increases PTs by 0.19 s while controlling for other factors. But surprisingly the effect is insignificant. This is likely due to the measurement error in dependent variables issue discussed in Section 2, which would lead to greater standard errors for independent variables. Another possibility is that the presence of driver drowsiness is defined as a binary variable (with vs. without), but the effect of different levels of driver drowsiness on PTs may vary.

4. Conclusion and discussion

This study utilized the SHRP2 NDS data to help fill this gap by

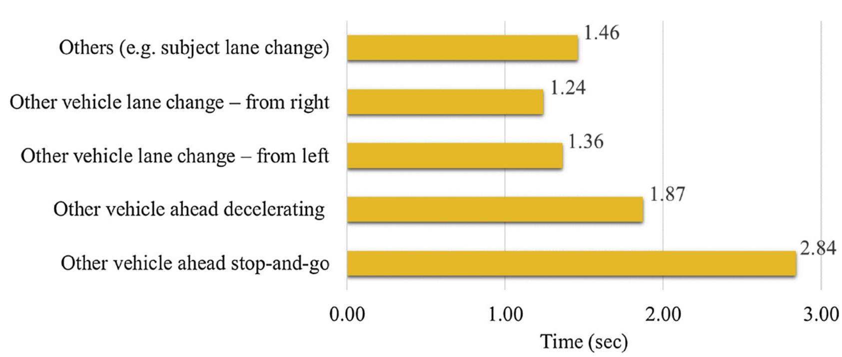


Fig. 7. The effects of different types of critical driving situations on PT in safety-related events.

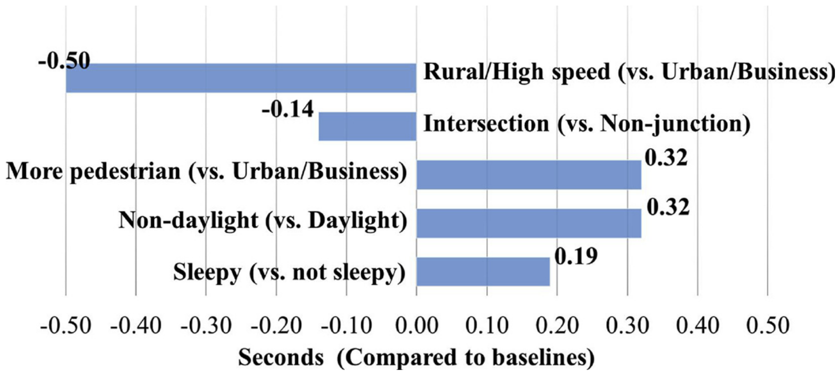


Fig. 8. The effects of driving environment and driver behavior on PT in safety-related events.

exploring the effects of critical driving situations on driver PT during real-world driving, and to quantify these effects on increasing or reducing PT. Among the major findings are:

1 Critical driving situations, driving environment, and driver behavior are influential factors in explaining the variation of PTs in safety-related events. Certain types of critical driving situations, the sleepiness of drivers, poor light or darkness, various area types, and roadway attributes were identified to significantly affect driver PT.
2 Critical driving situations have a greater effect on PT than driver heterogeneity.
3 The longest PTs are during critical driving situations where the vehicle ahead is stop-and-go, compared to other types of driving situations such as a vehicle ahead decelerating or lane changing.
4 The PT for driving situations where other vehicles change lanes from left or right, the subject changes lanes are significantly shorter than the driving situations where the vehicle ahead is stop-and-go, or decelerating.
5 Lighting conditions and locations have a measurable impact on driver PT when they encounter safety-related events.

The results reported in this study could potentially provide useful information for driving education and training programs, and the development of an advanced driver assistance system (ADAS). As an example, the PT required for drivers in situations where a vehicle ahead is stop-and-slow are longer than those in other situations. Although it may still be far from clear in what respect human factors are associated with the results, the results are consistent with crash statistics that show that these types of precipitating events are predominant in rear-end events. As such, drivers should be educated to be more vigilant and maintain a greater distance from the car in front in slow traffic situations. Along the same lines, both passive and active forward collision warning systems could take the driving environment or even event attributes into account to both reduce false alarms and increase the accuracy of alerts.

Future research is needed to address the following limitations of this study. First, different definitions of PT or ways in which PT is measured - due to the difficulty of pinpointing the exact start and endpoints - are likely to result in different results. Although measurement error in dependent variables would not result in biased estimates for predictors, the interpretations and applications of the results would still be impacted. As an example, additional research is needed to investigate the effects of drowsiness on PT, which was not found to be significant in this study potentially due to measurement error in the dependent variable which results in greater standard error for this effect. Furthermore, it should be noted that there are several studies showing that it is not possible to decide the level of a driver's sleepiness only by looking at driver face-view video. In this study, we applied a binary variable (an indication of sleepiness, or not) as a proxy variable to control for confounding effects due to driver drowsiness, sleepiness, or fatigue. Secondly, although this study also looked into the effects of the following factors on PT: time-to-collision; subject vehicle speeds; spatial headways; and their combinations or variety of transformations; only the effects of spatial headway is identified as significant in rear-end events.

Future research is recommended into the impact of other types of critical driving situations on PT and the inclusion of vehicle kinematic variables such as speed, headway, and acceleration or deceleration prior to a critical driving situation. As this study focused solely on rear-end events to minimize confounding factors that need to be controlled, future research is recommended to look into drivers' PTs in other types of events or the effects of different critical driving situations on PTs. Lastly, the NDS has proven to be advantageous for study into the coevolution of precipitating events, PT, and other crash contributing factors that lead to crash occurrence, and in future would be invaluable in informing more effective countermeasures.

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