A Human-in-the-loop Wireless Warning Message Notification Model and Its Application in Connected Vehicle Systems

Yiqi Zhang, Changxu Wu and Jingyan Wan

Abstract

Vehicle-to-Vehicle (V2V) communication has become one of the most active fields of research recently. The implementation of the wireless connected vehicles has widely extended the transmission range of warning messages to inform drivers of hazards ahead. The present study addressed the human component with mathematical modeling of the human reaction time to warning messages in the connected vehicle systems with different confidence intervals. With the modeling of human performance in responses to warning messages, warning message notification models were then proposed to optimize the settings of connected vehicle systems parameters including maximum available message notification delay, the maximum available machine processing time, the minimum acceptable message notification range and the designed message display delay. The optimal designs of connected vehicle systems parameters were presented in general and for specific conditions by applying the modeling of human performance with different confidence intervals (i.e. 95% and 99% C.I.) and the warning message notification model with human in the loop.

Keywords: connected vehicle system, human-machine interaction, driving performance

1. Introduction

Deaths and injuries resulting from road traffic accidents has become a major public health problem. According to statistic data published by the National Highway Traffic Safety Administration (NHTSA) in U.S., 5.3 million crashes occurred nationally in 2011, resulting in 29,757 lives lost and approximately one and a half million injuries (U.S. Department of Transportation, 2013). In order to improve driving safety, recent advances in Intelligent Transportation Systems (ITS) aim to establish a connected transportation environment enabling real-time information communication among vehicles and infrastructures (Dimitrakopoulos & Demestichas, 2010; Papadimitratos, de La Fortelle, Evenssen, Brignolo, & Cosenza, 2009). Compared to the traditional transportation environment, this connectivity of the ITS allows drivers to learn about the traffic status out of their sight, and provides them with more time to respond to warnings to avoid potential hazards.

Considerable research efforts have been devoted towards the design of the connected vehicle systems. With advances in technologies such as GPS receivers, internal gyroscopes, acceleration sensors, ranging sensors, systems and applications have been developed to inform drivers of traffic conditions and hazards ahead of them on the road (Ye, Adams, & Roy, 2008; Jerbi, Marlier, & Senouci, 2007; Xu, Mak, Ko, & Sengupta, 2004; Fujii, et al, 2011; Santa, Gómez-Skarmeta, & Sánchez-Artigas, 2008). Nolte et al. discussed and compared all possible technologies for wireless communication, including Bluetooth, ZigBee, Ultra Wide Band (UWB), and Wi-Fi (Nolte, Hansson, & Bello, 2005). The development of hazard detection systems along with the connected vehicle technology makes it possible to notify drivers of potential hazards with a longer time lead time in order to reduce or eliminate collision rates (White, Thompson, Turner, Dougherty, & Schmidt, 2011; Tewolde, 2012).

An example application scenario under this scheme is shown in Figure 1. The hazard is detected by nearby vehicles (Source vehicle) with sensors installed. The source vehicle will broadcast warnings about the hazards such as a collision to subject vehicles within its transmission range via dedicated short-range communication networks. The subject vehicle has to make a fully stop to avoid the hazard. The on-board automotive PC and sensors on the subject vehicle is responsible for receiving, processing and presenting warnings to drivers. The hazard detection time is dependent on the type of sensors being installed to include induction coil or video camera. The warning delivery delay can be influenced by warning composition time, warning transmission rate, and technique limitation of the network all of which depends on the network load. The warning encoding and decoding time can usually be negligible. To simplify the warning transmission process, we considered the warning transmission from one vehicle (Source vehicle) to other vehicles (Subject vehicle *i*) in the current work. But the algorithm could be extended to a more complex situation with multiple vehicles involved in the future.

Existing protocols of vehicle-to-vehicle (V2V) systems mainly focused on the probability of message reception to evaluate the effectiveness of the system (Challa & Cam, 2007; Torrent-moreno, Mittag, Member, Santi, & Hartenstein, 2009). Nevertheless the effectiveness of the V2V systems could not be achieved without drivers making proper responses in their interaction with systems even if the communication system is highly reliable in transmitting warning messages. Empirical studies have been recently performed regarding driver distractions in the interaction with ITS (Noy, 1997). It is noticed that even though driver assistance systems aim to support the driving tasks, the cognitive distraction associated with such systems may have negative effects on driving performance (Chisholm, Caird, & Lockhart, 2008; Horrey & Wickens, 2006). In the meantime, researchers studied the influence of warnings on driver behaviors and tried to propose guidelines for design of the in-vehicle human-machine interface to improve human performances (Lee & Strayer, 2004). For instance, a study about crash warning systems interfaces suggests the design guidelines regarding the prioritization of the warning messages, the presentation modalities of the warning messages, the warning timings, and the adaptation between each type of warning systems to each hazard situation (Campbell, Richard, Brown, & McCallum, 2007).

To the best of our knowledge, although associated human factors topics have received some attention in the last few years, human performance has not been adequately taken into consideration when designing V2V communication protocols (Jerbi et al., 2007; Shivaldova & Maier, 2011). Most of the research focuses on technical issues in connected vehicle systems (e.g., communication layers, transmission protocols) without considering effects of those system parameters on human performance (Ros, Ruiz, & Stojmenovic, 2009; Zang, Weiss, Stibor, Chen, & Cheng, 2007). As human drivers would still be in the loop of ITS systems at least for the foreseeable future, it is necessary to consider human performance in order to achieve the effectiveness of the connected vehicle systems.

In the present study, human performance in warning responses is modeled by extending an existing mathematical model of human performance with the complexity level of tasks. The modeling of human performance (reaction time) with different levels of uncertainty is then integrated to propose the warning message notification model in the connected vehicle system settings. The message notification model is applied to explore the optimal design of parameters in general with regard to achieve the optimal performance of the connected vehicle system with a human in the loop. Finally associated design criteria with different confidence levels are present considering specific conditions in reality with exampled inputs.

2. The Mathematic Model of Warning Messages Notification in Connected Vehicle Systems

2.1 Basic Structure

The basic structure of the models is shown in the Figure 2. The example inputs of the traffic event is the time to collision of subject vehicle calculated by the locations, speeds and accelerations of the source vehicle and subject vehicles. The inputs of machine features include the hazard detection ability of the source vehicle, and the machine processing time range of the subject vehicle. The human reaction time is modeled with queuing network-model human processor (QN-MHP), a computational model applied to model how warning is processed in the human brain. The settings of connected vehicle communication parameters are obtained from the outputs of the model, including the maximum available message notification delay, the maximum available machine processing time, the minimum acceptable message notification range, and the designed message display delay.

The optimal design of the protocol of connected vehicle is proposed based on the human-machine total response time. The time range of the human-machine total response time plays an important role in determining the available lead time range. In terms of the effect of the lead time on human performance, a triangular distribution of general in-vehicle warning message usefulness has been proposed (Lee, Bricker, & Hoffman, 2008). The distribution indicated that the usefulness of a warning message is impaired if the warning is displayed too early or too late. Early warnings with longer lead time provide drivers with sufficient time to respond appropriately, and have the potential to reduce variation in braking reaction time, resulting in a more gradual and stable responses. However, a warning provided too early without visual feedback may be treated as a false alarm or nuisance alarm, fail to assist the driver and instead generate an inappropriate braking response. By contrast, late warnings with shorter lead time have less trust issues and may not likely be ignored or forgotten. However, such warnings leave drivers only a short time to interpret the hazardous situation and respond appropriately. Late warnings may even disrupt an ongoing braking process and lead to a higher probability of collisions. Accordingly, a designed connected vehicle system should be able to present warnings to drivers within an optimal range to achieve the best human performance.

2.2 Modeling of Human Reaction Time to Warnings

2.2.1 Overview of Queuing Network-Model Human Processor (QN-MHP). *QN-MHP* was developed by combining the mathematical theories in queuing networks (QN) with the Model Human Processor (MHP) to represent human information processing based on neuroscience and psychological findings and predict human performance in multiple tasks (Liu, Feyen, & Tsimhoni, 2006; Wu & Liu, 2008). It is a computational architecture that integrates three discrete serial stages of human information processing including perceptual, cognitive, and motor processing into three continuous subnetworks of servers (see Figure 3). Each subnetwork is constructed of multiple servers and links among these servers. Each individual server is an abstraction of a brain area with corresponding functions, and each link between two servers represent neural pathways among these functional brain areas. The processing of stimuli is represented in the transformation of entities passing through routes in QN-MHP. As for the processing of auditory warnings, Servers 5-8 perform auditory perception. Servers A-C and F perform working memory and decision-making. Finally, Server X performs feedback information collection; Server Y performs motor program assembling and error detecting; and

Server Z is for sending information to body parts (e.g., eye, hand, foot), which are modeled by servers 21-25. Since this architecture was established, QN-MHP has been applied to quantify various aspects of human cognition and performance, for instance, driver workload (Wu, Liu, & Quinn-Walsh, 2008), speed control in car following and free flow driving (Bi & Liu, 2009; Zhao & Wu, 2013), lateral control and lane change (Bi et al., 2012; Bi et al., 2013), and driver distraction (Bi et al., 2014; Bi et al., 2012; Fuller et al., 2012; Liu et al., 2006).

In the present work, the QN-MHP was used to model human reaction time in warnings responses with ongoing driving tasks. Figure 3 presented how auditory warnings are processed and responded by humans. The auditory stimuli was entered into the auditory perceptual subnetwork with entries on all four servers. The stimuli firstly arrived at Server 5 (common auditory processing) representing the middle and the inner ear. The parallel auditory pathways transmitted the auditory information through the neuron pathway from the dorsal and ventral cochlear nuclei to the inferior colliculus presented by Server 6 (auditory recognition), and from the ventral cochlear nucleus to the superior olivary complex represented by Server 7 (auditory location). Then the auditory information would be integrated at Server 8 representing the primary auditory cortex and the planum temporale (auditory recognition and location integration). The entities with phonological information were then transmitted to the left-hemisphere posterior parietal cortex presented by Server B (phonological loop). A route choice was located at Server B including a shorter route connecting to Server W directly to retrieve motor programs; and a longer route connecting to Server C (central executive) and Server F (complex cognitive function) involving a decision making process, and eventually leading to Server W. The shorter route represented a processing in emergent situations and the longer route involved detailed information processing with a stage of hazard evaluation. Those motor programs were then assembled at Server Y and initialized at Server Z (primary motor cortex), sending out the neural signals to body parts (Servers 21-25).

2.2.2 Modeling of Human Reaction Time to Warnings in Connected Vehicle Systems. Reaction time is modeled by extending an existing human response to warning model with the complexity level of tasks (Zhang and Wu, Eq.3, 2014). The reaction time of warning response can be modeled by summarizing processing time of all servers on the route where a stimulus is transformed into a response. The task complexity is modeled with number of words in a warning message (*N*). Therefore, n processing cycle is added to the processing time at Server 8. The reaction times to an auditory warning (RT) are modeled in the following equation, respectively.

$$RT = (T_5 + T_6 + T_{8(N)} + T_B + T_W + T_Y + T_Z) \cdot p_I + (T_5 + T_6 + T_{8(N)} + T_B + T_C + T_F + T_C + T_W + T_Y + T_Z) \cdot p_{II} \quad (1)$$

where T_k denotes the processing time of stimulus at Server *k*. p_I and p_{II} is probability of choosing route I (the shorter route) and route II (the longer route), respectively. *N* is number of words in the warning message (e.g. signal words, direction, location, and hazard event). The detailed derivation of equations and parameter settings are included in Zhang and Wu's work (Zhang and Wu, 2014).

The confidence interval of warning reaction time of the driver on *i*th subject vehicle to *j*th warning message is then calculated with confidence level α in equation (2)

$$RT - t_{\alpha/2}\frac{s}{\sqrt{n}} < t_{reaction}(i,j) < RT + t_{\alpha/2}\frac{s}{\sqrt{n}} \quad (2)$$

where *RT* is reaction time to an auditory warning. $t_{\alpha/2}$ is the t score with confidence level α. *s* is standard deviation of reaction time. *n* is the sample size.

2.3 Definition and Mathematical Models of Warning Message Notification

The timeline of the proposed model for human-in-the-loop connected vehicle system regarding the vehicle collision event with warning messages was present in Figure 4. The model starts from the time when the hazard occurs (e.g. an accident) (*t=0*) till the time when the subject vehicle reaches the hazard location. A complete timeline includes the hazard detection time, message delivery delay and lead time. The lead time is composed of designed display delay, machine processing time, driver reaction time to the warning message, and driver braking time. The components of the warning message notification process shown on Figure 4 were defined as follows:

- Detection time (t_{detect}) is the time duration from the time when the hazard event occurs to the time when the source vehicle detects the hazard.
- Message notification delay (t_{MND}) is the time duration from the time when the source vehicle being able to send the warning message to the time when the first corresponding wireless collision warning messages is received by the subject vehicle (SV).
- Designed display delay ($t_{display\ delay}$) is the time duration that the in-vehicle information system hold a warning message before alarming the drivers.
- Machine processing time ($t_{machine}$) is the processing time of a message in the automotive PC of the in-vehicle information system on the subject vehicle.
- Reaction time ($t_{reaction}$) is the time duration a driver needed to process the warning information.
- Braking time ($t_{braking}$) is the time duration a driver needed to brake and stop a vehicle.
- Lead time (t_{lead}) is the time to collision when the in-vehicle information system on the subject vehicle is able to send the warning message to the driver.
- Human-machine total response time ($t_{total\ response}$) is defined as the time duration from the time when the source vehicle is able to send out the warning message to the time when the subject vehicle arrives at the collision site or avoids the potential hazard.

2.3.1 Total Time and Human-Machine Total Response Time. $t_{total}(i)$ is defined as the time to collision (*TTC*) of the subject vehicle when hazard occurs, which is a commonly used safety indicator. The total time is computed according to the following equation based on vehicle kinematics for *i*th vehicle.

$$t_{total}(i) = \frac{\sqrt{v_i(t)^2 + 2a_i(t)(X_i(t) - 0.5 \times L_i)} - v_i(t)}{a_i(t)} \tag{3}$$

where *i=0*; $v_i(0)$ is the initial velocity of *i*th vehicle when hazard occurs. $a_i(0)$ is the initial acceleration of *i*th vehicle. $X_i(0)$ is its initial location away from the collision location and L_i is the length of *i*th vehicle.

Human-machine total response time ($t_{total\ response}(i)$) is defined as the time duration from the time when the source vehicle is able to send out the warning message to the time when the ith subject vehicle arrives at the hazard location.

$$t_{total\ response}(i) = t_{total}(i) - t_{detect}(h) \tag{4}$$

where hazard detection time ($t_{detect}(h)$) is defined as the time duration from hazard occurrence to the hazard being detected. The shorter the detection time is the higher ability of the hazard detection the V2V communication system has.

2.3.2 Minimum Safe Headway. $Mint_{safe}\,(i,j)$ is the minimum amount of time for the *i*th Subjective Vehicle (SV) to make response to *j*th warning message successfully before colliding the lead (*i-1*) th SV or reaching the hazard location (if *i*=1) (Anderson, 2006). Previous studies indicated the driver reaction time to the potential collision event can be reduced by the warnings with an early alarm timing compared to the warnings with a late alarm timing(Abe & Richardson, 2004). Braking time might vary based on the initial velocity and the maximum deceleration of the subject vehicle during braking response processes.

$$\begin{aligned} Mint_{safe}\,(i,j) &= t_{reaction}(i,j) + t_{braking}(i,j) \\ &= t_{reaction}(i,j) + \frac{v_r(i)}{2a_{max(i)}} + \varepsilon_1 \text{ (Anderson, 2006)} \end{aligned} \tag{5}$$

where $v_r(i)$ is the initial speed of the *i*th SV when the warning message broadcasting to the driver; $a_{max}(i)$ is the maximum braking deceleration, which is mainly dependent on vehicle parameters. ε_1 is a random error that is affected by various factors (e.g. situation urgency level, driving experience, driver personality). Most existing method to quantify this random error is based on normal distribution. We still adopted the most common function to represent the distribution of ε_1 due to its simplicity [0, 0.3] (Abe, G., & Richardson, J., 2004).

2.3.3 Minimum Acceptable Lead Time. There is an optimal lead time range for drivers to respond to warnings with optimal performance, namely, with least collision rates $[Min\,t_{optimal\ lead}, Maxt_{optimal\ lead}]$. Given all that, the minimum safe headway represents the minimum acceptable time for drivers to brake and stop safely. Then, Minimum acceptable lead time ($Min\,t_{lead}(i,j)$) left for a driver to respond to the warning message is $Mint_{safe}\,(i,j)$. Likewise, the $Min\,t_{lead}(i,j)$ left for drivers to reach the optimal performance in their responses is $Min\,t_{optimal\ lead}$.

2.3.4 Designed Display Delay ($\boldsymbol{t_{display\ delay}(i,j)}$). It is the delay of message *j* displaying, which indicated how long the system hold the warning message over before alarming the drivers so as to achieve the optimal safety benefit of information system.

$$t_{display\ delay}(i,j) \le \max(0, t_{total\ response}(i) - Maxt_{optimal\ lead} - Maxt_{machine}) \tag{6}$$

To be more specific, larger message notification range (e.g. notification distance 1 in Figure 4) enlarges the available range to design the display delay, whereas smaller message notification range (e.g. notification distance 2 and 3 in Figure 4) leaves a smaller range for designing the delay. In the former case, the on-board information system is able to delay the warning message broadcasting if the available time for driver response is relatively long (i.e. $\ge Max\,t_{optimal\ lead}$). Therefore the message will hold for a certain amount of time before broadcasting to the drivers so that the manipulated lead time will drop into the optimal lead time range. In the latter case, the designed display delay can be shortened or cancelled by the on-board information system, when the available time for driver response is short.

2.3.5 Machine Processing Time ($t_{machine}(i,j)$). It is the required message processing time of *j*th message in the automotive PC of the in-vehicle information system of the *i*th SV. Any messages to be sent to the driver required a certain time ahead of its present to be processed in the in-vehicle information system. In the real design of the system, there might be an available range for choosing $t_{machine}(i,j)$, namely, [min $t_{machine}$, max $t_{machine}$]. ***Maximum available machine processing time*** is defined as the longest $t_{machine}(i,j)$ that an intended SV can tolerate to process warning messages with enough lead time left for its driver to effectively respond to the warning messages.

$$Max\ t_{machine}(i,j) = \begin{cases} \min\ t_{machine}\ , & Min\ t_{lead}(i,j) < Min\ t_{optimal\ lead} \\ \max t_{machine}\ , & otherwise \end{cases} \tag{7}$$

When $t_{total\ response}(i)$ is shorter than the time length for drivers to make effective response to the warning messages, min $t_{machine}$ is assigned to the machine processing time in order to leave more time for human responses; whereas $\max t_{machine}$ is assigned to the machine processing time when $t_{total\ response}(i)$ is long enough for drivers to make responses safely.

2.3.6 Message Notification Delay ($t_{MND}(i,j)$). $t_{MND}(i,j)$ is defined as the time duration from the source vehicle being able to send out the warning messages to the corresponding wireless collision warning message j is delivered to the *i*th SV successfully (Biswas, Tatchikou, & Dion, 2006). ***Maximum available message notification delay*** ($Max\ t_{MND}(i,j)$) is then defined as the longest $t_{MND}(i,j)$ that an intended SV can tolerate to effectively respond to the warning messages. This parameter can be influenced by the default design of the communication system and the real time network load during the warning message transmission.

$$Max\ t_{MND}(i,j) \leq\ t_{total\ response}\ (i) - Max\ t_{machine}(i,j) - Min\ t_{lead}(i,j) \tag{8}$$

Minimum available lead time ($Min\ t_{lead}(i,j)$) is assigned different value according to the time left ($t_{total\ response}\ (i)$) for the entire system in the SV to respond to the warnings. Only when the lead time reaches its minimum value, the connected vehicle system has the potential to help driver avoid the collision completely. In other words, if the lead time left for the SV to respond is less than $t_{\min safe\ headway}(i,j)$, the SV could not be able to avoid the collision even the driver make correct response immediately. Nevertheless, when the available lead time is longer than the minimum optimal lead time and shorter than the maximum optimal lead time, $Min\ t_{optimal\ lead}$ is assigned to $Min\ t_{lead}(i,j)$to calculate message notification delay in order to achieve the optimal performance in human responses to the warning messages. When the available lead time is longer than the maximum optimal lead time, $Max\ t_{optimal\ lead}$ is assigned to $Min\ t_{lead}(i,j)$ in the design criteria of message notification delay in order to achieve the optimal performance in human responses to the warning messages.

2.3.7 Message notification range. In the connected vehicle communication, only vehicles in message notification range will be able to receive the warning messages from the source vehicle. Generally speaking, the message notification range serves as an important parameter in such communication processes since it determines the remaining time for message delivery and appropriate driver's response. ***Minimum acceptable message notification range*** (*Min MNR* (*i*)) is the range, which allows the closest vehicle to the potential collision site in this range to be able to avoid the collision safely.

$$Min\ MNR(i) \geq \int_0^{tr} (v_i(t)t + \frac{1}{2} a_{max}(t)t^2)dt \quad (9)$$

where *tr* is the time needed for drivers to achieve optimal performance.

When $t_{total\ response}(i)$ is long enough for drivers to achieve optimal performance, the t will be the summation of the minimum optimal lead time and machine processing time. Otherwise, the message notification range should be extended to ensure the driver within the range has a chance to achieve optimal performances.

$$tr = Min\ t_{optimal\ lead} + Max\ t_{\mathrm{machine}}(i,j) + \max(0,\ Min\ t_{optimal\ lead} + Max\ t_{\mathrm{machine}}(i,j) - t_{total\ response}(i) \quad (10)$$

2.4 Explore the Optimal Lead Time Range

In order to obtain the optimal lead time range, an experimental study was conducted by our research group exploring the effect of lead time on driver responses to speech warinings (Wan, Wu, & Zhang, 2014). The experiment design and results of the experiment is presented in the appendix and the detail of the experiment can be referred to Wan et al's study. Table 1 presented the statistic models of safety benefits of the warning messages (i.e. crash rates and reduced kinetic energy) as a function of lead time (t_{lead}). The optimal lead time range is obtained for normal drivers in non-distracted, sober conditions with an average age of 21.13 years (SD = 2.54) and an average lifetime driving experience of 40,054.62 miles (SD = 57,911.04).

To achieve the best estimation, data were separated into different segments based on their trends. The R^2 of the statistic models of collision rate and the reduced kinetic energy are 0.99 and 0.21, respectively. In particular, there is an abrupt decrease of collision rate appearing with the lead time getting longer when the lead time is shorter than 4.5s; while the rate of such decrease tended to slow down when the lead time ranging from 4.5s to 10s and a slight pick-up occurred after the lead time became longer than 10s. In the meantime, a significant increase of reduced kinetic energy was suggested when the lead time was shorter than 3.5s, while a slow decrease occurred after the lead time got longer than 3.5s. The results of the curve estimation indicated the optimal safety benefits of warning messages (i.e. lowest collision rate and highest reduced kinetic energy) were obtained with the lead time ranging from 4.5s to 10s.

3. The Model Application in the Design of Connected Vehicle Systems

3.1 Parameter Setting

The parameter settings of inputs were from the experiment as an example. The maximum deceleration $a_i(t)$ was $6.37\,m/s^2$. The initial velocity $v_i(t)$ when the warning message is broadcast to the driver is 19.81 m/s. The t_{total} and t_{detect} are set to be 15.00s and 5.00s, respectively. t_{machine} is ranging from 50.00-200.00ms.

The reaction time was calculated based on equation 3. The reaction time to auditory warning messages is computed as 2.62s. The standard deviation of reaction time (s) is 0.3 (Abe, G., & Richardson, J., 2004) for normal drivers. By normal drivers, we mean the drivers were driving in sober undistracted condition with age ranging from 23 to 61. The 95% confidence interval of modeled reaction time is 2.49-2.75, and the 99% confidence interval of modeled reaction time 2.45-2.79. The corresponding minimum safety headway in equation 9 is ranging from 4.34-4.60 with 95% confidence, and from 4.30-4.64 with 99% confidence.

3.2 The Optimal Design of the Vehicle-To-Vehicle System in General

Table 2 presented the optimal design of V2V systems in general with lead time fall into the optimal lead time range ($4.5s < t_{lead} \leq 10s$). Here, 4.5s and 10s are the minimum and the maximum threshold of the optimal lead time, respectively. A lower collision rate and more reduced kinetic energy, was achieved with lead time of the warning messages in this range. Therefore, the optimal design of the information system will be able to broadcast the message with the lead time ranging from 4.5s to 10s ahead of the vehicle reaching the hazard location.

The total time from the hazard occurrence to the vehicle receiving the warning messages reaching the hazard site is 15s. Therefore the human-machine total response time equals to the differential between t_{detect} (5s) and t_{total}, which is 10 seconds. In other word, the vehicle-to-vehicle communication system would be able to send out the warning message with 10 seconds left for the *i*th *vehicle* to reach the hazard site in order to achieve the most safety benefits.

In order to achieve the optimal performance of the human-in-the-loop connected vehicle systems, the human-machine total response time ($t_{total\ response}(i)$) should at least be longer than the summation of maximum message processing time of the subjective vehicle ($\max t_{\text{machine}}(i,j)$) and minimum amount of time for drivers to make optimal braking responses successfully before reaching the hazard location ($min\ t_{optimal\ lead}$). In this case, the human-machine total response time fulfill this requirement. The maximum available delivery delay of the warning messages will be determined by the human-machine total response time ($t_{total\ response}(i)$), the minimum optimal lead time ($min\ t_{optimal\ lead}$) and the maximum message processing time ($\max t_{\text{machine}}(i,j)$). As computed in equation (6), the maximum available $t_{delivery\ delay}$ should be no longer than 5.3s.

The maximum available machine processing time can be assigned the maximum machine time ($maxt_{machine}$) since the time left for the driver to respond is still longer than the minimum human response time in order to avoid the collision completely. Therefore, the maximum available machine processing time (maximum available $t_{machine}$) is no longer than 200ms.

The minimum acceptable message notification range (Min-MNR) can be calculated with the ($mint_{optimal\ lead}$), which is minimum acceptable lead time ($Min\ t_{lead}(i,j)$) to achieve the optimal driving performance. Here, the Min-MNR is the range to achieve the optimal driving performance. As computed in equation (9), the minimum acceptable message notification range (Min-MNR) should be at least 329 meters longer. In other word, the message should be broadcast to drivers to avoid collision when the drivers traveled to 329 meters from the potential hazard location.

In addition, there is no designed display delay in this condition since the lead time drops in the optimal lead time range ($t_{display\ delay} = 0$). Therefore the message will be sent right away after the potential hazard being detected to achieve an optimal performance in avoiding the hazard.

3.3 The Design of the Vehicle-To-Vehicle System in Specific Conditions

In reality, the optimal performance of V2V systems in general situation may not be achieved, for instance, for systems with lower hazard detection ability. Therefore, the following subsection proposed the design criteria of vehicle-to-vehicle systems considering different levels of hazard detection ability with different confidence intervals of modeling driver reaction time (see Tables 3 and 4).

With a higher hazard detection ability, the connected vehicle system was able to detect the hazard soon after the hazard occurred resulting in a longer human-machine response time; while with a lower hazard detection ability, the connected vehicle system may take longer time to detect the hazard resulting in a relatively short human-machine response time, and a small chosen range for the machine processing time and delivery delay. Different levels of hazard detection abilities were reflected by different time needed to detect hazards. The detection time was selected as example inputs from 1s to 14s to fit into different specific conditions.

Generally speaking, the optimal design will be suitable for the conditions that the lead time falls into the optimal lead time range (4.5s to 10s). In addition, Table 3 (95% C.I.) and Table 4 (99% C.I.) also indicated the detailed optimal design of the parameters based on example levels of the hazard detection ability with minimum acceptable lead time falls into any other ranges.

For each level of the hazard detection time, the *Minimum acceptable lead time* was chosen from the available range accordingly. The criteria for choosing the lead time is 1) within the available range of human-machine response time; 2) the shortest lead time which brought the optimal performance. In the meantime, other parameters such as maximum available delivery delay, maximum available machine time, minimum acceptable message notification range and designed display delay were calculated based on the corresponding equations (5-8) as the way of the calculation for the general situation. In the design of the delivery delay and the machine processing time, we may have to compromise the machine processing time in order to leave a larger range of delivery delay. This criterion is set since delivery delay is a major concern in designing the connected vehicle system.

As we could see from the above tables, the shorter the detection time is, the more severe the constraints for the human-machine total response time, and in turn constrained the design of message notification delay, machine processing time, message notification range and the designed message display delay. When the detection takes an extremely long time, the drivers will not be able to avoid the collision at the hazard location even in ideal conditions (i.e. no delivery delay and machine processing time). In order to achieve the optimal performance of the entire connected vehicle system and take the system design constraints into consideration, a proper level of detection time has to be achieved so that the corresponding lead time could drop into the optimal range, a reasonable design requirement of delivery delay and machine processing time could be selected, and a shorter message notification range can be established. Based on the results, designers are able to select an appropriate technology (e.g., Wi-Fi) in order to meet the requirements of the parameters with required confidence levels.

3.4 The Validation of the Proposed Design for Vehicle-To-Vehicle System

The simulation was run to validate the design criteria of vehicle-to-vehicle systems for each condition. The time-to-collision (*TTC*) at the time point when the subject vehicle reaches the collision location was utilized as a criterion to assess whether the designed parameters make the system safe to drivers. In particular, if *TTC*>0, the results indicated human drivers stopped before reaching hazard locations; if *TTC*=0, the results indicated human drivers stopped when reaching hazard locations; and if *TTC*<0, the results indicated human drivers failed to stop when reaching hazard location.

The simulation was performed for 4500 times in total. Each proposed condition in Tables 3 and 4 was simulated for 300 times to validate the optimal design criteria of the connected vehicle systems, with the values of the design parameters having equal chance to be less than, equal to, or higher than the proposed optimal design parameters. The reaction time inputted in the simulation was following a normal distribution of [2.62, 0.3] with the 95% confidence interval and the 99% confidence interval. The actual message notification delay was inputted with a range of $[Max\ t_{MND} - 1, Max\ t_{MND} - 1]$ so that we could test the resulted TTC as a function of the time difference between proposed and actual maximum acceptable message notification delays. The same logic was utilized to test the other two time parameters, the maximum acceptable machine processing time and the maximum acceptable message display delay. The actual machine processing time was inputted with a range of $[Maxt_{machine} - 0.1, Maxt_{machine} - 0.1]$. The actual message display delay was inputted with a range of $[t_{display\ delay} - 1, t_{display\ delay} - 1]$. The time difference for all three parameters is calculated as: Time difference=Actual value-Proposed maximum acceptable value.

The simulation results were presented in Figures 5-7. The TTC was plotted as a function of the time difference between the actual value and the value of the proposed threshold. Simulation results showed the proposed parameters well captured the boundaries of the TTC trends. For all proposed parameters, the TTC<0 for most of cases when actual parameters exceeded the proposed maximum acceptable values across all conditions, and the TTC>0 for most of cases when actual parameters were below the proposed maximum acceptable values across all conditions. As it shown in Figure 5, the average TTC was 0.57s for $Actl\ t_{MND}$ below $Max\ t_{MND}$, and the average TTC was -0.44s for $Actl\ t_{MND}$ exceed $Max\ t_{MND}$. The difference of TTC was significantly different for these two groups ($F(1, 1982)=5534.38$, $p<.001$). As it shown in Figure 6, the average TTC was 0.09s for $Actl\ t_{machine}$ below $Max\ t_{machine}$, and the average TTC was -0.04s for $Actl\ t_{machine}$ exceed $Max\ t_{machine}$. The difference of TTC was significantly different for these two groups ($F(1, 1197)=761.76$, $p<.001$). As it shown in Figure 7, the average TTC was 0.49s for $Actl\ t_{display\ delay}$ below $Max\ t_{display\ delay}$, and the average TTC was -0.50s for $Actl\ t_{display\ delay}$ exceed $Max\ t_{display\ delay}$. The difference of TTC was significantly different for these two groups ($F(1, 798)=183.240$, $p<.001$).

4. Discussion

The present study modeled human reaction time and proposed the models of the human-in-the-loop warning message notification in the connected vehicle. The application of the models were presented in the design of the corresponding intelligent transportation system based on different levels of the lead time resulting from different hazard detection abilities of systems with different confidence intervals.

Previous connected vehicle protocol designs mainly studied the algorithm of the vehicular network in the communication. Researchers evaluated the performance of different connected vehicle systems and protocols including the reliability of the warning transmission processes (Biswas et al., 2006; Chen, Jiang, & Delgrossi, 2009; Willke, Tientrakool, & Maxemchuk, 2009), and efficiency of the connected vehicle using different strategies and techniques (Sikdar, 2008). It is generally assumed that connected vehicle systems would still have the human in the loop. The warnings would be broadcast to the drivers through the connected vehicle system and the drivers would respond to the warning messages accordingly at least in the short-to-medium time frame. As far as we know, human factor issues do not appear to have been explicitly addressed, particularly in the interaction between humans with connected vehicle systems (Challa & Cam, 2007). Previous studies which considered the human factor issues mainly focused on the human-machine interface design and the user acceptance of the system rather than driver performance in their interaction with the connected vehicle systems (Farah et al., 2012). Even though driving behaviors were investigated in previous studies, very few studies have specifically taken the human component into consideration in the design and development of the connected vehicle system to achieve the optimal performance of the human-machine system. In that case, drivers in the vehicles receiving the warnings will not be able to avoid the collision without making proper responses to the dangerous events even if there is a highly reliable and efficient communication system to transmit warning messages. Therefore the performance of the whole system would be impaired without deliberating the human-machine interaction even when the optimal performance of the connected vehicle system is achieved.

The current study addressed the human component in the connected vehicle system design by modeling human performances in their interaction with warnings issued by a connected vehicle systems. With different levels of the hazard detection ability, the available range of the lead time would constrained the setting of parameters to optimize the human-in-the-loop connected vehicle system design. In general, the optimal design would be achieved with the lead time dropping in the optimal range, in which the warning messages broadcasted by the connected vehicle system would bring the most safety benefits. In the meantime, design criteria were illustrated in detail for various systems with different hazard detecting abilities with different confidence intervals (95% and 99%). The design criteria derived for four parameters could be further applied to a V2I communication system including the designed message display delay, the maximum available machine processing time, the maximum available message notification delay, and the minimum acceptable message notification range. The further software can be designed based on the models developed for specific conditions. Figure 8 displays the interface of such software as an example. With the hazard detection time of different connected vehicle systems inputting into the software, the designers of the warning system will be able to obtain the following parameters, including maximum available delivery delay, the maximum available machine processing time, the minimum acceptable message notification range and the designed message display delay.

Although the study was carefully prepared, there are several limitations in our work. First of all, the current warning message notification model is built with the distribution of reaction time of average drivers in non-distracted, sober conditions. Given the complex nature of individual differences, it is very difficult to model the effects of factors such as driver age, traffic complexity, and driver attentiveness all together. Although multiple factors have been found to have impacts on driver reaction time, studies showed disparate results regarding the effects of age and traffic conditions. The results of the available studies make it very difficult to model those factors at this moment. In terms of driver age, studies found this factor to be either affect or not affect driver's reaction time in literature. In particular, Porter, Irani, & Mondor, (2008) found young drivers responded to auditory alerts more quickly than older drivers when events were expected, but no significant difference when events were unexpected. Makishita, H., & Matsunaga, K. (2008) found young and middle aged drivers responded more quickly to a buzzer sound than older drivers when there was a distracting in-vehicle task, whereas there was no significant effect of age on reaction time when driving was the only task. In contrast, Kramer, Cassavaugh, Horrey, Becic, & Mayhugh, J (2007) found no effect of age on driver reaction time to collision avoidance warnings in varying traffic and collision configurations both without and with a distracting in-vehicle task. Dozza (2013) also found driver's age did not significantly influence driver reaction times in real driving tasks. Moreover, the results of the effects of traffic conditions on driver reaction times are equivocal. Dozza (2013) found traffic density did not affect driver reaction times in real driving task. Edquist, Rudin-Brown, & Lenné (2012) found an parking vehicle on roadside increased drivers reaction time to critical events compared to no parking vehicle condition. However no warnings were presented in both studies. Chang, Lin, Fung, Hwang, & Doong (2008) found that it took longer for a driver to react to the critical event at an intersection than on a straight roadway segment. However, no statistical significance regarding the effect of hazard location was reported in their study. Built on the model developed in the current work, individual differences in driving performance under different traffic conditions could be considered in the next step of the model development. The standard deviation to calculate the confidence interval can vary among drivers in practice. The parameter designs can be further investigated for different types of drivers such as drunk drivers and distracted drivers.

In addition, the optimal design of the connected vehicle system was proposed with several parameters obtained from the setting and results of the human experiment, including the initial velocity when a driver receives the initial message, the maximum acceleration. In future work, the study of the optimal design of the connected vehicle system could examine the different setting of these parameters.

Finally, we quantified the warning transmission from only one vehicle (Source vehicle) to other vehicles (Subject vehicle *i*) in the current work. The collision location could be influenced by the existence of other vehicles between the source vehicle and the subject vehicle. However, the current model could still be applied to situations with multiple vehicles between the source vehicle and subject vehicle since the equation to calculate the total time keeps the same with the distance away from the collision location as the input in the current model. The prediction of the collision location could be complex since the behavior and response of drivers on other vehicles is a chain of events and a dynamic process. A more complete model of drivers to predict driver responses in critical events is still needed to optimize the design of the connected vehicle systems. However, the current work is one step towards the quantification of connected vehicle parameter settings.

5. Conclusion

The current study developed the message notification models in connected vehicle settings by modeling human performance in warning responses. By addressing the human performance, the message notification model was applied to optimize the connected vehicle systems parameters in general to achieve optimal performance, which including maximum available message notification delay, the maximum available machine processing time, the minimum acceptable message notification range and the designed message display delay. The optimal design of such systems considering different hazard detection abilities were also presented with different confidence intervals (95% and 99%). A software interface with the message notification model implemented was presented to discuss the practical benefits of the current work in the design of intelligent transportation systems.

Acknowledgment

We appreciate the support from National Science Foundation.

Reference

Abe, G., & Richardson, J. (2004). The effect of alarm timing on driver behaviour: an investigation of differences in driver trust and response to alarms according to alarm timing. *Transportation Research Part F: Traffic Psychology and Behaviour*, *7*(4-5), 307–322.

Anderson, J. E. (2006). The future of high-capacity Personal Rapid Transit. In *PRT International, LLC. Minneapolis, MN.*

Bi, L., Gan, G., & Liu, Y. (2014). Using queuing network and logistic regression to model driving with a visual distraction task. *International Journal of Human-Computer Interaction, 30*(1), 32-39.

Bi, L., Gan, G., Shang, J., & Liu, Y. (2012). Queuing Network Modeling of Driver Lateral Control With or Without a Cognitive Distraction Task. *IEEE Transactions on Intelligent Transportation Systems, 13*(4), 1810-1820. doi: 10.1109/TITS.2012.2204255

Bi, L., Yang, X., & Wang, C. (2013). *Inferring driver intentions using a driver model based on queuing network.* Paper presented at the Intelligent Vehicles Symposium (IV), 2013 IEEE.

Bi, L. Z., & Liu, Y. L. (2009). Modeling driver car-following based on the queuing network cognitive architecture. *Proceedings of the 2009 International Conference on Machine Learning and Cybernetics, 2*(July), 895-900. doi: 10.1109/ICMLC.2009.5212407

Biswas, S., Tatchikou, R., & Dion, F. (2006). Vehicle-to-vehicle wireless communication protocols for enhancing highway traffic safety. *IEEE Communications Magazine*, 44(1), 74–82.

Campbell, J., Richard, C., Brown, J., & McCallum, M. (2007). Crash warning system interfaces: human factors insights and lessons learned. In *Report HS 810 697, National Highway Traffic Safety Administration*. Washington, DC.

Challa, N., & Cam, H. (2007). Adaptive Multicasting using Common Spreading Codes in Infrastructure-to-Vehicle Communication Networks. In *2007 Mobile Networking for Vehicular Environments*, *Anchorage, AK,* 61–66.

Chang, S. H., Lin, C. Y., Fung, C. P., Hwang, J. R., & Doong, J. L. (2008). Driving performance assessment: Effects of traffic accident location and alarm content. *Accident Analysis & Prevention*, *40*(5), 1637-1643.

Chisholm, S. L., Caird, J. K., & Lockhart, J. (2008). The effects of practice with MP3 players on driving performance. *Accident; Analysis and Prevention*, *40*(2), 704–13.

Dimitrakopoulos, G., & Demestichas, P. (2010). Intelligent transportation systems. *IEEE Vehicular Technology Magazine*, *5(1)*, 77–84.

Dozza, M. (2013). What factors influence drivers' response time for evasive maneuvers in real traffic?. *Accident Analysis & Prevention*, *58*, 299-308.

Edquist, J., Rudin-Brown, C. M., & Lenné, M. G. (2012). The effects of on-street parking and road environment visual complexity on travel speed and reaction time. *Accident Analysis & Prevention*, *45*, 759-765.

Farah, H., Koutsopoulos, H. N., Saifuzzaman, M., Kölbl, R., Fuchs, S., & Bankosegger, D. (2012). Evaluation of the effect of cooperative infrastructure-to-vehicle systems on driver behavior. *Transportation Research Part C: Emerging Technologies*, *21*(1), 42–56.

Fuller, H. J. a., Reed, M. P., & Liu, Y. (2012). Integration of physical and cognitive human models to simulate driving with a secondary in-vehicle task. *IEEE Transactions on Intelligent Transportation Systems, 13*(2), 967-972.

Horrey, W. J., & Wickens, C. D. (2006). Examining the impact of cell phone conversations on driving using meta-analytic techniques. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *48*(1), 196–205.

Jerbi, M., Marlier, P., & Senouci, S. M. (2007). Experimental Assessment of V2V and I2V Communications. In *2007 IEEE Internatonal Conference on Mobile Adhoc and Sensor Systems*, 1–6.

Kramer, A. F., Cassavaugh, N., Horrey, W. J., Becic, E., & Mayhugh, J. L. (2007). Influence of age and proximity warning devices on collision avoidance in simulated driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *49*(5), 935-949.

Lee, J. D., Bricker, D. L., & Hoffman, J. D. (2008). A Dynamic Programming Algorithm for Scheduling In-Vehicle Messages. *IEEE Transactions on Intelligent Transportation Systems*, *9*(2), 226–234.

Lee, J. D., & Strayer, D. L. (2004). Preface to the special section on driver distraction. *Human Factors*, *46*(4), 583–6.

Lim, J. H., & Liu, Y. (2009). Modeling the Influences of Cyclic Top-Down and Bottom-Up Processes for Reinforcement Learning in Eye Movements. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *39*(4), 706–714.

Liu, Y., Feyen, R., & Tsimhoni, O. (2006). Queueing Network-Model Human Processor (QN-MHP): A computational architecture for multitask performance in human-machine systems. *ACM Transactions on Computer-Human Interaction (TOCHI), 13*(1), 37-70.

Makishita, H., & Matsunaga, K. (2008). Differences of drivers' reaction times according to age and mental workload. *Accident Analysis & Prevention*, *40*(2), 567-575.

Mejri, N., Kamoun, F., & Filali, F. (2010).Cooperative Infrastructure Discovery Through V2X Communication. In *Ad Hoc Networking Workshop (Med-Hoc-Net), The 9th IFIP Annual Mediterranean*, *Juan Les Pins, France*, 1-8.

Noy, Y. I. (1997). Human factors in modern traffic systems. *Ergonomics*, *40*(10), 1016–24.

Neale, V. L., Perez, M. A., Lee, S. E., & Doerzaph, Z. R. (2007). Investigation of driver-infrastructure and driver-vehicle interfaces for an intersection violation warning system. *Journal of Intelligent Transportation Systems*, *11*(3), 133-142.

Papadimitratos, P., de La Fortelle, A., Evenssen, K., Brignolo, R., & Cosenza, S. (2009). Vehicular Communication Systems : Enabling Technologies, Applications, and Future Outlook on Intelligent Transportation. *Communications Magazine, IEEE*, *47*(11), 84–95.

Porter, M., Irani, P., & Mondor, T. (2008). Effect of Auditory Road Safety Alerts on Brake Response Times of Younger and Older Male Drivers: A Simulator Study. *Transportation Research Record: Journal of the Transportation Research Board*, (2069), 41-47.

Ros, F. J., Ruiz, P. M., & Stojmenovic, I. (2009). Reliable and efficient broadcasting in vehicular ad hoc networks. In *Vehicular Technology Conference, 2009. VTC Spring 2009. IEEE 69th*, 1–5.

Santa, J., Gómez-Skarmeta, A. F., & Sánchez-Artigas, M. (2008). Architecture and evaluation of a unified V2V and V2I communication system based on cellular networks. *Computer Communications*, *31*(12), 2850-2861.

Shivaldova, V., & Maier, G. (2011). Performance evaluation of IEEE 802.11 p infrastructure-to-vehicle tunnel measurements. *Wireless Communications and Mobile Computing Conference (IWCMC), 2011 7th International. IEEE,*, 848–852.

Sikdar, B. (2008). A Broadcasting Scheme for Infrastructure to Vehicle Communications. *Proceeding of the 2008 IEEE Global Telecommunications Conference*, 1–5.

Torrent-moreno, M., Mittag, J., Member, S., Santi, P., & Hartenstein, H. (2009). Vehicle-to-Vehicle Communication : Fair Transmit Power Control for Safety-Critical Information. *Vehicular Technology, IEEE Transactions On*, *58*(7), 3684–3703.

U.S. Department of Transportation. (2013). *2011 Traffic Safety Facts Data Summary Booklet*. April. Retrieved from http://wwwnrd.nhtsa.dot.gov/cats/listpublications.aspx?Id=E&ShowBy=DocType

Wan, J., Wu, C., & Zhang, Y. (2014, September). The Effect of Lead Time of Collision Warning Messages on Driver Performance. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 58*(1)*,* 2088-2092. SAGE Publications.

Willke, T., Tientrakool, P., & Maxemchuk, N. (2009). A survey of inter-vehicle communication protocols and their applications. *IEEE Communications Surveys & Tutorials*, *11*(2), 3–20.

Wu, C., Berman, M., & Liu, Y. (2010). Optimization in Brain? - Modeling Human Behavior and Brain Activation Patterns with Queuing Network and Reinforcement Learning Algorithms. In W. Chaovalitwongse, P. M. Pardalos, & P. Xanthopoulos (Eds.), *Computational Neuroscience* (Vol. 38, pp. 157–179). New York, NY: Springer New York.

Wu, C., & Liu, Y. (2008). Queuing network modeling of the psychological refractory period (PRP). *Psychological review*, *115*(4), 913.

Wu, C., Liu, Y., & Quinn-Walsh, C. M. (2008). Queuing Network Modeling of a Real-Time Psychophysiological Index of Mental Workload-P300 in Event-Related Potential (ERP). *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, *38*(5), 1068–1084.

Ye, F., Adams, M., & Roy, S. (2008, May). V2V wireless communication protocol for rear-end collision avoidance on highways. In *Communications Workshops, 2008. ICC Workshops' 08. IEEE International Conference on* (pp. 375-379). IEEE.

Xu, Q., Mak, T., Ko, J., & Sengupta, R. (2004). Vehicle-to-vehicle safety messaging in DSRC. *Proceedings of the First ACM Workshop on Vehicular Ad Hoc Networks - VANET '04*, 19.

Zang, Y., Weiss, E., Stibor, L., Chen, H., & Cheng, X. (2007). Opportunistic Wireless Internet Access in Vehicular Environments Using Enhanced WAVE Devices. *Future Generation Communication and Networking (FGCN 2007)*. doi:10.1109/FGCN.2007.174

Zhao, G., Wu, C., & Qiao, C. (2013). A Mathematical Model for the Prediction of Speeding with its Validation. *IEEE Transactions on Intelligent Transportation Systems*, *14*(2), 828–836.

Figures 1-8

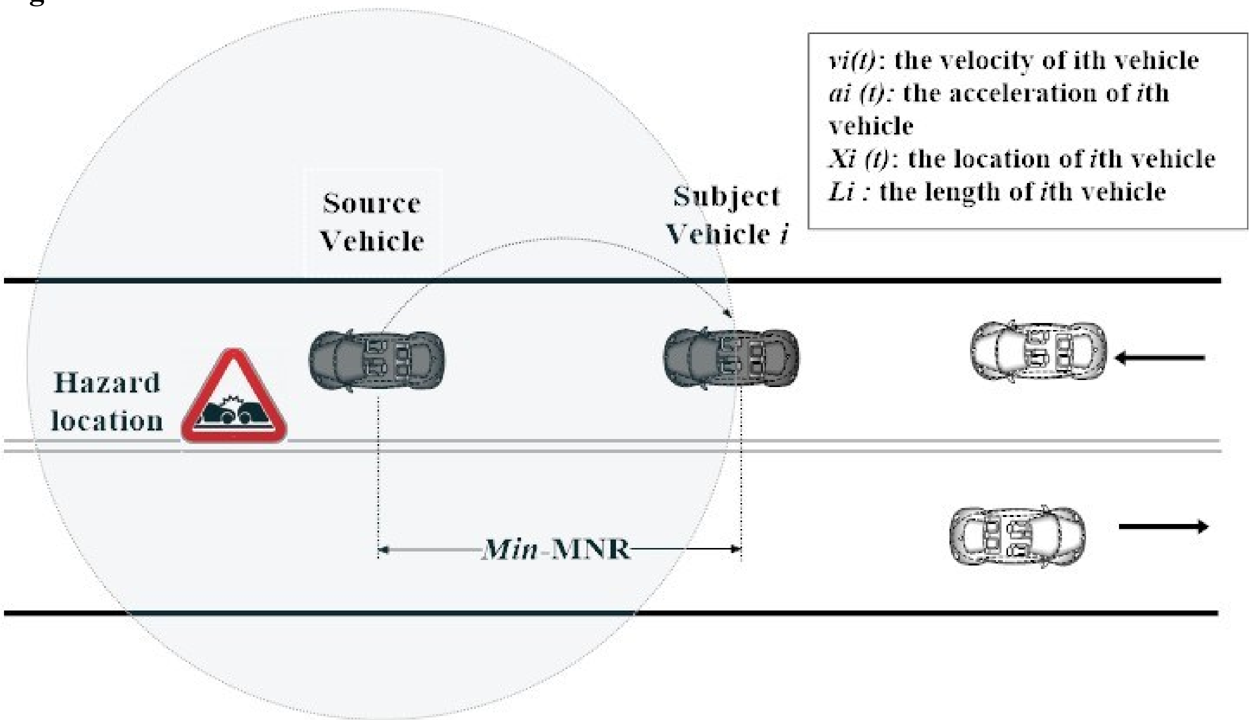


Figure 1. Illustration of connected vehicle communication with the dissemination of the collision avoidance warnings to subject vehicles in the notification range of the source vehicle

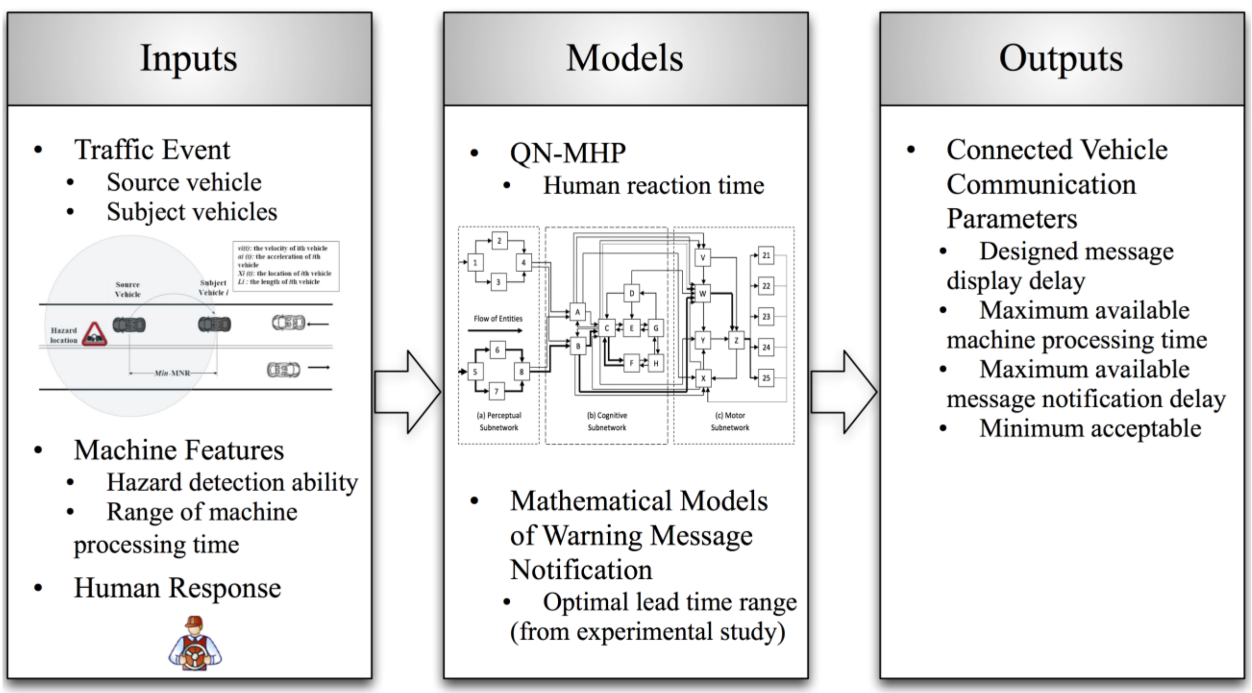
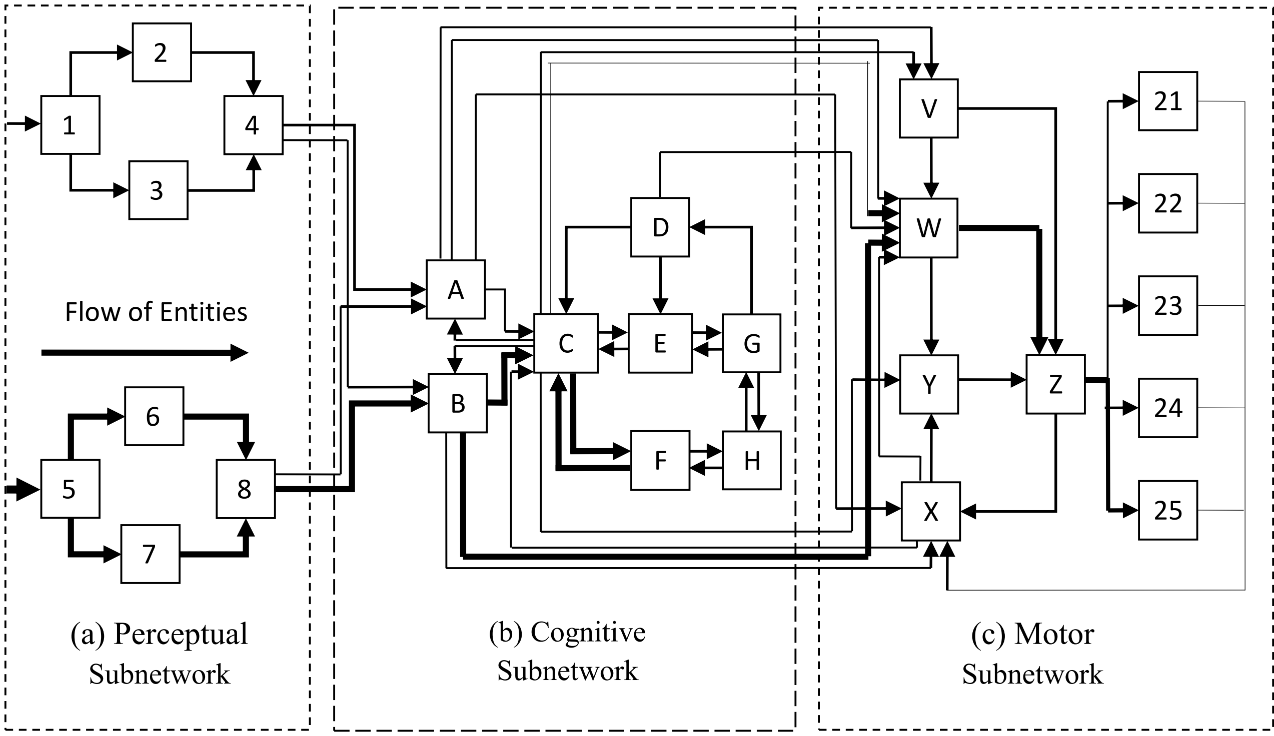


Figure 2. The structure of warning message notification model.



Perceptual Subnetwork	Cognitive Subnetwork	Motor Subnetwork
1. Common visual processing	A. Visuospatial sketchpad	V. Sensorimotor integration
2. Visual recognition	B. Phonological loop	W. Motor program retrieval
3. Visual location	C. Central executive	X. Feedback information collection
4. Visual recognition and location integration	D. Long-term procedural memory	Y. Motor program assembling and error detecting
5. Common auditory processing	E. Performance monitor	Z. Sending information to body parts
6. Auditory recognition	F. Complex cognitive function	21-25: Body parts: eye, mouth, left hand, right hand, foot
7. Auditory location	G. Goal initiation	
8. Auditory recognition and location integration	H. Long-term declarative & spatial memory	

Figure 3. The general structure of QN-MHP (developed in Wu et al., 2008-2013; and all of the published mathematical equations in QN-MHP can be found at: http://www.acsu.buffalo.edu/~seanwu/QNMHPMath/MathModelQNMHP_Online.htm)

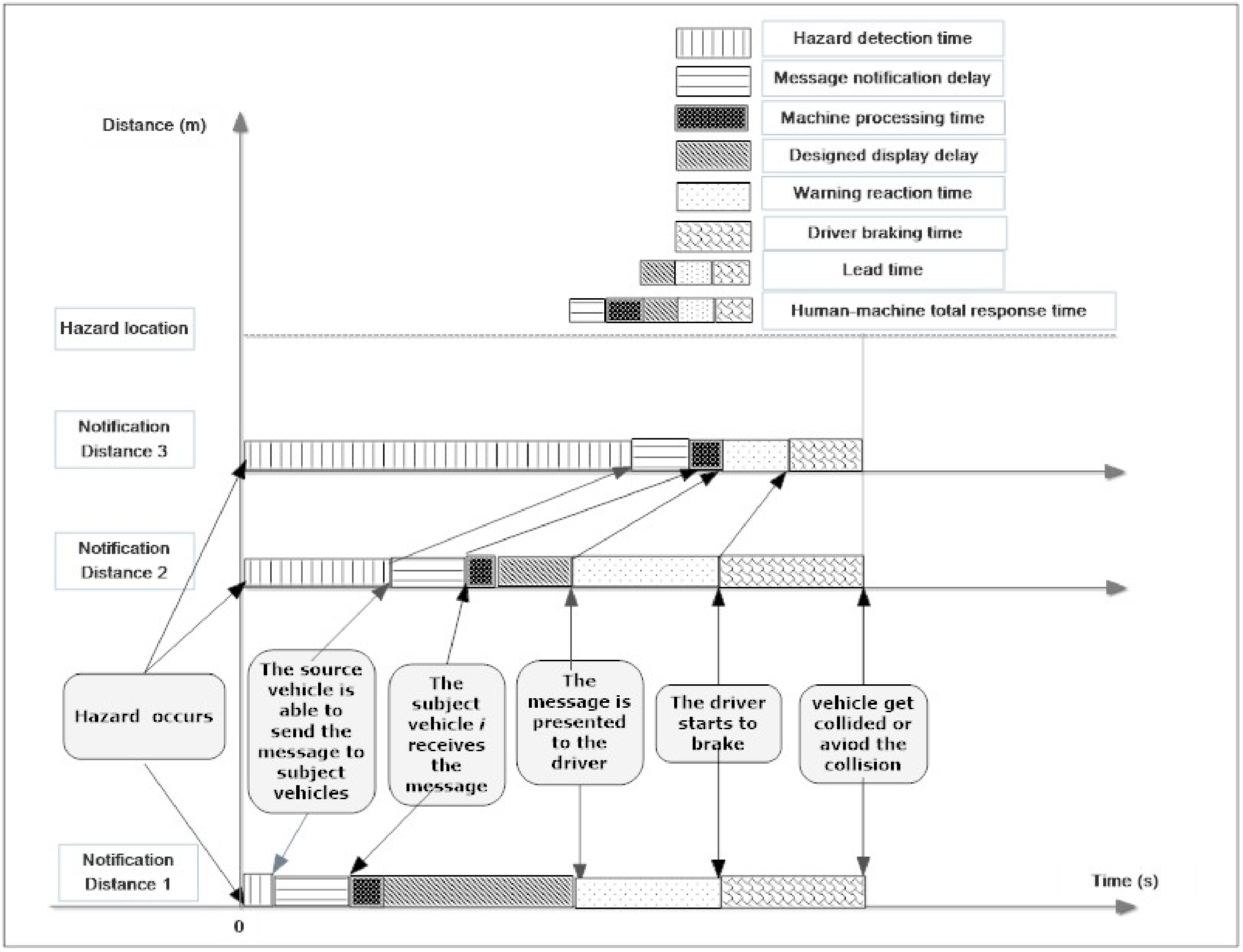


Figure 4. Proposed timeline of potential collision event.

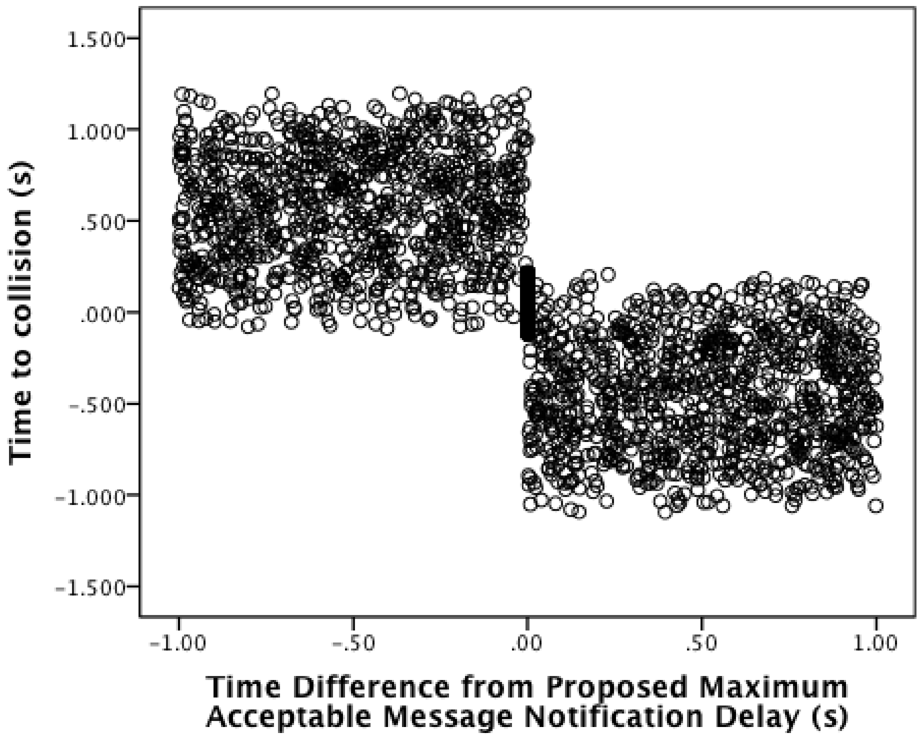


Figure 5. The resulted TTC when subject vehicle stopped when varying the message notification delay.

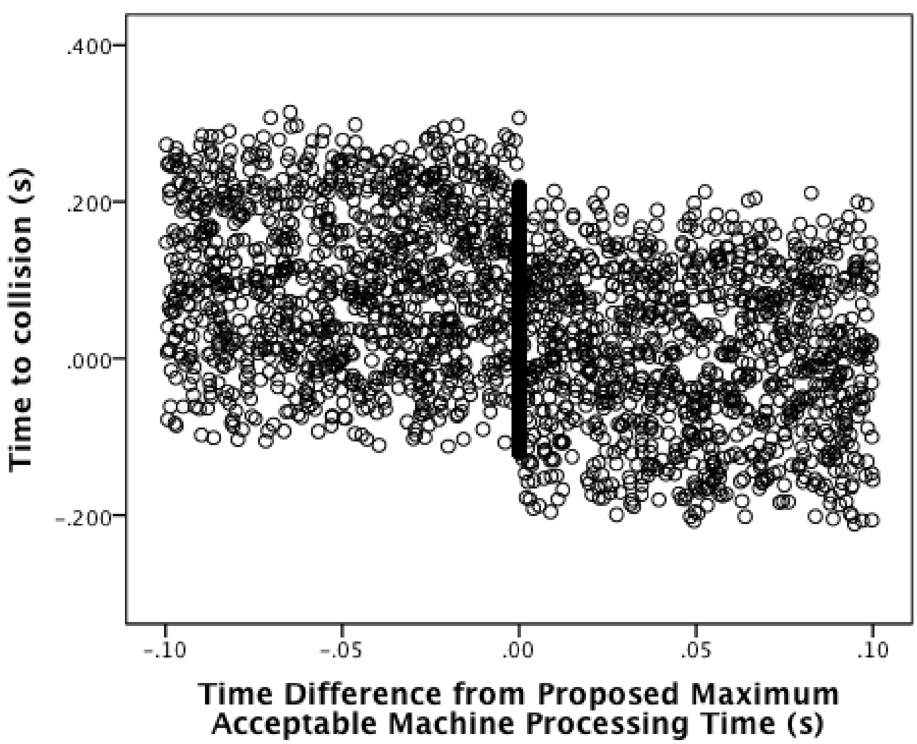


Figure 6. The resulted TTC when subject vehicle stopped when varying the machine processing time.

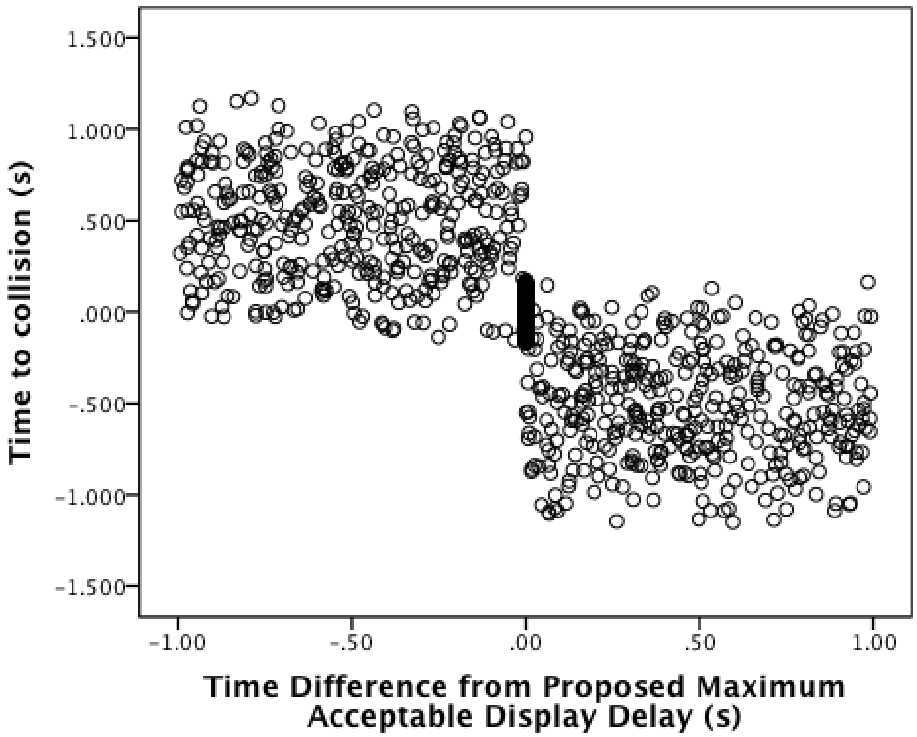


Figure 7. The resulted TTC when subject vehicle stopped when varying the display delay.

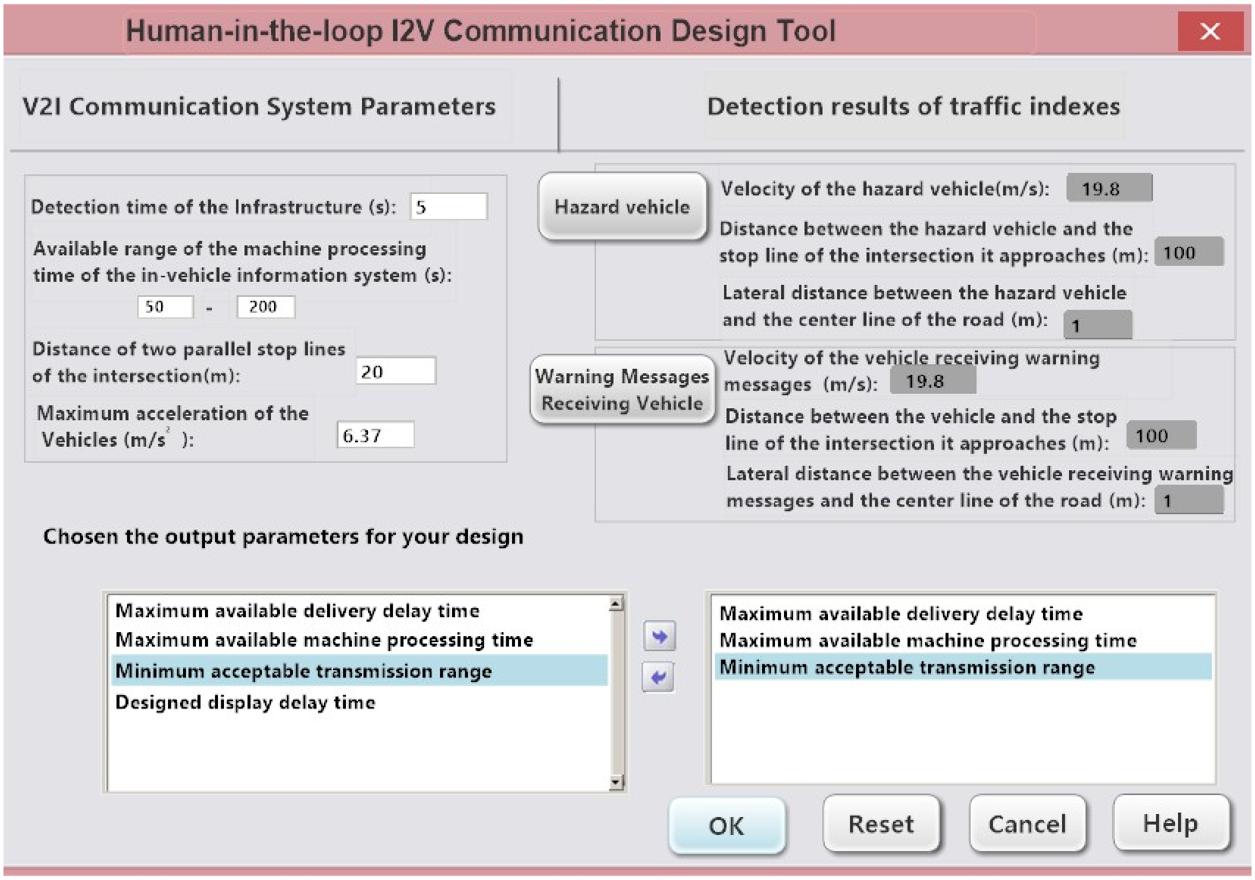


Figure 8. The interface of the human-in-the-loop connected vehicle system design.

Table 1-4

Table 1

The Statistic Model of Warning Message Safety Benefits as a Function of the Lead Time

Dependent variables	Curve estimation functions
Collision rate	$\begin{cases} 1.172 - 0.254 \times t_{lead} & (t_{lead} \leq 4.5\text{s}) \\ 0.099 - 0.003 \times t_{lead} & (4.5\text{s} < t_{lead} \leq 10\text{s}) \\ 0.019 + 0.005 \times t_{lead} & (t_{lead} > 10\text{s}) \end{cases}$
Reduced kinetic energy	$\begin{cases} 163.697 + 63.801 \times t_{lead} & (t_{lead} \leq 3.5\text{s}) \\ 398.127 - 0.230 \times t_{lead} & (t_{lead} > 3.5s) \end{cases}$

Table 2

Parameters of the Optimal Design in General (4.5s<Lead time<10s)

Input parameters	Output parameters	Suggested design of the parameters
$t_{total\ response}$, t_{machine} range, $Mint_{safe}\ (i,j)$	*Maximum available message notification delay* **(**$Max\ t_{MND}(i,j)$**)**	The time to successfully deliver the warning message from the source vehicle to the vehicles within the message notification range should be no longer than 5.3s, which includes the transmission time, the waiting time and the message retransmission delay.
$t_{machine}$ range	*Maximum Available machine processing time (Max* $t_{machine}$*)*	The time to process the warning message in the in-vehicle information system should be no longer than maximum threshold of the machine processing time (200ms).
V, a_{max}, $Min\ t_{optimal\ lead}$, t_{machine} range,	*Minimum acceptable message notification range* **(***Min MNR*(i)**)**	The minimum acceptable message notification range should be at least longer than 329m in order to achieve the most safety benefits.
$Min\ t_{optimal\ lead}$	$t_{display\ delay}$	There is no designed display delay in the optimal design.

Table 3
The Optimal Design of the Connected Vehicle System Parameters Based on Example Inputs by Modeling the Normal Driver Reaction Time With 95% Confidence Interval

Example Inputs		**Outputs (Based on example inputs)**							
		Outputs of parameter setting thresholds		Outputs of the human reaction time model		Outputs of the Message Notification Parameters			
Total time $t_{total}(i)$ =15s	$t_{detect}(i)$ (second)	*Available range of* $t_{total\ response}(i)$ (second)	*Minimum acceptable lead time* $(Min\ t_{lead}(i,j))$ (second)	*Reaction Time RT*	*Minimum Safe Headw* $Mint_{safe}$ (i,j)	*Maximum available message notification delay* $(Max\ t_{MND})$ (second)	*Maximum Available machine processing time* $(Maxt_{machine})$ (second)	*Minimum acceptable message notification range* (*MinMNR*) (meter)	*Designed display delay* $t_{display\ delay}$ (second)
$t_{machine}$ *range:* [50-200ms]	1	≥10.2	4.5			9.3	0.2	329	3.8
	2					8.3	0.2	329	2.8
	3					7.3	0.2	329	1.8
	4					6.3	0.2	329	0.8
Initial velocity $v_i(t)$=19.81 m/s.	5	[4.7, 10.2]	4.5			5.3	0.2	329	0
	6					4.3	0.2	329	0
	7			2.49-2.75 with 95% C.I.	4.34-4.60 with 95% C.I.	3.3	0.2	329	0
	8					2.3	0.2	329	0
	9s					1.3	0.2	329	0
Max deceleration $a_i(t)$ =6.37 m/s^2	10					0.3	0.2	329	0
	10.3	[4.54, 4.7]	4.34			0.46	0.05	330	0
	11	≤ 4.39	4.34			0	0	437	0
	12					0	0	520	0
	13					0	0	776	0
	14					0	0	1075	0

Table 4
The Optimal Design of the Connected Vehicle System Parameters Based on Example Inputs by Modeling the Normal Driver Reaction Time With 99% Confidence Interval

Example Inputs		**Outputs (Based on example inputs)**							
		Outputs of parameter setting thresholds		Outputs of the human reaction time model		Outputs of the Message Notification Parameters			
Total time $t_{total}(i,j)$ =15s	$t_{detect}(i)$ (second)	*Available range of* $t_{total\ response}(i$ (second)	*Minimum acceptable lead time* ($Min\ t_{lead}(i,j)$) (second)	*Reaction Time RT*	*Minimum Safe Headway* $Mint_{safe}(i,j)$	*Maximum available message notification Delay* ($Max\ t_{MND}$) (second)	*Maximum Available machine processing time* (*Max*$t_{machine}$) (second)	*Minimum acceptable message notification range* (*MinMNR*) (meter)	*Designed display delay* $t_{display\ delay}$ (second)
$t_{machine}$ *range:* [50-200ms]	1	≥10.2	4.5	2.45-2.79 with 99% C.I.	4.30-4.64 with 99% C.I.	9.3	0.2	329	3.8
	2					8.3	0.2	329	2.8
	3					7.3	0.2	329	1.8
Initial velocity $v_i(t)$=19.81 m/s.	4					6.3	0.2	329	0.8
	5	[4.7, 10.2]	4.5			5.3	0.2	329	0
	6					4.3	0.2	329	0
	7					3.3	0.2	329	0
	8					2.3	0.2	329	0
Max deceleration $a_i(t)$ =6.37 m/s^2	9s					1.3	0.2	329	0
	10					0.3	0.2	329	0
	10.3	[4.5, 4.7]	4.3			0.11	0.05	337	0
	11	≤ 4.35	4.3			0	0	354	0
	12					0	0	551	0
	13					0	0	806	0
	14					0	0	1123	0

Appendix: The Experiment Design to Explore the Optimal Lead Time (Wan, Wu, & Zhang, 2014)

1. Method

1.1 Participants

Thirty-two participants (24 males, 8 females) with an average age of 21.13 years (SD = 2.54) and an average lifetime driving experience of 40,054.62 miles (SD = 57,911.04) participated in the study. All of them were licensed drivers and had normal or corrected-to-normal vision. None of the drivers had previously participated in any simulator or crash avoidance studies.

1.2 Apparatus

A STISIM® driving simulator (STISIMDRIVE M100K, Systems Technology Inc, Hawthorne, CA) was used in the study. It comprises a Logitech Momo® steering wheel with force feedback (Logitech Inc, Fremont, CA), a throttle pedal, and a brake pedal. The resting position of the throttle pedal is 38.2° (the angle between the pedal surface and the ground) and the maximal throttle input is 15.2°. For the brake pedal, the resting position is 60.1° and the maximal brake input is 28.6°. The STISIM simulator was installed on a Dell Workstation (Precision 490, Dual Core Intel Xeon Processor 5130 2 GHz) with a 256 MB PCIe×16 nVidia graphics card, Sound Blaster® X-Fi™ system, and Dell A225 Stereo System. Driving scenarios were presented on a 27-inch LCD with 1920×1200 pixel resolution. A speaker in front of the participant provided auditory information in the form of a digitized human female voice with a speech rate of ~150 words/min and loudness level of ~70dB. Another speaker provided driving sound effects with a loudness level of ~55dB.

The behavioral measures (time elapsed (s), speed (m/s), acceleration (m/s^2), and distance to the initial location where the scenario starts (m)) were automatically collected from the driving simulator and outputted to another identical Dell Workstation. This computer would calculate the time to collision (TTC) in real time based on the vehicle's speed and acceleration at each time point. Once the calculated time to collision reached the expected value (lead time), the warning would be broadcasted.

1.3 Scenarios Setting

The experiment scenario was a simulated two-lane (in each direction) urban environment with traffic lights, and road signs (e.g., stop signs) involved. There were running vehicles in each direction. Speed limit signs with a constant speed limit of 45mph (20.12m/s) were displayed 200 feet (60.96m) in front of the driver. Participants were instructed to adjust their speed within the range from 40mph (17.88m/s) to 50mph (22.35m/s) as if they were driving a real vehicle on the road. No distracting in-vehicle task was involved. Visual cues were controlled in the present study. The views of participants were blocked by source vehicles, parked vehicles, approaching vehicles and buildings so that participants did not have visual cues of hazard vehicles before the auditory warnings. Therefore, the subject only relied on the warning to learn about the upcoming collision event.

Sixteen different collision scenarios were designed and programmed to represent the common forward collision events in real world. All collision events had a hazard vehicle violating traffic regulations (e.g. vehicle running a red light or stop sign) or exhibiting unsafe driving behaviors (e.g. ahead vehicle stopped suddenly). When there was a potential collision event, an auditory warning would sound before the appearance of any visual cues (e.g. the hazard vehicle running stop sign or braking light of ahead vehicles). Each warning message started with a signal word "Caution" and followed by a description of the collision scenario. The signal word was used for calling driver's attention to the warning message and the upcoming collision event. The description of collision scenario comprised the hazard vehicle's location and behavior, which provided the driver with specific information in order to reduce confusion. To make the warning as clear and concise as possible, the content of each warning message was determined by a focus group involving five native speakers.

1.4 Experiment Design

The current experiment adopted a one-factor experiment design with lead time as independent variable and collision rate and reduced kinetic energy as dependent variables. The lead time had 16 levels (0s, 1s, 1.5s, 2s, 2.5s, 3s, 3.5s, 4s, 4.5s, 5s, 6s, 8s, 10s, 15s, 30s, and 60s). When the lead time was 0, the warning sounded at the same time when the collision event happened. Each subject would go through all 16 collision events with each event assigned with one of the sixteen levels of lead time. The order of the assigned level of lead time and collision events was randomized.

To address the issue of a learning effect, normal traffic events at 120 intersections and on 121 road segments (e.g., a stop sign with pedestrians crossing the road, a red light with a crossing vehicle at the intersection, a horizontal curve, the emergence and departure of a lead vehicle, a parked vehicle in the parking lane, etc.) were designed and randomly assigned between the adjacent two collision events. Among the 16 collision scenarios, 8 scenarios randomly appeared at intersections and the other 8 collision scenarios randomly appeared at road segments. The distance between the adjacent two collision locations were randomly assigned between 1000 feet and 10,000 feet as long as such distance can fulfill the warning lead time. In addition, in order to prevent drivers from anticipating collision events in association with the emergence of warning messages, forty normal auditory messages such as weather forecast and news were presented to drivers with similar speech rate and loudness level of warning messages.

Upon arrival, all participants were first asked to sign a consent document and then complete the self-report questionnaire. After, all participants were briefed on the operation of the simulator and completed a Practice Block that allowed them to get familiar with the driving simulator control. The scenario in the Practice Block was designed similarly with the one in the Test Block. Following the Practice Block, participants completed the Test Block comprising 16 collision events under an urban environment. In the formal experiment, all participants were required to be observant of the traffic rules and try to keep the speed at 45mph.

The following behavioral measurements were automatically collected from the driving simulator: time elapsed (s), speed (ft/s), acceleration (ft/s^2), and distance (ft). These experimental driving data were used to obtain the dependent variables. The first dependent variable was collision, which specified whether there was collision between a subject's vehicle and a hazard vehicle. The collision rate was then calculated as the percentage of collisions for each level of lead time. The reduced kinetic energy of the subject's vehicle specified the impact reduction led by the warning messages. Because the mass of the vehicle can be different in reality, the reduced kinetic energy was calculated by the initial speed, reduced speed after driver responding to warnings, and a unit mass of vehicles in the current study. Based on the results of collision rate and reduced kinetic energy, the optimal range of lead time will be obtained to achieve best human performance in responses to warnings (i.e. lowest collision rate and highest reduced kinetic energy).

2. Results

A multivariate analysis of covariance (MANCOVA) was conducted with the measurements of potential safety benefit of the warning messages as dependent variables, and lifetime driving experience (driving experience (year) ×annual mileage (mile)) and initial velocity (instantaneous velocity when the warning message broadcasted) as covariates to determine if the safety benefit could be differentiated by the lead time of warnings. The MANCOVA analysis results indicated significant effects of lead time on collision rate ($F(15, 225)= 5.38$, $p<.001$) and reduced kinetic energy ($F(15, 225)=5.72$, $p<.001$) by controlling the initial speed and driving experience. Referring to Figure 6, there is an abrupt decrease of collision rate appearing with the lead time getting longer when the lead time is shorter than 4.5s; while the rate of such decrease tended to slow down when the lead time ranging from 4.5s to 10s and a slight pick-up occurred after the lead time getting longer than 10s.

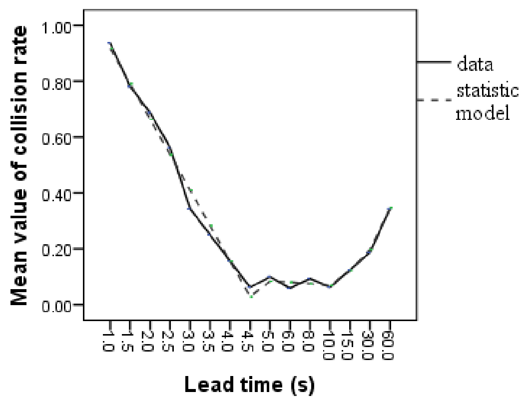


Figure 6. The collision rate at different levels of the lead time (Error bars: +/-1 SE).

According to Figure 7, a significant increase of reduced kinetic energy was suggested when the lead time shorter than 3.5s, while a slow decrease occurred after the lead time getting longer than 3.5s.

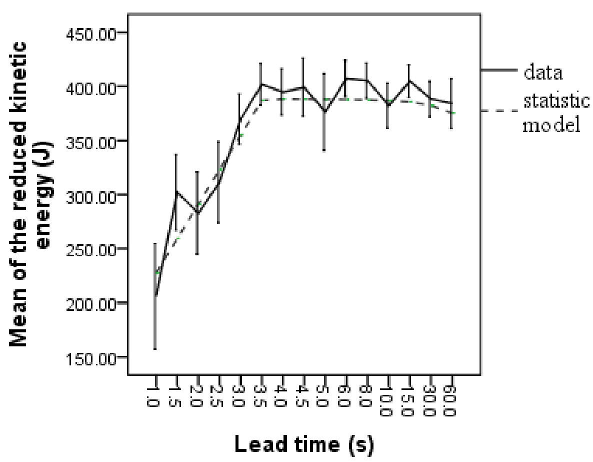


Figure 7. The reduced kinetic energy at different levels of the lead time (Error bars: +/-1 SE).