Who is Better at Anticipating Traffic Crashes, Human or Artificial Intelligence? A Gaze Data-based Exploratory Study

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1 Abstract

Enhancing roadway safety is a priority of transportation. Hence, Artificial Intelligence (AI)-powered crash anticipation is receiving growing attention, which aims to assist drivers and Automated Driving Systems (ADSs) in avoiding crashes. To gain the trust from ADS users, it is essential to benchmark the performance of AI models against humans. This paper establishes a gaze data-based method with the measures and metrics for evaluating human drivers’ ability to anticipate crashes. A laboratory experiment is designed and performed, wherein a screen-based eye tracker collects the gaze data of six volunteers when they are watching 100 videos that include both normal and risky driving scenes. Statistical analyses (at the 0.05 significance level) of experimental data show that on average drivers can anticipate a crash up to 2.61±0.100 seconds before it occurs. The chance whereby drivers have anticipated crashes before they occur, termed humans’ recall, is 0.928±0.0206. An AI model achieving the same recall value can anticipate crashes 2.22 seconds earlier than drivers on average, and the anticipation precision is 0.959. The study finds that crash involved traffic agents in driving scenes can vary drivers’ instant attention level, average attention level, and spatial attention distribution. This finding supports AI models that learn a dynamic spatial-temporal attention mechanism for strengthening their ability to anticipate crashes. Results from the comparison suggests benefits of keeping human-in-the-loop, including further refining AI
models with human inputs and using AI-rendered anticipation to increase the situational awareness of drivers in partial or conditional automation.

**Keywords:** Roadway safety, Human factors, Eye tracking, Gaze data, Artificial intelligence model, Crash anticipation, Driver attention

2 Introduction

Safety enhancement is a priority of transportation. In 2019, there were 6,756,000 crashes in the U.S. and 33,244 of these were fatal crashes [19]. 36,096 people were killed in the crashes, and 2740,000 people were injured. The consequence of crashes is huge. The average comprehensive cost is $11.1 million per death and $1.2 million per disabling [17]. The major factor in 94% of all fatal crashes is human error. Technologies that can enhance roadway safety are receiving growing attention. Automated Driving Systems (ADSs) [18] have a promise to help drivers avoid crashes.

The crash anticipation of ADSs has been an important research problem for computer vision and deep learning that develop deep neural networks to analyze dashcam videos for predicting crashes in advance [3, 24, 2, 15, 14]. AI models that can perform better than or comparably to humans, and those whose decisions are explainable to humans, are likely to gain trust from ADS users and the public [27, 22]. AI models were also developed to predict humans’ visual attentions [6, 5, 26, 20, 12], which are used for a wider range of safety applications such as saliency detection, hazard anticipation, attention allocation to name a few. AI-powered research on crash anticipation and safety enhancement is developing rapidly. Yet, how well humans anticipate crashes visually is less known.

Unlike existing AI models that have methods, measures, and metrics for evaluating the performance of crash anticipation, those for humans do not exist. Drivers’ anticipation of a crash is a subjective judgment. Precisely measuring their ability to anticipate crashes are challenging. Methods, measures, and metrics established for AI models may not directly applicable to drivers. For example, the earliness of an AI model in anticipating a crash is measured by the Time-To-Crash (TTC), from the earliest time when the AI model’s the prediction score has reached a threshold to the starting time of the crash. The TTC for a human is difficult to measure. The self estimation of TTC by drivers, for example using a survey method, is not precise and may have biases. It is difficult for a driver to tell exactly when she/he has been aware of the risk and anticipated a crash, 1 second earlier or 1.5 seconds earlier? The performance of an AI model in classifying a driving scene as normal or risky without seeing the an accident can be measured by metrics such as recall and precision. Yet, these are not directly applicable to humans because of the difficulty in measuring humans’ judgement precisely. Self-reporting methods usually are time-consuming.

An eye tracker is a sensor that can sense and measure humans’ gaze points, pupil diameters, and eye positions with high accuracy. It has been used widely for studying diagnostic systems by providing objective and quantitative evidence of users’ visual attention, or serving as an input device of interactive systems in a host of visually mediated applications [8]. For example, eye trackers can extract humans’ fixation points from their gaze points. Fixation points of a person can tell what she/he attended to, when, and how long, thus revealing the person’s thinking, reasoning, responding, and judgment. Metrics created based on humans’ fixations may provide accurate measurements for inferring drivers’ ability to anticipate crashes.

Facing the need for studying humans’ ability to anticipate traffic crashes and the lack of methods, measures, and metrics for the research, this paper is motivated to perform a gaze data-based
exploratory study, which aims to reduce the gap to the rapid advancement of AI research. Contributions of this paper are threefold:

- gaze data-based methods, measures, and metrics for measuring drivers’ ability to anticipate traffic crashes in advance,
- a laboratory experimental study whereby gaze data were collected and analyzed for an inference of drivers’ ability in the crash anticipation, and
- a comparison between an AI model and humans on their crash anticipation performance.

The remainder of the paper is organized as the following. The next section reviews the related literature to determine the state-of-the-art. Then, the proposed methods, measures, and metrics for assessing humans’ ability to anticipate traffic crashes are presented. After that, results from an experimental study are discussed, and major research findings are summarized. At the end, the paper concludes the study and proposes future work.

3 Literature Review

Eye tracker has been adopted by transportation safety studies since the 2000s. In the early stage, it was mainly used for understanding drivers’ behavior. For example, the situational awareness of drivers increases in high levels of automation, which is more likely to happen in scenarios that encourage drivers to gaze the road center [16]. Geometric and illumination conditions of highways are found to influence drivers’ visual attention [23]. Drivers often concentrated on the end of the road in front their vehicles [6]. Gaze data are also used for detection of drowsiness [21, 4], lane change [13, 11, 7], and hazard perception [1, 10]. For example, results from [21] showed that gazing time is related to the drowsiness level with a statistical significance. [13] proposed a model for identifying drivers’ implicit intent of lane changing through analyzing their pupil size change. By measuring the fixation duration on a danger area, training is found to be effective for improving hazard anticipation [10].

The glance-monitoring technology enhanced our theoretical understanding of drivers’ behavior and, thus, it can be further used for roadway safety enhancement [25]. Crash anticipation of ADS is advantageous for avoiding crashes. Attention anticipation serves the purpose of crash anticipation. For example, [5] proposed a human-like driving model that uses a convolutional-deconvolutional neural network to predict drivers’ eye fixations by providing the most relevant regions or targets, thus largely reducing the interference of irrelevant scene information. [26] built a driver attention prediction model that uses driver eye movements to identify more crucial driving moments and weight them more during model training. More attention prediction models were proposed including, but not limited to, a top-down attention guided framework designed to simulate a driver’s attention areas [6], a computer vision model DR(eye)VE based on a multi-branch deep architecture to estimate surrounding areas attracted more attention from the driver [20], and a data-driven multi-resolution neural network for attention prediction using calibration-free gaze data on dual-view driving scenes [12]. Applications of those neural networks implicitly assume that humans’ visual attention is highly reliable and effective. This assumption needs to be verified.

Inspired by humans’ visual attention behavior, a steam of deep learning research has integrated human-like attention models in crash anticipation neural networks. [3] and [2] all learned a spatial attention model that weighed different traffic agents for crash anticipation. [14] developed a dynamic
spatial-temporal attention model that largely improves the crash anticipation performance. Unlike these attention models learnt from crash video data, [15] developed a spatio-temporal attention mechanism from big crash report data, which supplements the attention learnt from crash video data by extending theearliness of risk perception. Although those neural networks for crash anticipation have good performance, they are like a black-box for ADS users and the public. AI models that are explainable to humans are more likely to gain the trust from users and be accepted by them [27, 22]. An intuitive method to improve the explainability of these AI models is to reveal how humans are making the same decision.

4 Methods, Measures, and Metrics

4.1 Gaze Data Collection

This study collected drivers' gaze data by letting participants watch dashcam captured videos of driving scenes in the lab setting. This approach has been proved to be valid and it has some advantages over collecting the data in the field study [7]. 100 videos of diverse driving scenes, indexed by \( v \), were sampled from the CCD dataset [2]. 50 of these are positive videos that each contains a crash, and the remaining 50 are negative videos that have no crash at all. These 50 positive videos are a sample of risky driving scenes and the 50 negative videos are a sample of normal driving scenes. Each video lasts 5 seconds and the frequency of the videos is 10 Hz. That is, each video is a sequence of 50 frames of images, indexed by \( t \). The starting time of the crash in each positive video is random, ranging from 3 to 5 seconds. The sequence of the 100 videos were randomized so that subjects did not know the class of the next video. A one-second interval of a blank image is placed into any two adjacent videos so that participants have a chance to rest for a short period before transitioning to the next video. Therefore, the entire video sequence for collecting human gaze points lasts 10 minutes.

Tobii Pro Fusion is a screen-based eye tracker used in this study for collecting gaze points. The eye tracker provides the coordinates of each gaze point on a video frame and the timestamp. The frequency of the eye tracker is 120 Hz, which allows for collecting up to 12 gaze points per frame from each participant, approximately. According to their angular speed, gaze points are classified as fixation points, saccade points, or unknown. Fixations are further defined. A group of successive fixation points of a person is named a fixation. Let \( k \) be the index of the sequential fixations of a participant in watching a video. A fixation is described as

\[
F_k = \{s_k, S_k, C_k\},
\]

where \( s_k \) is the starting time of the fixation, \( S_k \) is its duration, and \( C_k \) is its coordinates calculated as the centroid of gaze points belonging to this fixation. Regions of a frame where drivers fixates on are those attracting their attention. The time series of fixation points of a driver can tell what attracts the driver's attention, when, and how long.

The study invited six volunteers to participate in the study. Their ages are between 21~45 years old. All participants have a drivers' license with 2~18 years driving experience. Each volunteer watched the video sequence twice. They took a break for at least 30 minutes between the two times of experiments. In total, the study collected 720,000 gaze points from this study, approximately, about 144 gaze points per frame. The size is comparable to those in the literature.
4.2 Measuring the Earliness of Crash Anticipation

While metrics for measuring the earliness of AI models in anticipating future crashes are well established, those for humans do not exist. This study developed metrics for measuring the earliness of drivers in anticipating traffic crashes.

4.2.1 Earliness of Drivers’ Anticipation

FIGURE 1 illustrates the sequential events associated with a positive video. The earliest time when a Crash-Involved Object (CIO) appears in the video splits each positive video into two stages: the duration before any CIO appears, $T_B$, and the duration with CIOs, $T_A$. After a CIO appears, the driver may not attend to it immediately. Latency, $L$, is defined as the duration from the earliest time a CIO appears to the first time that the driver’s fixation point falls on a CIO. If there are multiple CIOs, the time when the earliest appeared CIO shows in the video is taken as the start of the latency. A short latency indicates a better ability to anticipate crashes earlier.

Time-To-Crash ($TTC$) is defined as the time span from the time a crash has been anticipated to the start of the crash. The longer the $TTC$ value, the earlier the crash anticipation. Measuring $TTC$ for drivers is difficult because their anticipation of a crash is a subjective judgment. However, it is safe to claim that the driver anticipates the occurrence of a crash somewhen between the earliest time a CIO captures the driver’s attention and the start of the crash. This time period is termed early attention duration, $D$. During this period, the driver’s attention on CIOs accumulates, and so the driver’s perception of the crash risk is developing. $D$ is the upper boundary of $TTC$ (i.e., $D \geq TTC$) and $D$ can be measured accurately by an eye tracker. Therefore, this study chose to use the early attention duration to infer drivers’ $TTC$. $D$ varies among drivers and driving scenes. $mD$ denotes the video-level mean value of different participants’ $D$ values.

![Diagram](image)

Figure 1: Schematic diagram for defining the measures and metrics for the earliness in crash anticipation

4.2.2 Earliness of AI’s Anticipation

This study used the AI model that [14] recently developed to represent crash anticipation models because it establishes a new state-of-the-art. Videos are in two classes - positive (normal) and negative (risky). At time $t$, the AI model reads the frame that the dashcam captures at that time to predict the class of the video. The prediction scores are further converted to the softmax
probability of anticipating a crash in future frames, \( a_t \). As FIGURE 2 illustrates, the \( \text{TTC} \) that the AI model achieves is defined as the earliest time when \( a_t \) exceeds a pre-specified threshold \( \bar{a} \):

\[
\text{TTC}(\bar{a}) = \max\{t - \tau | a_t \geq \bar{a}, 0 \leq t \leq \tau\},
\]

where \( \tau \) is the start of the crash. \( \text{TTC}(\bar{a}) \) means \( \text{TTC} \) is varied by the choice of the threshold value \( \bar{a} \). The expectation of \( \text{TTC} \) with respect to \( \bar{a} \) is defined as the mean \( \text{TTC} \) for the AI model:

\[
m\text{TTC} = E_{\bar{a}}[\text{TTC}(\bar{a})].
\]

4.3 Spatial Attention Allocation

In this study, a method is developed to measure how drivers allocate their visual attention spatially. This allows for comparing the spatial attention allocation by the AI model.

4.3.1 Spatial Attention Learned by the AI model

Drivers have both global visual perception of the overall driving scene and attention on specific traffic agents (e.g., pedestrians, vehicles, and traffic signs). Inspired by humans’ visual behavior in driving scenes, AI models detect traffic agents from frames and extract their features. The agent-level features are combined with the frame-level global feature, becoming the input to the AI model. For example, [14] attempts to detect up to \( N \) traffic agents, indexed by \( n \), from each frame. These agents are from the classes of pedestrian, car, bus, motorcycle, and traffic sign. The bounding box of agent \( n \) in frame \( t \) of a video, \( B_{t,n} \), is defined by the coordinates of the lower left point \( (x_{t,n,1}, y_{t,n,1}) \) and the upper right point \( (x_{t,n,2}, y_{t,n,2}) \) of the box:

\[
B_{t,n} = \{(x_{t,n,1}, y_{t,n,1}), (x_{t,n,2}, y_{t,n,2})\}.
\]

Spatial attention weights on these agents, \( w_{t,n} \), are learned by the AI model for aggregating the agent-level features. \( \sum_{n=1}^{N} w_{t,n} = 1 \) for any frame of any video. The higher the weight on an agent, the more attention the agent receives in the crash anticipation.
4.3.2 Spatial Attention Allocation by Drivers

Unlike the AI model that has spatial attention on multiple agents, a human can focus on only one spot at one time. Therefore, the study defines drivers’ spatial attention at each frame by collecting fixation points from multiple participants and then allocating the points to the bounding boxes that the AI model proposes. Figure 3 illustrates an example wherein the yellow boxes represent regions of interests that the AI model proposes. Many of them are the bounding boxes of correctly detected traffic agents. Some fixation points on or near some of the bounding boxes. Here, \( \tilde{w}_{t,n} \) represents the percentage of fixation points in frame \( t \) of a video which are on or near the bounding box of agent \( n \) in the frame. Drivers may look at other traffic agents or regions rather than those \( N \) agents proposed by the AI model. Therefore, \( \tilde{w}_{t,N+1} \) is created to capture the percentage of fixations points in frame \( t \) which do not fall on any of the \( N \) bounding boxes, and \( \sum_{n=1}^{N+1} \tilde{w}_{t,n} = 1. \)

Figure 3: Spatial distribution of fixation points on a frame with AI proposed regions of interests

Let \( \tilde{w}_t = [\tilde{w}_{t,1}, \ldots, \tilde{w}_{t,N+1}] \) be the vector of drivers’ spatial attention weights in frame \( t \), and \( w_t = [w_{t,1}, \ldots, w_{t,N}, 0] \) be the AI model’s weight vector. A distance between these two vectors,

\[
d_t = ||\tilde{w}_1 - w_t||_2
\]

measures the dissimilarity of their spatial attention at frame \( t \), for \( t = 1, \ldots, T \).

4.4 Drivers’ Early Attention Level on Crash Involved Objects

Coming to the early attention duration \( D \) of a driver in watching a video, CIOs have caught the driver’ attention, as Figure 1 illustrates. The more attention that CIOs receive during \( D \), the larger of the likelihood that the driver has perceived the crash risk. This study annotated the CIOs in the 50 positive videos using the VGG annotator [9]. \( B_{t,n'} \) denotes the bounding box of the \( n' \)th CIO in frame \( t \) of a video. Since not all gaze points are fixation points, fixations may just be part of any time period. For example, the driver’s cumulative fixation duration, as a fraction of the the early attention duration, is calculated as
\[ \rho_F(D) = \frac{(\cup_k[s_k, s_k + S_k]) \cap [T_B + L, T_B + L + D]}{D}. \]  

(6)

\( \rho_F(D) \) measures the average attention level of the driver during her/his early attention duration \( D \).

The study also measures the driver’s cumulative fixation duration on CIOs, as a fraction of the early attention duration:

\[ \rho_R(D) = \frac{(\cup_k[s_k, s_k + S_k] \cdot 1\{C_k \in \cup_{t,n}B_{t,n}\}) \cap [T_B + L, T_B + L + D]}{D}. \]  

(7)

\( \rho_R(D) \) is the average attention level of the driver on CIOs during \( D \). The ratio \( \rho_R(D)/\rho_F(D) \) measures the fraction of the driver’s average attention in \( D \) allocated to CIOs. The higher this ratio is, the larger the likelihood whereby the driver has perceived the crash risk and thus anticipated a crash in advance. In the remainder of the paper.

4.5 Reliability in Crash Anticipation

Metrics for the reliability of AI models in crash anticipation are well established, but not the counterpart of human drivers. Thereby, this study established the metrics for measuring the reliability of drivers in crash anticipation.

4.5.1 Reliability of the AI Model

The reliability of the AI model in crash anticipation is built on its ability to successfully classify a testing dataset, like the 100 videos in this study, before crashes occur. Commonly used metrics include recall and precision:

\[ R = \frac{\text{#correctly predicted positive videos}}{\text{#positive videos}}. \]  

(8)

\[ P = \frac{\text{#correctly predicted positive videos}}{\text{#positive predictions}}. \]  

(9)

The recall and precision values are varied by the choice of the classification threshold value \( \bar{a} \). Accordingly, a precision-recall curve can be obtained. Let \( P_R \) be the precision value at a specific recall value on the curve. The average precision is the area below the precision-recall curve, calculated as

\[ AP = \int P_R dR, \]  

(10)

which is independent of the threshold value \( \bar{a} \).

4.5.2 Reliability of Drivers’ Anticipation

Due to the difficulty in evaluating the drivers’ subjective judgement of video classes, this study is not able to precisely measure the recall and precision of a driver in anticipating crashes from the sample of videos. Instead, their upper bounds are estimated based on the driver’s fixation points. On a positive video, if a driver never fixated on CIOs before the crash occurs, the driver failed to perceive the risk in advance. This driver’s classification result on this positive video must be a false negative. However, having fixations on CIOs before the crash occurs is a necessary condition, but
not a sufficient condition for a driver to develop the early perception of crash risk. Therefore, the
study defines

\[ R_{in} = \frac{\text{\# positive videos wherein CIOs receive attention before the crashes occur}}{\text{\# positive videos}} \]  

(11)
as the upper bound of a driver’s recall. Drivers’ false positive rate usually is low and the consequence
of a false positive classification is way less severe than that of a false positive. Therefore, this study
assumes drivers’ precision is assumed 100% in this study.

5 Result Analyses

With the methods, measures, and metrics developed in this study, humans’ ability to anticipate
traffic crashes are analyzed and compared to the AI model. The significance level \( \alpha \) is 0.05 in all
the statistical analyses.

5.1 Temporal and Spatial Dynamics of Drivers’ Attention

5.1.1 Temporal Dynamics of Drivers’ Instant Attention Level

A portion of a driver’s gaze points on each frame is fixation points. The driver’s fixation points
on each frame in percent is a proxy of the driver’s instant attention level in the experimental study. Results pertaining to the positive
videos are in the first row, and those with the negative videos are displayed in the second row. The two time series plots in the first column are individual participants’ instant attention level. Overall, a driver’s instant attention level is dynamic, varying from one frame to another frame and
from one video to another video. Drivers’ instant attention level on negative videos is more stable
along the timeline than that on positive videos. Plots in columns 2 and 3 are example time series
of instant attention level. The plots indicate that the participant’s instant attention level could
be varied largely by the occurrence of crashes. Column 4 further shows the distributions of the
instant attention level. The two distributions have different shapes, central locations, and range,
indicating drivers’ instant attention level can be varied by driving scene classes. For example, the
mean instant attention level on risky scenes is 0.85±0.004 and that on normal scenes is 0.82±0.004
(\( \alpha = 0.05 \)). The instant attention level on risky scenes is distributed more widely (from 0.25 to 1)
than that on normal scenes (from 0.5 to 1).

5.1.2 Spatial Distribution of Drivers’ Attention

The spatial distribution of drivers’ fixations represents their spatial attention. FIGURE 5 shows the
heat maps of fixations for the two classes of videos. Colored regions in the heat maps are regions with
fixations, and red colored spots are regions with a high density of fixations. Differences between the
two heat maps are noticed. Firstly, fixations on the positive videos span wider along the horizontal
line than on the vertical line, whereas the distribution asymmetry is minimal for fixations on the
negative videos. Secondly, red spots in the heat map of the negative videos are clustered closely on
a narrower area at the center of frames, whereas those of the positive videos clearly have a wider
distribution. The heat map of fixations on the negative videos reveals the attention behavior of
drivers in normal driving scenes. That is, drivers often fixate on the end of the road in front of their
vehicles and check the surrounding traffic agents and the environment occasionally. The heat map of fixations on the positive videos indicates that drivers look at surroundings more often instead of a straight-ahead stare when they are driving in risky scenes. That is, CIOs and their motions could partially attract drivers' attention away from what they normally fixate.

5.2 Earliness in Crash Anticipation

5.2.1 How Early Can Drivers Anticipate a Crash?

Both the early attention duration $D$ and the latency $L$ are metrics of the earliness of drivers in the crash anticipation. Among the 600 experiments on the positive videos, there are 27 experiments wherein the participant missed the CIOs. Figure 6 displays the distributions of the latency $L$ and the early attention duration $D$ based on the data from the remaining 573 experiments. From the statistics in Figure 6a, drivers’ mean latency is $0.81\pm0.078$ seconds ($\alpha = 0.05$). That is, on average,
drivers notice CIOs 0.73~0.89 seconds after they appear. After CIOs showed up in the video, with 70% chance drivers will notice the CIOs within 1 second. But the latency has a wide distribution, with a long tail skewed to the right, indicating the latency could be long for some drivers under some circumstances. The statistics in Figure 6b indicates the mean value of the early attention duration $D$ is 2.61±0.100 seconds ($\alpha = 0.05$). That is, on average drivers can anticipate traffic crashes up to 2.61 seconds in advance. The chance that $D$ is longer than 2 seconds is about 70%, and the chance that it is longer than 3 seconds is reduced to 35%. A negative value of $D$ means the driver did not notice the COIs before the crash occurs.

![Figure 6: Distributions of the latency $L$ and the early attention duration $D$](image)

### 5.2.2 Does the Earliness in Crash Anticipation vary Among Drivers?

A one-way ANOVA was performed to determine if the early attention duration $D$ varies among drivers. The null hypothesis is that all participants have the same mean value of $D$. The critical F-value $F_{0.05}(6 - 1, 100 - 1)$ at $\alpha = 0.05$ is 2.31. The ANOVA on $D$ shows the F-value and P-value are 3.5695 (> 2.31) and 0.0035 (< 0.05), respectively. Therefore, the null hypothesis is rejected safely, indicating at least one participant has different mean value of $D$. Similarly, the ANOVA on latency $L$ shows F-value and P-value are 5.6809 (> 2.31) and 0.00004 (< 0.05), respectively. Again, the null hypothesis, which says all participants have the same mean value of $L$, is rejected at the 0.05 significance level, meaning that at least one participant has a different mean value of the latency than other participants. The ANOVA studies indicate drivers are heterogeneous in terms of the earliness in crash anticipation.

### 5.2.3 Is the Earliness of Crash Anticipation Varied by Ego-vehicle Involved/Uninvolved Crashes?

Among the 50 positive videos, ego-vehicle involved and uninvolved crashes respectively count for 50%. Figures 7a and 7b are the distributions of the early attention duration $D$ by crash type. The mean values of $D$ are 2.28±0.135 seconds and 2.96±0.138 seconds ($\alpha = 0.05$) for ego-vehicle involved and uninvolved crashes, respectively. That is, the mean value of drivers’ early attention duration for ego-vehicle involved crashes is 0.68 seconds shorter than ego-vehicle uninvolved crashes at the 5% significance level. In 4 out of the 300 experiments on the ego-vehicle involved crashes, the participants never fixated on CIOs; in another 3 experiments, the participants noticed CIOs
Figure 7: Distributions of $D$ and $L$ on ego-vehicle involved/uninvolved accidents
but after the crash happened. Yet, these counts for ego-vehicle uninvolved crashes are 23 and 10. That is, 97.7 ± 1.71% ego-vehicle involved crashes can be anticipated by drivers, whereas they can anticipate only 89.0 ± 3.54% ego-vehicle uninvolved crashes. Although the mean values of drivers’ early attention duration for ego-vehicle uninvolved and involved crashes are similar, drivers are more likely to miss anticipating ego-vehicle uninvolved crashes.

FIGURE 7c and 7d are distributions of the latency $L$ by accident type. The mean values of $L$ are 0.92 ± 0.101 seconds and 0.70 ± 0.119 seconds ($\alpha = 0.05$) for ego-vehicle involved and uninvolved crashes, respectively. The latency varies more widely on ego-vehicle uninvolved crashes (from 0 to 4.9 seconds) than that on ego-vehicle involved crashes (from 0 to 3.6 seconds). The observation, again, confirms that drivers are more likely to fail in anticipating ego-vehicle uninvolved crashes although on average they fixate on CIOs of such accidents earlier.

5.2.4 Whose is Earlier in Crash Anticipation, Human or AI?

FIGURE 8 compares drivers’ early attention duration $D$ with $mTTC$ of the AI model, on each of the 50 positive videos. Each dot is the $D$ value obtained from one experiment, and 573 effective values are obtained from the 600 experiments. The green line is the video-level mean value of $D$, denoted by $mD$, and the red line is the video-level $mTTC$. Only 13 out of 573 values of $D$ exceed their corresponding $mTTC$, and only 3 out of 50 $mD$ values are longer than their corresponding $mTTC$. The video-level difference between $mTTC$ and $mD$ ranges from 0.04 to 4.61 on the 50 videos. The mean difference is 2.25 ± 0.299, greater than 0 ($\alpha = 0.05$). Since $D$ is the upper boundary of drivers’ $TTC$, the difference in $mTTC$ between the AI model and humans is expected to be larger than 2.25 seconds. From the analysis, it is concluded that on average the AI model is at least 2.25 seconds earlier than drivers in anticipating traffic crashes.

This study further split the video-level $mTTC$ and $mD$ from Figure 8 by accident type. The boxplots are presented in FIGURE 9. FIGURE 9a compares the distributions of THE video-level
$mTTC$ on ego-vehicle uninvolved crashes and involved crashes. The mean value of the former is 4.89 seconds whereas 4.72 seconds for the latter. While their mean values are very close, the video-level $mTTC$ on ego-vehicle involved crashes is wider than that of uninvolved crashes. The max value is 5.0 for both of them, but the min values are 2.5 and 4.76 for ego-vehicle involved and uninvolved crashes, respectively. FIGURE 9b shows the boxplots of video-level $mD$ by accident type. Compared to AI’s video-level $mTTC$, drivers’ video-level $mD$ has a wider IQR on both types of crashes. From the figure it can be concluded that the AI model is not only faster than humans in the crash anticipation, but less sensitive to the variation of driving scenes.

![Boxplots of video-level mTTC and mD](image)

(a) AI’s video-level mTTC  
(b) Drivers’ video-level mD

Figure 9: Comparison of AI’s $mTTC$ to humans’ $mD$, by crash type

### 5.3 Drivers’ Average Attention Level on CIOs Before Crashes Occur

FIGURE 10a compares drivers’ average attention level before fixating on CIOs, $\rho_F(T_B \cup L)$, with their average attention level during $D$, $\rho_F(D)$. Before drivers noticed CIOs, the distribution of $\rho_F(T_B \cup L)$ is located at 0.65 and slightly skew to the left (skewness=-1.02). During the early attention duration $D$, the location of drivers’ average attention level moves to 0.83 and the distribution becomes slimmer (kurtosis=6.94) with a long tail on the left (skewness=-2.41). That is, drivers’ average attention level has a clear change after they fixated on CIOs. The difference between the two distributions indicates drivers become more alert after they catch CIOs.

To determine the fraction of the average attention level during $D$ allocated to CIOs, the ratio $\rho_R(D)/\rho_F(D)$ defined in Equation (7) is calculated for each of the 560 experiments with a positive $D$ value. FIGURE 10b illustrates the distribution of the ratio $\rho_R(D)/\rho_F(D)$. The mean ratio value is $0.65 \pm 0.023$ ($\alpha = 0.05$). That is, on average and at the 5% significance level, 65% of the attention in the early attention duration is allocated to CIOs.

### 5.4 Reliability of Humans in Crash Anticipation

Drivers’ anticipation of a crash is a subjective judgment. As discussed early in the paper, it is difficult to precisely measure the recall and the precision of drivers in the crash anticipation. In 557 out of 600 experiments, participants fixated on CIOs during the early attention period. $R_H$ in this study is $0.9283 \pm 0.02064$. Because $R_H$ is an upper boundary of drivers’ true recall value, 0.9283 is the best chance that drivers may perceive the crash risk.

At the same recall value as humans, the precision that the AI model can achieve, $P_{R_H}$, is 0.9592, and the Time-to-Crash, $TTC_{R_H}$, is 4.830 seconds. The precision and TTA achieved by the
AI model at the same recall value are still full of promise, even humans may be 100% precise in their prediction.

The dissimilarity of the spatial attention distributions between humans and the AI model defined in Equation (5), $d_t$, is measured on each frame of each video. The mean value and the standard distribution of $d_t$ are 0.68 and 0.27, respectively. That is, the spatial attention allocation by the AI model is somewhat different than that by humans. If the spatial-temporal attention weights that the AI model learned are replaced by the attention weights calculated using humans’ fixation points, the ability of the AI model to anticipate crashes are deteriorated, according to TABLE 1. The comparison suggests that the dynamic spatial-temporal attention that AI model learned seems superior to humans’ attention for the crash anticipation. Although humans are not as early as the AI model in anticipating crashes and their attention is not better than that of the AI model, humans’ precision and recall values are not low. This indicates that humans have certain strengths in processing the sensed information to make a near-crash prediction.

|                  | AP   | $mTTC$ (sec) | $P_{RH}$ | $TTC_{RH}$ (sec) |
|------------------|------|--------------|----------|------------------|
| AI learned attention | 0.9484 | 4.8066 | 0.9592 | 4.8300 |
| Human fixation-based attention | 0.8877 | 4.7223 | 0.8545 | 4.7930 |

### 6 Research Findings

Drivers’ instant attention level is dynamic, varying over time and driving scenes. The instant attention level on normal driving scenes is relatively stable over time, and the estimated mean and standard deviation are 0.82 and 0.09, respectively. The instant attention level on risky scenes is less stable, has a wider range (0.25∼1), and a slightly higher mean value (0.85). Moreover, drivers’ average attention level in the early attention duration is 0.83±0.012, higher than the average attention level before CIOs appear (0.65±0.019). The temporal dynamics of drivers’ attention are evidences supporting AI models that learn temporally dynamic attention for the crash anticipation.
Drivers' spatial attention distribution on risky scenes differ from that on normal scenes. CIOs may attract drivers' attention away from what they usually fixate during driving. For instance, in the early anticipation duration, 65±2.3% of drivers' cumulative fixation duration is allocated to CIOs. The change of the spatial attention distribution under risky scenes and the large amount of attention attracted by CIOs in the early attention duration all support AI models that learn spatially dynamic attention for the crash anticipation.

The AI model’s mTTC is 2.25±0.299 seconds longer than mD, the upper boundary of drivers’ mTTC. Moreover, the AI model's mTTC is less sensitive to the variation of driving scenes than drivers because AI model’s mTTC has a smaller IQR than mD. That is, on average the AI model anticipates crashes at least 2.25 seconds before drivers do. The earliness of the AI model’s anticipation is a timely assistance to drivers or autonomous vehicles.

The chance that drivers noticed CIOs before the crash occurs and, thus, may develop the perception of the crash risk is 92.83±2.064%. The chance that drivers did not perceive the risk of ego-vehicle uninvolved crashes (with a false negative rate 11.0±3.54%) is higher than that of ego-vehicle involved crashes (with a false negative rate 2.3±1.71%). At the same level of recall, the AI model is 0.9592 precise in its prediction and the prediction on average is 2.22 seconds faster than humans. Therefore, humans and the AI model can collaboratively improve the roadway safety in partial or conditional automation.

Drivers are heterogeneous in their ability to anticipate crashes earlier, manifested by the not-all-equal mean values of the early attention duration among the participants (P-value =0.0035) and the not-all-equal mean values of the latency (P-value = 0.00004). The more consistent performance of the AI model would mitigate the negative consequence due to the lack of a good capability to anticipate crashes by some drivers.

7 Conclusion

This paper developed a gaze data based method with measures and metrics for evaluating drivers’ ability to anticipate traffic crashes. This establishment allows for performing comparative studies AI models of crash anticipation. An experiment was designed and performed to collect gaze data from six volunteers when they were watching dashcam captured traffic scene videos. Statistical analysis of the experimental data shows that on average drivers can anticipate a crash up to 2.61 seconds before it occurs. Drivers’ recall value is about 0.928. At the same recall value, the AI model can predict crashes 2.22 seconds earlier than drivers and achieve the 0.959 anticipation precision. To ADS users, the AI model’s performance is promising. The analysis also found that crash involved agents change drivers’ instant attention level, average attention level, and spatial attention distribution. The findings suggests learning a dynamic spatial-temporal attention mechanism and embedding it to crash anticipation neural networks. Humans and AI are found to have complementary strengths, thus forming a collaborative relationship between them will improve the crash anticipation capability.

The comparison between humans and AI in the study of crash anticipation can be further expanded. For example, to what extent do AI-proposed traffic agents overlap with those fixated by drivers? On traffic agents that attract attention from both AI and humans, what are the attention weights assigned by AI and by humans, respectively? Besides human fixations, other data captured by the eye tracker can also be included to perform an elaborated analysis. These include pupil diameters, the spatial leap of gaze points, and eye images data. To further explore these research questions, additional data will be collected from a larger size of subjects with more diverse
background. Data will be collected both from the field and in the lab using more comprehensive design of experiments. Improving the accuracy of object detection and creating a weakly-supervised object tracking deep neural network are desired to better support the study.

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