Intention of Risk-Taking Behavior at Unsignalized Intersections Under the Connected Vehicle Environment

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ABSTRACT

With the rapid emergence of connected vehicle (CV) technologies, there is a shortage of research to understand CV technology’s effect on drivers’ risk-taking behavioral intentions. This article aims to analyze driver responses to the real-time information by comparing their reactions to driving intentions between the CV and non-CV environments. A multi-group structural equation model (SEM) is employed to explore the heterogeneity in the relationships between behavioral intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions under the two different environments. This study reveals two key findings: 1) regarding driver responses to the theory of planned behavior (TPB) model, there are significant differences in attitudes and risk perceptions between the CV and non-CV environments; 2) irrespective of driving environments, risk-taking behavioral intentions are directly related to perceived behavioral control and risk perceptions. While intentions are directly related to attitudes but not associated with subjective norms under the non-CV environment. In contrast, intentions are directly related to subjective norms but not associated with attitude under the CV environment. The findings provide a theoretical basis for using TPB to evaluate CV technology’s effects and understanding the differences between the CV and non-CV environments.

INDEX TERMS

Connected vehicles, risky driving intentions, structural equation model, theory of planned behavior, unsignalized intersections.

I. INTRODUCTION

Traffic fatalities ranked the eighth leading cause of death, reached 1.35 million in 2016, and continues to rise steadily worldwide [1]. Around 90% of traffic crashes are related to human factors, and 41% caused by human recognition errors [2]. A variety of advanced ITS technologies have been applied to deal with this problem. Connected vehicle (CV) technologies, as an essential component of the intelligent connected vehicle system, have been employed to protect drivers from crashes due to human errors by providing real-time warning information. The key CV technologies include vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and infrastructure-to-vehicle (I2V) wireless communications [3]–[5]. With the development of information and communication technologies, V2I and V2V technologies can reduce injury severity by up to 80% of non-impaired crashes [6]. Furthermore, some researchers have proven that CV can help drivers to avoid being involved in crashes with the provision of real-time information by enhancing their awareness and attentiveness of risky situations [7], [8]. Therefore, improving traffic safety and operation has been the most important goal of CV technologies [9], [10].

Driver awareness of risky situations is difficult to measure but can be indirectly measured from their driving intentions in a specific situation [11]. Specifically, Yeo et al. [12] found
that drivers could effectively protect themselves from crashes caused by lane-closure on freeways with V2V technologies. Porfyri et al. [7] found that drivers would increase the headways appropriately to their preceding vehicle to avoid collisions when they were aware of the hazard through V2I technologies. Zhao et al. [13] found that drivers would follow the speed advised by the variable speed limit under the CV environment to escape from the potential danger in reduced visibility conditions.

Theory of planned behavior (TPB) has been proposed to explain and predict a person’s behavioral intentions [14], especially for aggressive behavioral intentions. Based on the TPB, some researchers [15]–[17] found that driving intentions were significantly affected by attitudes, subjective norms, risk perceptions, and perceived behavioral control in the traditional driving environment. Under the traditional driving environment, i.e., non-CV environment, drivers did not install the CV equipment and cannot receive real-time information. However, there is a shortage of researches in analyzing risky driving intentions for receiving real-time information under the CV environment. Because unsignalized intersections have been considered as one of the most dangerous facilities on highways [18]–[20], the intentions to risk-taking behaviors under the two different environments are tested at unsignalized intersections.

For these reasons, this article aims to fill the knowledge gap by analyzing the differences in driver responses to driving behavioral intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions between the CV and non-CV environments. This topic is important for both CV developers and governments to understand how CV technologies enhance the behavioral intentions of drivers in very dangerous locations. The findings from this study are expected to have useful practical implications for them.

II. THEORETICAL BACKGROUND

Fishbein et al. [21] proposed the theory of reasoned action (TRA) for identifying individual behaviors. The theory holds that when an individual has complete control over a specific behavior, his/her behavioral intentions (BI) have a direct effect on the behavior. In this theory, individuals’ behavioral intentions are affected by their “behavioral attitudes” and “subjective norms”. Simultaneously, their attitudes and subjective norms have a strong association with each other. However, the TRA assumes that behavioral intentions are mainly affected by individual variables, limiting the theory’s scope of application. Therefore, Ajzen [22] introduces a new variable, “perceived behavioral control,” into the TRA, forming the TPB. The TPB extended the TRA to improve the theoretical model’s explanatory ability and remain open for further addition of other relevant explanatory variables [17], [23], [24].

Ajzen [14] pointed out that attitudes, subjective norms, and perceived behavioral control were regarded as the main factors predicting whether a person wants to show a specific behavior or not. More specifically, the intentions to a particular behavior come from a positive evaluation of the advantages and disadvantages of that behavior (attitudes), the perceptual recognition of important people in the implementation of the behavior (subjective norms), and the expected control of the behavior (perceived behavioral control). The TPB model added risk perceptions that could accurately predict behavioral intentions [25]. Therefore, an extended version of TPB is formed. Furthermore, Hsieh [26] found that attitudes, subjective norms, risk perceptions, and perceived behavioral control towards behaviors were essential predictors of behavioral intentions.

Behavioral intentions (BI) are regarded as an indicator that expresses how hard people are willing to try and how much of an effort they are planning to make [14]. The stronger behavioral intentions people have, the more likely they would perform the behaviors [27]. The behavioral intentions in a particular manner are predictive of one’s actual behaviors [11], [28], [29]. Furthermore, the extended TPB is useful in predicting driving intentions and behaviors, such as cycling [28], pedestrians’ road crossing [30], and speeding [31].

Attitudes (ATT) are regarded as a positive or negative evaluation of behavioral intentions [14]. Attitudes describe an individual’s personal mindset towards a particular behavior. The way an individual thinks about a specific behavior (positive or negative) is related to his/her intentions to perform it [27]. The more positive someone’s attitude towards the actions, the higher the behavioral intentions, and the more likely it is to conduct the behaviors [16], [29], [32].

Subjective norms (SN) refer to the perceived social pressure on performing the behaviors. Subjective norms describe the views of people who are important to themselves on their behaviors [27]. When planning specific actions, people usually keep in mind the opinions of those, who are important to them. The substantial social pressure on someone to perform a behavior leads to an increase in the behavioral intentions as well as the tendency to perform the actions [16], [32], [33].

Perceived behavioral control (PBC) refers to the degree of control over a particular behavior by perceived promotional or hindering factors in the process of behavior execution [28]. PBC indicates how difficult it is for an individual to perform the behaviors. In addition to the indirect effects of intentions, PBC is also directly related to behaviors, which can occur if perceived behavioral control is closely associated with actual behavior control. The stronger the PBC of the behaviors, the stronger the behavioral intentions, and the more likely it is to produce the behaviors [29], [33].

Risk perceptions (RP) refer to cognitive interpretations regarding the probability of road traffic crashes and the potential severity of their consequences, which has a significant relation effect on drivers’ risky behavioral intentions [25], [34], [35]. The higher the risk perception level of someone who produces the behaviors, the lower behavioral intentions, and the less likely it is to have the actions [32], [33], [36].
Thus, we hypothesized that:

H1. Irrespective of the CV or non-CV environments, attitudes positively affect driving intentions significantly to take risky behaviors.

H2. Irrespective of the CV or non-CV environments, subjective norms positively affect driving intentions significantly to take risky behaviors.

H3. Irrespective of the CV or non-CV environments, perceived behavioral control has a significant positive effect on drivers’ intentions to take risky behaviors.

H4. Irrespective of the CV or non-CV environments, risk perceptions negatively affect drivers’ intentions to take risky behaviors.

H5. Irrespective of the CV or non-CV environments, risk perceptions negatively affect attitudes significantly to take risky behaviors.

H6. Irrespective of the CV or non-CV environments, risk perceptions negatively affect subjective norms significantly to take risky behaviors.

H7. Irrespective of the CV or non-CV environments, risk perceptions negatively affect subjective norms significantly to take risky behaviors.

H8. Drivers tend to have a significantly lower intention to take risky behavior under the CV environment than that under the non-CV environment.

H9. Drivers tend to have a significantly more negative attitude to take risky behavior under the CV environment than that under the non-CV environment.

H10. Drivers tend to have a significantly lower risk perception of risky behavior under the CV environment than that under the non-CV environment.

Based on the above hypotheses, we constructed a preliminary theoretical model of the risky driving intentions based on the TPB, as shown in Fig. 1.

FIGURE 1. Theoretical model framework.

III. METHODOLOGY
A. QUESTIONNAIRE DESIGN
To understand the differences in driver responses to TPB variables under the CV and non-CV environments, we took a conflict point at an unsignalized intersection as the test scenario [19], [20], [37]. As an intersection is a point where numerous vehicles, pedestrians, and bicycles meet from different directions. Thus, it is one of the most dangerous and congested road facilities due to the complexity of traffic conflict movement. Statistics showed half of the crashes occurred at intersections in San Francisco, California [38] and Victoria, Australia [39]. Because the majority of crashes occur at an intersection, many transportation researchers have investigated intersection safety [40].

Unsignalized intersections are common in rural areas of China. Meanwhile, there are no effective control measures to reduce traffic conflict points, so the probability of crashes at unsignalized intersections is higher than that at signalized intersections [38]. How to improve the safety and efficiency of unsignalized intersections has become an urgent problem to be solved worldwide. To address the above problems, many researchers [3], [4] have proposed that the CV technologies, which provide real-time guidance and warning information for drivers through V2V, V2I, and I2V wireless communication technologies, can be a solution by making drivers aware of dangerous situations. Thus, we chose to investigate the intentions of risky behavior at unsignalized intersections under the CV and non-CV environments.

After comprehending the two scenarios, respondents were asked if they intend to accelerate through the unsignalized intersections under the CV and the non-CV environments, respectively. More specifically, respondents receive real-time information from the in-vehicle device under the CV environment, while respondents under the non-CV environment do not. More detailed descriptions of these two environments are as follows:

Non-CV Environment: On a two-lane road, you are driving along the main road at 41 km/h and about to go across the unsignalized intersection ahead of you. At that moment, you can see a vehicle in your right direction approaching the intersection. The speed of the vehicle is the same as yours (Fig. 2a).

CV Environment: On a two-lane road, you are driving along the main road with a speed of 41 km/h and preparing to drive across the unsignalized intersection 42 meters ahead of you, while the in-vehicle system with CV technologies informs you, “Please slow down.” Because the in-vehicle equipment finds a vehicle without CV technology, which is approaching the intersection with 36 km/h from the minor road and distancing 40 meters from this intersection (Fig. 2b), in this situation, you have two options: 1) if you decelerate to 28.0 km/h or below in D2, the non-CV on the minor road will pass the D1 safely and arrives at D3; 2) if you accelerate to 54.4 km/h or above, but less than the speed limit (60 km/h) you also can pass the D1 safely and arrives at D4.

Based on the hypotheses previously explained in Fig. 1, respondents were asked to express their driving intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions to such two scenarios. In the two scenarios, respondents need to answer 15 questions (items) under the CV environment and the non-CV environment, respectively. These items adapt 5-point Likert scales. A more detailed description of each variable is described as follows:
Behavioral Intentions (BI). Driving intentions toward acceleration at an unsignalized intersection are measured by four items adapted from Zhou et al. [30]: “BI1: How likely is it that you would accelerate through the unsignalized intersection as described in the scenario? (unlikely/very likely)”; “BI2: How likely is it that you would accelerate through such an unsignalized intersection in the same manner in the near future? (unlikely/very likely)”; “BI3: How much do you expect to accelerate through an unsignalized intersection as described in the scenario? (not at all to very much)”; “BI4: How much do you expect to accelerate through such an unsignalized intersection in the same manner in the near future? (not at all to very much)”. Attitudes (ATT). Attitudes are measured by two items adapted from Zhou et al. [30]: “ATT1: I agree that accelerating through such an unsignalized intersection would get me to my destination more quickly. (strongly disagree to agree strongly)”; “ATT2: I agree that accelerating through such an unsignalized intersection would be safe and save my time. (strongly disagree to agree strongly)”. Subjective norms (SN). Two items are used to measure subjective norms [18]: “SN1: my parents, spouse or children would think that I could take a chance to accelerate through such an unsignalized intersection. (strongly disagree to agree strongly)”; “SN2: my friends or colleagues would think that I could take a chance to accelerate through such an unsignalized intersection. (strongly disagree to agree strongly)”. Perceived behavioral control (PBC). Three items, i.e., controllability, confidence, and capability, are used to measure perceived behavioral control [28], [41]. Controllability: “PBC1: It is easy for me to control myself from accelerating through such an unsignalized intersection”, strongly disagree/strongly agree. Confidence: “PBC2: I am confident that I can refrain from accelerating through such an unsignalized intersection. (strongly disagree to agree strongly)”. Capability: “PBC3: my capability can match the challenge of the situation when I accelerate through such an unsignalized intersection. (strongly disagree to agree strongly)”. Risk perceptions (RP). Four items adapted from previous works were used to measure each risk perception aspect [15], [19]. “RP1: I think being concerned about myself being injured in a crash if I accelerate through such an unsignalized intersection. (strongly disagree to strongly agree)”; “RP2: I think being concerned about hurting others in a crash if I accelerate through such an unsignalized intersection. (strongly disagree to strongly agree)”; “RP3: I think being worried about myself being injured in a crash if I accelerate through such an unsignalized intersection. (strongly disagree to strongly agree)”; “RP4: I think being worried for others being injured in a crash if I accelerate through such an unsignalized intersection. (strongly disagree to strongly agree)”. B. SAMPLE SIZE REQUIREMENTS AND PROCEDURES Referring to Kline [42], the minimum sample size for the SEM model is 200. Researchers are recommended to have a sample size at least 15 times the number of observed variables [43], which constitutes a minimum sample size requirement of 225 for this study. Following the maximum likelihood approach of SEM, we have supported the notion that a larger sample size would empower results’ generality. A pilot questionnaire survey was conducted during 25-29 September 2019, consisting of 30 drivers. Based on their feedback, the two scenarios and items of the questionnaire were revised to improve its clarity and readability. The primary survey was administered from 15-22 October 2019 by face-to-face interviews and an online survey. Before filling out the questionnaire, we obtained the informed consent of the respondents. We told them that the survey results would
TABLE 1. Descriptions of respondents’ socio-demographic information and driving experience (N = 980).

| Variables                                | Description & Definitions     | Frequency | Percent |
|------------------------------------------|--------------------------------|-----------|---------|
| Gender                                   | 0: Male                        | 689       | 70.3%   |
|                                          | 1: Female                       | 291       | 29.7%   |
| Age                                      | 1: 18-25                        | 230       | 23.5%   |
|                                          | 2: 26-30                        | 242       | 24.7%   |
|                                          | 3: 31-40                        | 317       | 32.3%   |
|                                          | 4: 41-50                        | 139       | 14.2%   |
|                                          | 5: 50+                          | 52        | 5.3%    |
| Employment status                        | 0: Stable salaried employees    | 379       | 38.7%   |
|                                          | 1: Unstable salaried employees  | 601       | 61.3%   |
| Education                                | 1: Middle school or less        | 24        | 2.4%    |
|                                          | 2: High school                  | 101       | 10.3%   |
|                                          | 3: Some college or Associate’s degree | 167     | 17.0%   |
|                                          | 4: Bachelor’s degree             | 412       | 42.0%   |
|                                          | 5: Master’s and beyond          | 276       | 28.2%   |
| Driving age                              | 1: Less than three years        | 340       | 34.7%   |
|                                          | 2: 3 to 6 years                 | 241       | 24.6%   |
|                                          | 3: More than six years          | 399       | 40.7%   |
| Annual driving mileage (kilometers)      | 1: Less than ten thousand       | 389       | 39.7%   |
|                                          | 2: Ten-thousand                 | 390       | 39.8%   |
|                                          | 3: Thirty-five thousand         | 136       | 13.9%   |
|                                          | 4: More than fifty thousand     | 65        | 6.6%    |
| Have you been involved in traffic crashes in the past three years? | 0: No                           | 405       | 41.3%   |
|                                          | 1: Yes                          | 575       | 58.7%   |
| Frequencies of crossing the unsignalized intersection per week | 1: Less than two times          | 436       | 44.5%   |
|                                          | 2: 2-4 times                    | 244       | 24.9%   |
|                                          | 3: More than four times         | 300       | 30.6%   |

For the face-to-face survey, we distributed the questionnaires to residents living in six administrative districts (Wangcheng, Kaifu, Furong, Yuelu, Tianxin, and Yuhua) in Changsha, China. The data for each district were collected and recorded by six investigators who stood at railway stations, shopping malls, and other places. We first confirmed that all the respondents have a driver’s license and then asked them to watch the videos about the CV and non-CV environments and ensured that they understood the two environments’ differences before filling in the questionnaire. We collected a total of 585 responses. After excluding survey data with incomplete information, 508 were available for analysis, with a significant 86.84% rate.

For the online survey, we have attached two videos to illustrate the CV and non-CV environments. All respondents were required to watch the videos and understand the two environments before answering the questionnaire. We collected 588 complete responses through the Star Asking Platform, an online platform for collecting questionnaire data. Using the IP address and filling time as the filtering mechanism, we excluded the survey data with invalid information to ensure that the respondents were drivers and filled in the information required in the responses carefully. A total of 472 available responses were obtained, with an effective rate of 80.27%.

Overall, there were a total of 980 valid responses including both online (web-based) and offline (face-to-face interview), with an effective rate of 83.55%.

C. RESPONDENTS

A total of 980 respondents (70.3% male, n = 689, 29.7% female, n = 291) are included in the data analysis. Respondents (n = 640) have been driving for more than three years at 65.3% percent. And 60.3% of the respondents travel more than 10,000 kilometers a year. Respondents with an age of 18-30 years have the largest proportion (48.2%), followed by 31-40 years old (32.3%). More than half of respondents (55.5%) drive at unsignalized intersections more than twice a week. 61.3% of respondents (n = 601) are unstable salaried employees who get income according to their performance, such as self-employed; and the rest of the respondents (n = 379) are stable salaried employees who obtain a fixed salary every month, such as government officers. 70.2% of respondents (n = 688) have bachelor’s degrees and above. More than half of the respondents (n = 575) have been involved in traffic crashes in past three years. And more detailed information on respondents’ characteristics and experiences as Table 1 shows.
To explore the relationship of latent variables that affect risky behavioral intentions, the structural equation model (SEM) is employed. SEM can analyze the relationships between the exogenous and endogenous latent variables and accommodate measurement errors when exploring these latent variables [44]. The model can also deal with multiple dependent variables, making up for traditional statistical models [45]. This model includes two components: the structural model and the measurement model, as Fig. 3 shows.

The structural model analyzes the path relationship between variables. The abstract latent variables are measured indirectly by the observed variables. The model combines factor analysis with path analysis. The specification of the structural model as (1) shows.

$$\eta = \Gamma \xi + B \eta + \zeta$$  

where
- $\eta$ is the vector of endogenous latent variables;
- $\Gamma$ is the path coefficient matrix between exogenous and endogenous latent variables;
- $\xi$ is the vector of exogenous latent variables;
- $B$ is the coefficient matrix of correlation between endogenous latent variables;
- $\zeta$ is the residual term that cannot be predicted or explained.

Meanwhile, as an explanatory model, the measurement model composes abstract latent variables and observed variables, confirming the relationship between measured variables and abstract latent variables.

The specification of the measurement model as (2) and (3) show.

$$Y = \Lambda_\gamma \eta + \epsilon$$  

$$X = \Lambda_\xi \xi + \delta$$

where
- $Y$ is the vector of endogenous measurement variables;
- $\Lambda_\gamma$ is the coefficient matrix for the effects of the endogenous latent variables on the observed variables;
- $\epsilon$ is the measurement error term of endogenous variables.
- $X$ is the vector of exogenous measurement variables;
- $\Lambda_\xi$ is the coefficient matrix for the effects of the exogenous latent variables on the observed variables;
- $\delta$ is the measurement error term of exogenous variables.

### IV. RESULTS

#### A. FACTOR ANALYSIS

We used SPSS 26.0 software for the factor analysis. Factor analysis is employed to integrate the original items into fewer factors and greatly reduce the data analysis workload [46]. The principal component analysis is used to determine the factor loadings. Furthermore, the maximum variance method is used for the interaction process. KMO = 0.847 and Bartlett’s test of sphericity show a significance level of $p < 0.001$, indicating that the data are suitable for factor analysis. We have removed the item (RP4) because of cross-loaded at a more excellent value than 0.32 [47]. The eigenvalues of the five factors are more significant than 1. The five elements (BI, ATT, SN, PBC, and RP) could explain 20.1%, 12.53%, 11.3%, 14.2%, and 14.6% of the variation. And the cumulative variance contribution rate is 72.774%. Each item’s factor loading under each factor is greater than 0.6, indicating that these variables have good construct validity and satisfy the questionnaire design requirements. The following Cronbach’s alpha is used to assess the reliability. All coefficients are greater than the general value of 0.6, which indicates that the questionnaire has adequate internal consistency and high reliability [48] (see Table 2).

#### B. CONFIRMATORY FACTOR ANALYSIS

Confirmatory factor analysis (CFA), as a measurement model of SEM, is employed to test the reliability and validity of the relationships between observed variables and latent variables using AMOS 24 software. These latent variables include driving intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions. Six indicators, Chi-square with degrees of freedom ($\chi^2/df$), Root Mean Square Error of Approximation (RMSEA), Goodness of Fit Index (GFI), adjusted goodness-of-fit index (AGFI), incremental fit index (IFI), and comparative fit index (CFI), are employed to evaluate the CFA model. More specifically, the Chi-square test with degrees of freedom ($\chi^2/df$) between 1 to 3 shows that the model fits the data well [49]. The RMSEA is less than 0.05, indicating a good fit [48]. The values are more significant than 0.90 on the GFI, AGFI, IFI, and CFI, which indicates a good model fit [49]. As Table 3 shows, $\chi^2/df$ of the initial fit was not up to standard. By checking the factor entry content and the factor load, we deleted the item (PBC1) with a lower loading. After that, all six indicators of model fit are good; hence the CFA model is acceptable.

Cronbach’s alpha ($\alpha$), factor loading (FL), composite reliability (CR), and average variance extracted (AVE) are applied to measure the available reliability and validity of the CFA model, as Table 4 shows. Cronbach’s alpha and CR refer to latent variables’ reliability or latent constructs underlying a set of observed indicator variables. As for validity indicators, FL and AVE reflect the observed variables’ predictive and explanatory ability to latent variables. Table 4 shows the acceptable reliability and validity of driving intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions as their Cronbach alpha ($\alpha$) and Composite
TABLE 2. Results of exploration factor analysis (N = 980).

| Construct                   | Items | Factor loading | Eigen-values | Variance explained (%) | Cumulative variance explained (%) | Cronbach’s alpha |
|-----------------------------|-------|----------------|--------------|-------------------------|-----------------------------------|------------------|
| Driving intentions          | B1i   | 0.685          | 2.814        | 20.100                  | 20.100                            | 0.85             |
|                             | B2i   | 0.798          |              |                         |                                   |                  |
|                             | B3i   | 0.871          |              |                         |                                   |                  |
|                             | B4i   | 0.834          |              |                         |                                   |                  |
| Attitudes                   | AT1i  | 0.851          | 1.755        | 12.533                  | 32.633                            | 0.82             |
|                             | AT2i  | 0.878          |              |                         |                                   |                  |
| Subjective norms            | SN1i  | 0.865          | 1.587        | 11.335                  | 43.968                            | 0.70             |
|                             | SN2i  | 0.826          |              |                         |                                   |                  |
| Perceived behavioral control| PBC1i | 0.707          | 1.989        | 14.208                  | 58.176                            | 0.72             |
|                             | PBC2i | 0.786          |              |                         |                                   |                  |
|                             | PBC3i | 0.784          |              |                         |                                   |                  |
| Risk perceptions            | RP1i  | 0.758          | 2.044        | 14.598                  | 72.774                            | 0.77             |
|                             | RP2i  | 0.728          |              |                         |                                   |                  |
|                             | RP3i  | 0.850          |              |                         |                                   |                  |

TABLE 3. Goodness fit indices of the CFA models (N = 980).

| Fit index            | χ²/df | RMSEA | GFI   | AGFI  | IFI   | CFI   |
|----------------------|-------|-------|-------|-------|-------|-------|
| Initial fit          | 3.604 | 0.036 | 0.982 | 0.972 | 0.984 | 0.984 |
| Measured value       | 2.851 | 0.031 | 0.988 | 0.980 | 0.991 | 0.991 |
| Standard value       | 1 < χ²/df < 3 | <0.05 | >0.90 | >0.90 | >0.90 | >0.90 |

TABLE 4. Evaluation indicators of the CFA models (N = 980).

| Factors               | Items | Factor loadings | Cronbach’s alpha value | CR | AVE  |
|-----------------------|-------|-----------------|------------------------|----|------|
| Driving intentions    | B1i   | 0.60            | 0.85                   | 0.86 | 0.62 |
|                       | B2i   | 0.73            |                        |     |      |
|                       | B3i   | 0.92            |                        |     |      |
|                       | B4i   | 0.85            |                        |     |      |
| Attitudes             | AT1i  | 0.87            | 0.82                   | 0.82 | 0.70 |
|                       | AT2i  | 0.80            |                        |     |      |
| Subjective norms      | SN1i  | 0.66            | 0.70                   | 0.70 | 0.55 |
|                       | SN2i  | 0.81            |                        |     |      |
| Perceived behavioral control | PBC2i | 0.78            | 0.74                   | 0.73 | 0.58 |
|                       | PBC3i | 0.74            |                        |     |      |
| Risk perceptions      | RP1i  | 0.82            | 0.77                   | 0.79 | 0.57 |
|                       | RP2i  | 0.84            |                        |     |      |
|                       | RP3i  | 0.57            |                        |     |      |

Reliability (CR) are generally above 0.6 [48]. The FL and AVE should be greater than 0.5 [50], [51].

C. ANALYSIS OF RELATIONSHIPS BETWEEN LATENT VARIABLES

To ensure the validation of all latent variables, we first exclude the potential multicollinearity of these variables. Pearson’s correlation coefficient is utilized to analyze the relationship among attitudes, subjective norms, perceived behavioral control, risk perceptions, and behavioral intentions [28].

Firstly, three indexes, kurtosis (KU), skewness (SK), and variance inflation factor (VIF), are employed to exclude the existing multicollinearity of variables by evaluating whether
TABLE 5. The correlation matrix between behavioral intentions and other factors of the scale (N = 980).

| Factors | BI   | ATT | SN     | PBC    | RP     |
|---------|------|-----|--------|--------|--------|
| BI      | 1    |     |        |        |        |
| ATT     | 0.354** | 1   |        |        |        |
| SN      | 0.269** | 0.318** | 1   |        |        |
| PBC     | 0.485** | 0.329** | 0.262** | 1    |        |
| RP      | -0.343** | -0.494** | -0.349** | -0.313** | 1    |

Note. ** p < 0.01 (two-tailed);

they follow a normal distribution or not. The KU’s absolute value is less than 2, indicating an acceptable fit [48]. The values of SK and VIF are less than 3 and 5, respectively, meaning a proper fit [48]. These three good fits present no severe bias to all variables’ normal distribution, which excludes multicollinearity.

Table 5 shows Pearson’s correlation coefficients for all variables. More specifically, attitudes, subjective norms, and perceived behavioral control are positively related to behavioral intentions. At the same time, risk perceptions are negatively associated with behavioral intentions to accelerate at unsignalized intersections in both scenarios. All variables have significant relationships with each other in two driving environments; hence, we consider them in the next analysis.

D. ANALYSIS OF DIFFERENCES BETWEEN THE TWO ENVIRONMENTS

The paired sample t-test is first employed to test the significance of latent variables. Then the Cohen’s d effect size is utilized to calculate the difference in these variables between two environments [52]. Table 6 shows means (M), standard deviations (SD), t-test differences, and Cohen’s d for all non-CV and CV environments variables.

From Table 6, there are significant differences in attitudes and risk perceptions to accelerate through an unsignalized intersection in the two situations where drivers can receive and cannot receive real-time information. Compared with the non-CV environment, drivers have higher risk perceptions and negative attitudes to accelerate through the CV environment’s unsignalized intersection. More specifically, seven items, BI1, BI4, ATT1, PBC2, RP1, RP2, RP3, have significant differences between the two environments. Drivers have higher values of BI1, PBC2, RP1, RP2, and RP3 and lower values of BI4 and ATT1 under the CV environment compared to the non-CV environment.

Cohen’s d values are employed to calculate the difference in behavioral intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions between two environments. The degree of differences larger with the increasing value of Cohen’s d values. Cohen’s d values between 0.2 and 0.4 indicate small effects, while the values between 0.5 and 0.7 show moderate effects, and the value greater than 0.8 consider as large effects [53]. Hence, risk perceptions have the most significant difference between the two environments, followed by attitudes.

E. PATH ANALYSIS

Path analysis, the structural model of SEM, has been widely used to analyze behavioral intentions [18], [27], [28]. Thus, this model explores factors that affect behavioral intentions when drivers are approaching the unsignalized intersections, using AMOS24.0 analysis software.

We set up a path analysis model to analyze the relationships between endogenous variables (behavioral intentions) and exogenous variables (attitudes, subjective norms, perceived behavioral control, and risk perceptions). Due to that, the goodness of fit indices for the initial model was unacceptable, new covariant relationships of the observed variables were added with the most extensive modification indices (MI) value to revise the model. The standardized estimates of the final model, as Fig. 4 shows.

Table 7 shows that six indicators (i.e., $\chi^2$/df, RMSEA, GFI, AGFI, IFI, and CFI) are acceptable in the final path analysis model. The final model explains 34% of the variance of
TABLE 6. Means (M), standard deviations (SD), t-test differences, and Cohen’s d effect size based on driving environments for all variables (N = 980).

|                  | Non-CV environment | CV environment | t(df) | p     | Cohen’s d |
|------------------|--------------------|----------------|-------|-------|-----------|
|                  | M  | SD  | M  | SD  |            |            |
| BI               | 1.60 | 0.72 | 1.56 | 0.68 | 1.305 (979) | 0.192 | 0.08 |
| BI1              | 1.86 | 1.05 | 1.59 | 0.82 | 6.237 | 0.000*** | 0.40 |
| BI2              | 1.65 | 0.92 | 1.67 | 0.87 | -0.634 | 0.526 | -0.02 |
| BI3              | 1.56 | 0.82 | 1.56 | 0.78 | 0.056 | 0.955 | 0.00 |
| BI4              | 1.35 | 0.68 | 1.43 | 0.73 | -2.400 | 0.017* | -0.15 |
| ATT              | 1.75 | 0.75 | 1.89 | 0.85 | -3.737 (979) | 0.000** | -0.24 |
| ATT1             | 1.71 | 0.83 | 1.96 | 0.91 | -6.016 | 0.000*** | -0.38 |
| ATT2             | 1.93 | 1.02 | 1.90 | 0.98 | -0.868 | 0.386 | 0.03 |
| SN               | 1.80 | 0.78 | 1.84 | 0.79 | -1.087 (979) | 0.277 | -0.07 |
| SN1              | 1.80 | 0.88 | 1.84 | 0.92 | -0.886 | 0.376 | -0.04 |
| SN2              | 1.79 | 0.87 | 1.84 | 0.93 | -1.059 | 0.290 | -0.06 |
| PBC              | 2.02 | 0.96 | 1.96 | 0.92 | 1.494 (979) | 0.066 | 0.10 |
| PBC2             | 2.09 | 1.06 | 1.97 | 1.01 | 2.633 | 0.000** | 0.17 |
| PBC3             | 1.95 | 1.12 | 1.94 | 1.03 | 0.101 | 0.919 | 0.01 |
| RP               | 4.35 | 0.65 | 3.96 | 0.72 | 11.362 (979) | 0.000*** | 0.73 |
| RP1              | 4.41 | 0.70 | 4.13 | 0.78 | 4.762 | 0.000*** | 0.30 |
| RP2              | 4.31 | 0.73 | 4.10 | 0.87 | 7.280 | 0.000*** | 0.47 |
| RP3              | 4.33 | 0.78 | 3.64 | 1.08 | 5.368 | 0.000*** | 0.34 |

Note. *p < 0.05; **p < 0.01; ***p < 0.001;

TABLE 7. Goodness fit indices of the final model for drivers’ risky behavioral intentions (N = 980).

| Fit index          | $\chi^2/df$ | RMSEA | GFI  | AGFI  | IFI   | CFI   |
|--------------------|-------------|-------|------|-------|-------|-------|
| Measured value     | 2.722       | 0.030 | 0.989| 0.980 | 0.992 | 0.992 |
| Standard value     | $<\chi^2/df<3$ | $<0.05$ | $>0.90$ | $>0.90$ | $>0.90$ | $>0.90$ |
| Adaptation judgment | Yes         | Yes   | Yes  | Yes   | Yes   | Yes   |

behavioral intentions to accelerate through the unsignalized intersections. More specifically, attitudes, subjective norms, and perceived behavioral control have significantly positive effects on behavioral intentions, while risk perceptions negatively affect such a situation. RP could also considerably affect behavioral intentions through attitudes, subjective norms, and perceived behavioral control.

F. MEDIATION ANALYSIS

The bootstrap procedure (5,000 resamples) is used to analyze the mediating effect with a 95% bias-corrected confidence interval (CI). If zero is not included on the CI between the lower and upper bound, the impact is statistically significant at $P < 0.05$ [48]. The results of the interaction between variables, as Table 8 shows. From Table 8, in the view of the total effects, risk perceptions have the most considerable impact on behavioral intentions (-0.437), followed by perceived behavioral control (0.386), attitudes (0.124), and subjective norms (0.082). Behavioral intentions increase with positive attitudes, subjective norms, and perceived behavioral control, decreasing negative risk perceptions.

G. MULTI-GROUP ANALYSIS

To understand the differences in driver responses to driving intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions in two environments, the multi-group analysis is applied [18]. Separately setting up the structural equation modeling (SEM) in different groups cannot demonstrate the configurable invariance across groups and has limitations in exploring the heterogeneity among groups. And the multi-group analysis can solve this problem by implementing research on the configurable invariance of multiple groups and simultaneously examining heterogeneous factors affecting driving intentions between groups.

The chi-square test tests the invariance of structural models in two groups. The critical ratio is applied to evaluate
The differences in the paths between the two environments. More specifically, there are significant differences in the paths between two groups with a critical ratio greater than 1.96 [54]. The goodness fit of the multi-group analysis, as Table 9 shows. Based on the comparison of the Chi-square test of the unconstrained model ($\chi^2 = 209.787; p < 0.001$) and the regression path constraint model (structural weights model; $\chi^2 = 321.246; p < 0.001$), we found that there is a significant difference in the relationship between TPB variables in two kinds of environment ($\chi^2 = 111.459; p < 0.001$). These TPB variables include driving intentions, attitudes, subjective norms, perceived behavioral control, and risk perceptions. Furthermore, the model accounts for 34% and 36% of driving behavioral intentions to accelerate through the unsignalized intersections under the non-CV (Fig. 5) and the CV environments (Fig. 6), respectively.

We test the differences in path estimation and structural covariance in the two kinds of environment. The critical ratio differences between parameters are calculated to test for differences. The regression path between risk perceptions and attitudes is significantly different (path diff. = 0.478; 95% CI [0.213; 0.779]; $p = 0.001$) for the non-CV environment ($\beta = −0.392$) and CV environment ($\beta = −0.608$). Finally, the regression path between attitude and behavioral intention is also significantly different (path diff. = 0.178; 95% CI [0.050; 0.330]; $p = 0.005$) for the non-CV environment ($\beta = 0.217$) and CV environment ($\beta = 0.051$).

In summary, attitudes, subjective norms, and perceived behavioral control have positive effects on risk-taking behavioral intentions, while risk perceptions have a negative effect on risk-taking behavioral intentions in both environments. There are significant differences in attitudes and risk perceptions between the two scenarios, of which risk perceptions have the largest differences (Cohen’s $d = 0.73$). Meanwhile, risk perceptions are indirectly related to driving intentions through attitudes, subjective norms, and perceived behavioral control and have the most considerable impact on risk-taking intentions ($\beta = −0.437$). Attitudes have a significantly positive effect on risk-taking intentions in the non-CV scenario, but not in the CV scenario. While subjective norms are the opposite. Besides, there are significant differences between risk perceptions and attitudes, risk perceptions and subjective norms, and attitude and risk-taking intentions in path estimation and structural covariance. Thus, the test results of ten hypotheses (H1–H10) in the proposed theoretical model are summarized in Table 10.
TABLE 9. Goodness fit indices of the multi-group model for drivers’ risky behavioral intentions (N = 980).

| Fit Index               | GFI  | AGFI | IFI  | CFI  |
|------------------------|------|------|------|------|
| Measured value         | 0.983| 0.971| 0.990| 0.990|
| Standard value         | >0.90| >0.90| >0.90| >0.90|
| Adaptation judgment    | Yes  | Yes  | Yes  | Yes  |

TABLE 10. Test results of hypothesis in the proposed theoretical model.

| Items                                                                 | Results |
|-----------------------------------------------------------------------|---------|
| H1: Irrespective of the CV or non-CV environments, attitudes positively affect driving intentions significantly to take risky behaviors. | Not support |
| H2: Irrespective of the CV or non-CV environments, subjective norms positively affect driving intentions significantly to take risky behaviors. | Not support |
| H3: Irrespective of the CV or non-CV environments, perceived behavioral control has a significant positive effect on drivers’ intentions to take risky behaviors. | Support |
| H4: Irrespective of the CV or non-CV environments, risk perceptions negatively affect drivers’ intentions to take risky behaviors. | Support |
| H5: Irrespective of the CV or non-CV environments, risk perceptions negatively affect attitudes significantly to take risky behaviors. | Support |
| H6: Irrespective of the CV or non-CV environments, risk perceptions negatively affect subjective norms significantly to take risky behaviors. | Support |
| H7: Irrespective of the CV or non-CV environments, risk perceptions negatively affect PBC significantly to take risky behaviors. | Support |
| H8: Drivers tend to have a significantly lower intention to take risky behavior under the CV environment than that under the non-CV environment. | Not support |
| H9: Drivers tend to have a significantly more negative attitude to take risky behavior under the CV environment than that under the non-CV environment. | Support |
| H10: Drivers tend to have a significantly lower risk perception of risky behavior under the CV environment than that under the non-CV environment. | Support |

V. DISCUSSION

A. DIFFERENCES IN THE RESPONSES BETWEEN NON-CV AND CV ENVIRONMENTS

The TPB was employed to explore the differences in the responses to real-time information at an unsignalized intersection between the non-CV and the CV environments, which is supported by Ajzen [55] and Zhou et al. [30], who found that the TPB could better and accurately explain and predict behavioral intentions. Also, the TPB factors explained the variance of driving intentions of the non-CV environment and the CV environment by 34% and 36%, respectively. The results showed remarkable differences in the responses to attitudes and risk perceptions. Also, it explored the relationships between attitudes, subjective norms, and driving intentions between the two environments.

Regarding the responses to the TPB model, there are significant differences in attitudes and risk perceptions. However, there are no significant differences in subjective norms, perceived behavioral control, and behavioral intentions between the CV and the non-CV environments. More specifically, although respondents have low risky driving intentions in both environments, the item BI1 of behavioral intentions has a significantly lower value under the CV environment than that under the non-CV environment. A possible explanation is that the CV technology can help drive safely by providing real-time information [13]. Compared with the non-CV environment, drivers under the CV environment have a higher value of attitudes to accelerate through the unsignalized intersection, which means drivers under the CV environment held a more negative attitude to accelerate the unsignalized intersection than those under the non-CV environment. This finding is in line with Yang et al. [56], who indicated that real-time information could significantly affect driver attitudes under the CV environment. Also, drivers under the CV environment have a lower risk perception than drivers under the non-CV environment if they accelerate through the unsignalized intersection. It can be explained by Zhang et al. [57], who claimed that CV technology allows drivers to better understand the surrounding driving environment. Hence, the drivers are less concerned and worried about traffic safety. Another explanation is that drivers believe if they are in danger, CV technology would promptly remind them how to avoid a crash; thus, they have a lower risk perception about dangerous situations [58].

The different environments, risk perceptions, and perceived behavioral control, directly and indirectly, affect driving intentions. However, there is a remarkable difference in the relationships between attitudes, subjective norms, and behavioral intentions between the CV and non-CV environments. More specifically, behavioral intentions to accelerate are significantly affected by attitudes under the non-CV environment, but not under the CV environment.

The finding that intentions of risk-taking behavior are affected by attitudes under the non-CV environment is consistent with the suggestion by Ajzen [14] and previous researches [11], [18]. The unique finding of this study is that
such intentions are not significantly influenced by attitudes under the CV. It implies that drivers trust the real-time information and are less affected by their attitudes [13]. Thus, they are less likely to take risky behavior because they rely more on CV real-time information rather than the conscious decision based on attitude [59].

Therefore, drivers’ attitudes toward accelerating through an unsignalized intersection under the CV environment, whether positive or negative, do not influence their driving intentions to take risky behavior. Subjective norms have a significantly positive effect on driver behavioral intentions to accelerate under the CV environment but an insignificant impact under the non-CV environment. One possible explanation is that the important people around these drivers are inclined to accept the real-time information provided by CV technology, thinking they should follow the provided information [60].

B. RELATIONSHIP BETWEEN TPB VARIABLES UNDER THE CV ENVIRONMENT
Subjective norms, perceived behavioral control, and risk perceptions have a direct effect on driving intentions to accelerate through an unsignalized intersection with the notification of real-time information under the CV environment, which confirms the previous findings [18], [61], [62]. Specifically, drivers with positive subjective norms, high perceived behavioral control, and low-risk perceptions are likely to have a robust behavioral intention in accelerating in such a situation, which is consistent with Zhou et al. [30]. However, attitudes have an insignificant effect on the driver’s behavioral intentions to accelerate through unsignalized intersections under the CV environment.

Also, risk perceptions indirectly affect intentions to take risky behaviors for receiving real-time information provided by CV, which confirms the previous findings [63], [64]. Drivers with high-risk perceptions are unwilling to take risky behaviors by developing negative attitudes, subjective norms and weakening their perceived behavioral control under the CV environment, which is consistent with previous works [64], [65]. Interestingly, drivers’ risk perceptions have a similar effect on attitudes as subjective norms. Previous works [64], [65] found that there was generally a higher correlation between attitudes and risk perceptions than subjective norms in terms of the relationships with behavioral intentions. One possible explanation is that the important people (e.g., parents, spouse) of drivers think they should follow the real-time information to decrease the risk, which increases the relationship with risk perceptions and subjective norms [70], [78]. Therefore, it might be a good strategy to appeal to their risk perceptions toward risky behaviors when designing prevention safety campaigns for drivers and driving education [30].

C. PRACTICAL IMPLICATIONS
The results have multiple practical implications for CV developers and the government to promote CV technologies and improve drivers’ safety under the CV environment. Particularly, PBC has the greatest positive effect on risky driving intentions in both scenarios, which indicates that future interventions should try to improve the driver’s control perceptions not to take risky driving behaviors. We suggest three ways to enhance drivers’ control perceptions over a behavior (or self-efficacy) [66], [67]: 1) by observing other people who decide not to take risky driving behavior (for example, modeling famous personalities who clearly stated not to take risky driving behaviors); 2) by standard persuasive techniques (for example, broadcasting security initiatives at the right time); 3) by trying to avoid the opportunity of risky driving behavior (for example, setting aside enough travel time or reducing traffic conflict points through intelligent transportation systems). Subjective norms were more strongly related to driving intentions among drivers under the CV environment than that under the non-CV environment. Subjective norms refer to the social pressure that an individual perceived when performing a specific behavior. Therefore, drivers are more likely to plan to do so themselves if they perceive that risky driving behavior while driving under the CV environment is normal or common among family and friends. Thus, it is important to make drivers aware that most family and friends will not take risky driving behavior under the CV environment.

Besides, the relation between risk perceptions and risky driving intentions under the CV environment was significantly higher than that under the non-CV environment. Risk perceptions refer to the driver’s perception and interpretation of the probability of specific behavior and the potential severity of its consequences. Therefore, CV developers should promote to comply with real-time information, such as increasing or decreasing the crash risk by using television, newspapers, and the internet to enhance drivers’ risk perceptions when they take risky driving behaviors under the CV environment. Additionally, CV developers should demonstrate the features of CV technologies that are useful to protect passengers in different driving environments (e.g., road situations, weather conditions).

Moreover, there are remarkable differences in driver responses to attitudes. Drivers have a higher attitude towards risky driving intentions under the CV environment. Therefore, to minimize the driver’s risky behavioral intentions, the traffic management authorities should actively take corresponding measures, put more effort to enhance drivers’ interactive behaviors, and emphasize the importance of traffic safety [51].

D. LIMITATIONS AND FUTURE WORKS
Although our research has important findings and implications, it has limitations that should be addressed in follow-up studies. First, we keep the CV scenario simple to understand to reveal the perceptions of the general public who will not find it easy to follow the complex traffic scenario through the pilot questionnaire, which may not fully reflect the characteristics of the CV environment. Second, considering the heterogeneity among drivers in the extended theory
of planned behavior under the CV environment, we should test more scenarios to verify the universal applicability of model differences. Third, due to the cross-sectional survey’s limitations, it is impossible to explore these latent variables’ causal relationships.

In future research, a questionnaire survey should consider more individual factors such as past behavior, descriptive norms, and personality traits (e.g., sensation seeking). Personal characteristics and traffic situations may affect complex risk-taking behavior [68]. Thus, it is needed to collect their experience data when imagining a specific case through driving simulation for comparison. Considering the heterogeneity among drivers under the CV environment, more scenarios, such as signalized intersection, should be considered.

VI. CONCLUSION

This article compared the factors affecting risky driver behavioral intentions under the CV and non-CV environments. Regarding the TPB model, there are significant differences in attitudes and risk perceptions. The different environments, risk perceptions, and perceived behavioral control, directly and indirectly, affect driving intentions. Behavioral intentions to accelerate are affected by attitudes under the non-CV environment, while not under the CV environment. Subjective norms have a significantly positive effect on driver behavioral intentions to accelerate under the CV environment, but an insignificant effect on their behavioral intentions under the non-CV environment. Inconsistent with the non-CV environment, subjective norms, perceived behavioral control, and risk perceptions directly affect drivers’ intentions to accelerate through an unsignalized intersection with the notification of real-time information under the CV environment.

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