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Research Article

Research on Risky Driving Behavior of Young Truck Drivers: Improved Theory of Planned Behavior Based on Risk Perception Factor

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In response to the issue of young truck drivers' weaker perception of potential risks, which makes them more prone to engaging in risky driving behaviors, the direct influence of risk perception on behavior was innovatively considered. An improved theory of planned behavior (TPB) model was developed and a study on risky driving behavior among young truck drivers was conducted. Valid questionnaire data from 330 young truck drivers in China were collected, and the improved TPB model was validated and analyzed through structural equation modeling. The results indicate that the improved TPB model can effectively explain the risky driving behavior among young truck drivers. Specifically, attitudes toward behavior, subjective norms, and perceived behavioral control have significant positive effects on behavioral intention, while behavioral intention and perceived behavioral control have significant positive effects on behavior. In addition, risk perception has a significant negative effect on behavioral intention and behavior. Furthermore, a comparison with the traditional TPB model reveals that the improved TPB model performs better in terms of fit and explanatory power. Fit indices CMIN/DF, RMSEA, and AGFI were optimized by 16%, 18%, and 1.5%, respectively, and there was a 5% increase in explanatory power for behavior variance, validating the rationality and effectiveness of the improved TPB model. This provides decision support for the development of intervention measures for risky driving behavior among young truck drivers in the future.

1. Introduction

In recent years, with the rapid development of China's road transportation industry, the number of commercial trucks has also increased rapidly. Trucks, characterized by a high center of gravity, large cargo capacity, long driving hours, and weak braking ability, often cause more severe traffic accidents than other vehicles [1]. As the controllers and decision-makers of vehicles, truck drivers' risky driving behavior is one of the main causes of road traffic accidents [2]. Risky driving behavior refers to any driving behavior that may increase the risk of traffic accidents, such as speeding, driving while fatigued, distracted driving, and aggressive driving [3]. Analyzing the risky driving behavior of truck drivers is crucial for improving road traffic safety.

Currently, research on the risky driving behavior of truck drivers mainly focuses on behavior identification. By using devices such as onboard sensors, eye trackers, and electroencephalographs [4], researchers can monitor real-time vehicle motion and driving operation data, and then use machine learning or deep learning models [5] to identify the risky driving behavior and take corresponding warning measures to reduce the accident rate. However, the detection equipment used in these studies is costly, and it is difficult to obtain data in real vehicle environments, thus limiting their applicability. In order to be applicable to a wider range of truck drivers and to explore the factors influencing risky driving behavior, some researchers have used survey questionnaires to collect data on gender, age, and mileage to analyze the influencing factors of risky driving behavior among truck drivers. However, the factors investigated in these surveys are not comprehensive. To more comprehensively analyze the influencing factors and mechanisms of risky driving behavior, some studies have analyzed risky driving behavior from the perspective of the theory of planned behavior (TPB) in social psychology. TPB, proposed by Ajzen [6] in 1985, is a social psychological theory used to explain the decision-making process of general behavior, including attitude toward behavior, subjective norms, perceived behavioral control, behavioral intentions, and behavior. Its core idea is that attitude toward behavior, subjective norms, and perceived behavioral control jointly influence behavioral intentions, which in turn directly affect behavior. In addition, Ajzen has also suggested that TPB is an open and expandable theory [7]. Through continuous improvement, some studies have shown that new factors can be added to TPB models to enhance their explanatory power in certain special scenarios. In the analysis of influencing factors of risky driving behavior among truck drivers, current research mainly focuses on improving TPB models by adding driving environment factors. Since the external driving environment of truck drivers is more complex, factors such as weather conditions, traffic conditions, and other drivers' behaviors may lead to risky driving behavior among truck drivers. However, the driving environment is an objective factor not controlled by drivers' psychological cognition, making it difficult to analyze in conjunction with drivers' psychological cognitive factors. In order to comprehensively consider the driving environment and drivers' psychological cognitive factors, some scholars have begun to introduce risk perception [8–11] into the field of driving behavior. Risk perception refers to drivers' perception and cognition of potential dangers in the driving environment, which can be improved through education and training to enhance drivers' perception abilities. For truck drivers, the nature of their work and working environment determines that they face higher risks during driving than other drivers. For example, truck drivers need to drive for long periods, which can lead to fatigue, and they also need to cope with adverse weather and road conditions such as rain, snow, and mountain roads, all of which increase the difficulty and risk of driving for truck drivers. Therefore, truck drivers should pay more attention to their risk perception abilities. It is feasible and necessary to integrate risk perception factors into TPB models and conduct research on risky driving behaviors among truck drivers. On the other hand, with the continuous improvement of road infrastructure and the rapid development of the logistics industry, the demand for truck drivers is also increasing, and the group of truck drivers is becoming younger. There is a correlation between age and risk perception ability [8–11]. Due to the limitations of life experience and cognitive level, young people are less sensitive to the potential dangers of certain behaviors. Therefore, compared to older truck drivers, young truck drivers (under 35 years old) have weaker risk perception abilities and are more likely to engage in risky driving behaviors. Research has shown that compared to older truck drivers, young truck drivers lack driving experience and skills, making it difficult for them to accurately judge and respond to constantly changing traffic conditions, thus increasing the likelihood of causing road traffic accidents [12]. Although there are existing studies [13] on risky driving behavior among truck drivers, there is no specific focus on young truck drivers. It is worthwhile to further explore whether risk perception ability affects risky driving behavior among young truck drivers and how it affects them. Therefore, it is necessary to analyze the influencing factors of risky driving behavior among young truck drivers in combination with risk perception factors. This is important for developing intervention measures for risky driving behavior among young truck drivers, helping them develop good driving behaviors, and laying a solid foundation for their future driving careers.

The research aims to delve into the influencing factors and mechanisms of risky driving behavior among young truck drivers. Two innovative approaches have been undertaken in analyzing the factors influencing risky driving behavior among young truck drivers. Firstly, innovative consideration has been given to the direct impact of risk perception on risky driving behavior, leading to the establishment of an improved TPB model. This model investigates the risky driving behavior of young truck drivers from the perspective of social psychology. By comparing with the traditional TPB model, the improved TPB model enhanced the fit indices CMIN/DF, RMSEA, and AGFI by 16%, 18%, and 1.5%, respectively, and increased the explanatory power for behavior variance by 5%. Second, based on the established research model, a survey questionnaire suitable for the demographic of young truck drivers has been designed by integrating risk perception factors. Data from the young truck driver population have been collected, and through structural equation modeling (SEM), the influence mechanisms of attitude toward behavior, subjective norms, perceived behavioral control, risk perception, and behavioral intentions on risky driving behavior have been quantitatively analyzed. This research aims to provide decision support for the development of intervention measures targeting risky driving behavior among young truck drivers, which is crucial for standardizing the driving behavior of young truck drivers and enhancing road traffic safety.

The remaining parts of this paper are arranged as follows. In Section 2, we conducted a literature review. In Section 3, we proposed the model, data, and analysis methods. In Section 4, we analyzed the data. In Section 5, we discussed these results and proposed recommendations. Finally, in Section 6, we drew research conclusions.

2. Literature Review

In the aspect of analyzing the influencing factors of risky driving behavior among truck drivers based on questionnaire surveys, Peng et al. [14] investigated the contributing factors affecting the severity of injuries to drivers and copilots involved in rear-end crashes between trucks on expressways. They found that male truck drivers exhibited significantly more speeding behavior than females. Sadeghi et al. [12] conducted a questionnaire survey among a group of Iranian truck drivers, and the results indicated that older truck drivers were less likely to engage in traffic violations. Moreover, truck drivers with longer driving distances and unstable emotions were more prone to committing traffic violations. Maslać et al. [15] developed a 5-factor structure driving behavior scale for Serbian truck drivers, with results indicating a positive correlation between average daily driving time and risky driving behavior. Mehdizadeh et al. [16] utilized a 4-factor structure driving behavior scale to study the driving behavior among Iranian truck drivers, revealing associations between age, driving experience, education level, driving distance, rest conditions, and traffic accidents. These studies demonstrate that personal attributes of truck drivers, such as gender, age, and driving mileage, are closely related to the risky driving behavior. However, they did not integrate psychological theories to consider and analyze more influencing factors and mechanisms. Regarding the analysis of risky driving behavior based on TPB, Rowe et al. [17] utilized TPB to study the risky behaviors such as speeding and distraction among novice drivers. They found that attitude toward behavior had the strongest explanatory power for the intention of risky driving behavior, while subjective norms and perceived behavioral control also significantly influenced the intention of risky driving behavior. Jiang et al. [18] explored the influencing factors of fatigue-driving behavior from a social psychological perspective and designed a questionnaire based on TPB. Hierarchical multiple regression analysis showed that subjective norms, perceived behavioral control, and behavioral intention significantly affected the fatigue-driving behavior. Wang et al. [19] designed a questionnaire using TPB to collect data, and SEM was used to analyze the data. The results showed that the behavioral intention was the strongest predictor of lane change violation behavior at urban intersections. Perceived behavioral control had both direct and indirect effects on lane change violation behavior. Furthermore, attitude toward behavior, subjective norms, and perceived behavioral control were found to have significant correlations with the intention of lane change violations at urban intersections. However, traditional TPB has limitations in explaining the driving behavior due to the lack of analysis of some additional influencing factors. In terms of integrating new factors with TPB, Xiao and Liang [20] introduced safety incentives to improve TPB and conducted a study on the violation behavior of rural bus drivers. The results showed that safety incentives significantly inhibited illegal driving behavior as an additional factor. Hu et al. [21] aimed to explore the mechanism of travelers' dependence on public transportation, and individual characteristics, travel environment, and travel features were added to form an extended TPB. They utilized the AGNES clustering algorithm and SEM to identify and analyze travelers' dependence on public transportation. Zhang et al. [22] exploratively introduced behavioral experience into the TPB model and conducted a study on unsafe behaviors among cyclists. The results showed that behavioral experience had a positive impact on behavioral intention and unsafe behavior, indicating that the accumulation of behavioral experience would promote the recurrence of unsafe behavior. These studies demonstrate that adding new factors can indeed enhance the explanatory power of the TPB model for behavior. In terms of integrating the driving environment and TPB, Hussain et al. [23] studied the risky driving behavior of Pakistani truck drivers by improving TPB with the inclusion of a safe environment. They concluded that the safety environment had a negative impact on risky driving behavior. Baikejuli et al. [24] investigated the factors influencing mobile phone use while driving among Chinese commercial truck drivers. By incorporating driving environment exposure (e.g., high driving frequency, long driving hours, and distance) into TPB, they found that the driving environment exposure had significant positive effects on attitude toward behavior, subjective norms, perceived behavioral control, and behavioral intention. However, the driving environment is an objective factor, making it difficult to analyze risky driving behavior from the psychological perspective of truck drivers. In terms of combining risk perception and TPB, Yang et al. [25] categorized novice drivers' risky driving behaviors into three types and discussed the influencing mechanism of risky driving behavior among novice drivers by integrating risk perception and TPB. They proved that risk perception had a significant negative impact on behavioral intention, which in turn affected the three types of risky driving behavior. Li et al. [13], targeting truck driver groups, combined sensation seeking, risk perception, and TPB to explain truck drivers' risky driving behavior. SEM and mediation analysis were used to fully examine the underlying mechanisms, and the results showed that risk perception had a significant negative impact on behavioral intention through the mediation of attitude toward behavior. Literature [13, 25] demonstrated that combining risk perception with TPB could effectively explore the influencing factors and mechanisms of driver risky driving behavior, but it did not explain the interaction between risk perception and TPB factors clearly, nor did it consider the direct impact of risk perception on risky driving behavior, which may lead to an incomplete research model and hinder the accurate interpretation of risky driving behavior. However, some studies in other fields have considered and validated the direct relationship between risk perception and behavior. For example, Sahul Hamid et al. [26] reported on the relationship between risk perception and adventurous behavior among emerging market investors. Through multiple regression analysis of survey data, it was found that risk perception had a direct negative impact on adventurous behavior. Man et al. [27] developed and validated a risk perception scale for construction workers. The results, obtained from a group of voluntary construction workers in Hong Kong, showed that risk perception had a direct negative impact on adventurous behavior. That is, enhancing their risk awareness could maximize the reduction of adventurous behavior among construction workers. Some studies have indicated that considering additional factors' direct impact on behavior also helps to increase the explanatory power of the TPB model. For instance, Shi et al. [28], in their study on driver fatigue-driving behavior, introduced behavioral experience into TPB to form an extended TPB model. The results showed that the extended TPB model had good explanatory and predictive power for driver fatigue-driving behavior. Behavioral experience had a significant positive impact on the intention of fatigue-driving behavior, and it also had a significant positive impact on fatigue-driving behavior. Liang and Xiao [29] conducted an analysis of the influencing factors of speeding behavior on Chinese highways, introducing punishment avoidance to correct TPB. In the process of model building, the mutual influence relationship between punishment avoidance and TPB factors was considered, especially the direct impact of punishment avoidance on speeding behavior. The results showed that the addition of punishment avoidance, an external variable, helped to improve the TPB model and increase its explanatory power. Punishment avoidance had a significant negative impact on speeding behavior. Xiao and Liang [20] conducted a study on the violation behavior of rural bus drivers, starting from the psychological perspective of drivers and introducing safety incentive indicators to improve the TPB model. The results showed that the improved TPB model could effectively identify the factors affecting rural bus drivers' violation behavior, and safety incentives had significant inhibitory effects on both the intention and behavior of violation driving. The aforementioned research provides new insights into studying risky driving behaviors among truck drivers by considering the direct impact of risk perception on behavior to establish an improved TPB model. However, literature [13, 23, 24] primarily focuses on the entire truck driver population, with limited research targeting young truck drivers specifically.

Thus, TPB and its improved models have gradually been applied in the analysis of risky driving behavior. Current research on analyzing risky driving behavior among truck drivers mainly focuses on improving the TPB by incorporating driving environments. In order to consider drivers' psychological cognitive factors, some scholars have introduced risk perception to improve the TPB. However, the direct impact of risk perception on risky driving behavior has not been considered, which may result in incomplete research models and hinder accurate explanations of risky driving behavior. In addition, due to their limited driving experience, young truck drivers may have weaker risk perception abilities, making them more prone to engaging in risky driving behavior. However, the current research lacks sufficient attention to this demographic, with a shortage of corresponding analyses of influencing factors.

3. Methods

3.1. The Improved TPB Model

3.1.1. The Theory of Planned Behavior. The theory of planned behavior (TPB), proposed by Ajzen [6, 7] in 1985, is a psychological theory used to explain the decision-making process of general behaviors, including attitude toward behavior, subjective norms, perceived behavioral control, behavioral intentions, and behaviors. Its core idea is that attitude toward behavior, subjective norms, and perceived behavioral control collectively influence behavioral intentions, which in turn directly impact behaviors. The application of TPB in explaining the risky driving behavior of truck drivers has been proven in previous studies [13, 23, 24]. Therefore, we chose TPB as the theoretical framework and incorporated the attitude toward behavior, subjective norms, perceived behavioral control, and behavioral intentions of young truck drivers towards risky driving behavior to study their risky driving behavior. Among them, attitude toward behavior (AB) refers to the positive or negative evaluation of risky driving behavior by young truck drivers. Subjective norms (SNs) refer to the perceived social pressure felt by young truck drivers when deciding whether to engage in risky driving behavior. Perceived behavioral control (PBC) refers to the perceived ease or difficulty of performing risky driving behavior by young truck drivers. Behavioral intentions (BIs) refer to the willingness of young truck drivers to engage in risky driving behavior. Risky driving behavior (B) refers to whether the young truck drivers engage in risky driving behavior or not.

We propose the following research hypotheses:

Hypothesis 1 (H1): AB has a significant positive impact on BI.

Hypothesis 2 (H2): SN has a significant positive impact on BI.

Hypothesis 3 (H3): PBC has a significant positive impact on BI.

Hypothesis 4 (H4): BI has a significant positive impact on B.

Hypothesis 5 (H5): PBC has a significant positive impact on B.

3.1.2. Risk Perception. Risk perception (RP) [8–11] refers to the driver's ability to identify the potential risks of risky driving behavior while driving. The ability of drivers to accurately perceive risks and make correct judgments is crucial for avoiding traffic accidents and improving driving safety. Previous studies have demonstrated the influence of risk perception on the attitude and intention of risky driving behavior. For example, Yang et al. [25] demonstrated that risk perception has a negative impact on the intention of risky driving behavior among novice drivers. Li et al. [13] found that risk perception has a negative impact on the attitude and intention of risky driving behavior among truck drivers. Furthermore, some studies in other fields have found a direct relationship between risk perception and behavior. For instance, Sahul Hamid et al. [26] found that risk perception has a negative impact on the risky behavior of emerging market investors. Man et al. [27] found that risk perception has a negative impact on the risky behavior of construction workers.

Based on the results of these studies, risk perception is considered a key influencing factor in risky driving behavior. We exploratively introduced RP into the TPB model, considering the direct impact of RP on BI and B, while also considering the mutual influence between RP and AB, SN, and PBC. We propose the following research hypotheses:

Hypothesis 6 (H6): RP has a significant negative impact on BI.

Hypothesis 7 (H7): RP has a significant negative impact on B.

3.1.3. The Research Model. Based on the abovementioned research hypotheses, an improved TPB model is established to conduct research on risky driving behavior among young truck drivers. As shown in Figure 1, the improved TPB model is built upon the traditional TPB model, considering the direct impact of RP on BI and B to enhance the model's explanatory power for risky driving behavior. In addition, the mutual influence between RP and AB, SN, and PBC is taken into account to comprehensively analyze the interrelationships among factors.

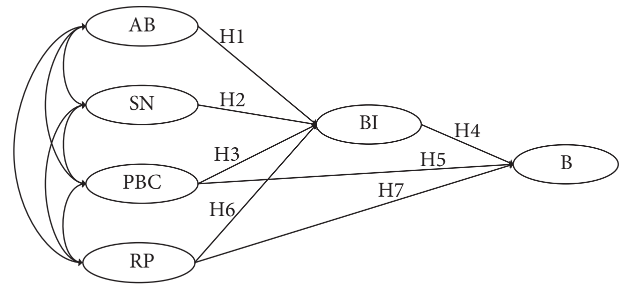

Figure 1: The improved TPB model.

3.2. Data Collection. Based on the constructed research model, a survey questionnaire tailored for the young truck driver population is designed by incorporating risk perception factors to collect data from this group. This includes the survey procedure, participants, and questionnaire design.

3.2.1. Procedure. The survey targeted professional truck drivers aged 35 and below, conducted from August 1st to August 31st, 2023, covering various regions in China, mainly the Anhui Province. Past literature has shown that Internet surveys are commonly used in modern research due to their low cost and high efficiency [30]. Therefore, we chose to conduct the study through an online survey to collect data. The questionnaire was distributed randomly with the assistance of the Wenjuanxing website, a professional online platform providing survey services in China, which strictly adheres to the principles of random sampling. At the beginning of the survey, we explained the purpose of the research, emphasized that participation was voluntary, and assured respondents that their answers would remain anonymous.

3.2.2. Participants. A total of 382 responses were received for this survey. After excluding incomplete responses, those with identical content, excessively short completion times, and those exhibiting clear contradictions, we retained 330 valid questionnaires, resulting in an effective response rate of 86.38%. Generally, the sample size should exceed 200 and be at least 15 times the number of questionnaire items [31]. A total of 330 valid samples were collected, meeting the requirements for sample size and ensuring the representativeness of the sample. The respondents comprised 286 males (86.67%) and 44 females (13.33%), aged between 18 and 35 years.

3.2.3. Questionnaire Design. The questionnaire consisted of two parts. The first part primarily investigated personal demographic factors, including gender, age, education level, monthly income, type of driving vehicle, daily average driving time, annual average driving distance, driving experience, frequency of traffic violations, and history of traffic accidents. The second part mainly investigated the factors in the improved TPB model, including AB, SN, PBC, RP, BI, and B. As shown in Table 1, each factor was designed with 3–6 items, totaling 21 items. Each item was assessed using a Likert 5-point scale [32], ranging from 1 (strongly disagree) to 5 (strongly agree).

In the process of questionnaire design, we referred to the TPB [23, 24] and the Driver Behavior Questionnaire (DBQ) [32, 33]. The DBQ, initially developed by Reason et al. [34], has been widely utilized for studying and assessing drivers' behaviors. To cater to young truck drivers, we considered the relationship between risk perception and risky driving behavior, and referred to the studies of Li et al. [13] and Yang et al. [25]. As a result, additional items corresponding to risk perception (RP1~RP3) were added to the questionnaire based on TPB and DBQ. The scores for risk perception were reverse-coded, so higher scores indicated a higher level of conceptual agreement among respondents.

3.3. Analysis Method. In this section, the data analysis procedures will be presented, as shown in Figure 2.

On one hand, to analyze the influence of personal demographic factors on risky driving behavior among young truck drivers, descriptive statistical analysis and analysis of variance were conducted using IBM SPSS 25.0. This aimed to study the relationship between personal demographic factors and risky driving behavior among young truck drivers.

On the other hand, to further analyze the magnitude and mechanisms of the impact of various factors in the improved TPB model on risky driving behavior among young truck drivers, several steps were taken. First, the validity and reliability of the questionnaire were tested using Cronbach's alpha coefficient and exploratory factor analysis. Then, Pearson's correlation analysis was employed to determine the correlations between factors in the improved TPB model. Finally, SEM was performed using IBM SPSS Amos 26.0 software to validate and analyze the improved TPB model. SEM is a statistical method that combines multiple regression analysis, factor analysis, and path analysis, capable of analyzing the relationships between variables based on covariance matrices [35].

Table 1: Contents of the scale.

Factors	Items	Content	References
AB	AB1	Long hours of driving inevitably lead to occasional speeding, fatigue, and violations	Hussain et al. [23] and Baikejuli et al. [24]
	AB2	Occasional speeding, fatigue, and violations pose no trouble when there are no traffic police or cameras	
	AB3	During urgent tasks, speeding, fatigue, and violations are advantageous for saving time and ensuring timely delivery	
SN	SN1	Even if family members discourage me, I may still occasionally engage in speeding, fatigue, and violations	
	SN2	Even if friends discourage me, I may still occasionally engage in speeding, fatigue, and violations	
	SN3	Even if traffic safety experts discourage me, I may still occasionally engage in speeding, fatigue, and violations	
PBC	PBC1	During occasional speeding, fatigue, and violations, I can still maintain safe driving conditions	
	PBC2	During occasional speeding, fatigue, and violations, I can still maintain a high level of attention and observation	
	PBC3	During occasional speeding, fatigue, and violations, I can handle potential dangers well	
RP	RP1	Occasionally not using turn signals when changing lanes may lead to vehicle collisions	Li et al. [13] and Yang et al. [25]
	RP2	Speeding during normal driving may result in rear-end collisions	
	RP3	Long-term fatigue driving may lead to decreased attention and accidents	
BI	BI1	In the next few months, there is a possibility that I may engage in speeding	Hussain et al. [23] and Baikejuli et al. [24]
	BI2	In the next few months, there is a possibility that I may drive while fatigued	
	BI3	In the next few months, there is a possibility that I may make illegal lane changes	
B	B1	Speeding on roads without speed cameras	Jiao et al. [32] and Useche et al. [33]
	B2	Continuing to drive for long periods when feeling fatigued or sleepy	
	B3	Retaliating with similar behavior when faced with provocative actions from other drivers	
	B4	Occupying the fast lane or overtaking lane for extended periods	
	B5	Not using turn signals and changing lanes arbitrarily	
	B6	Following other vehicles too closely and not maintaining a safe distance	

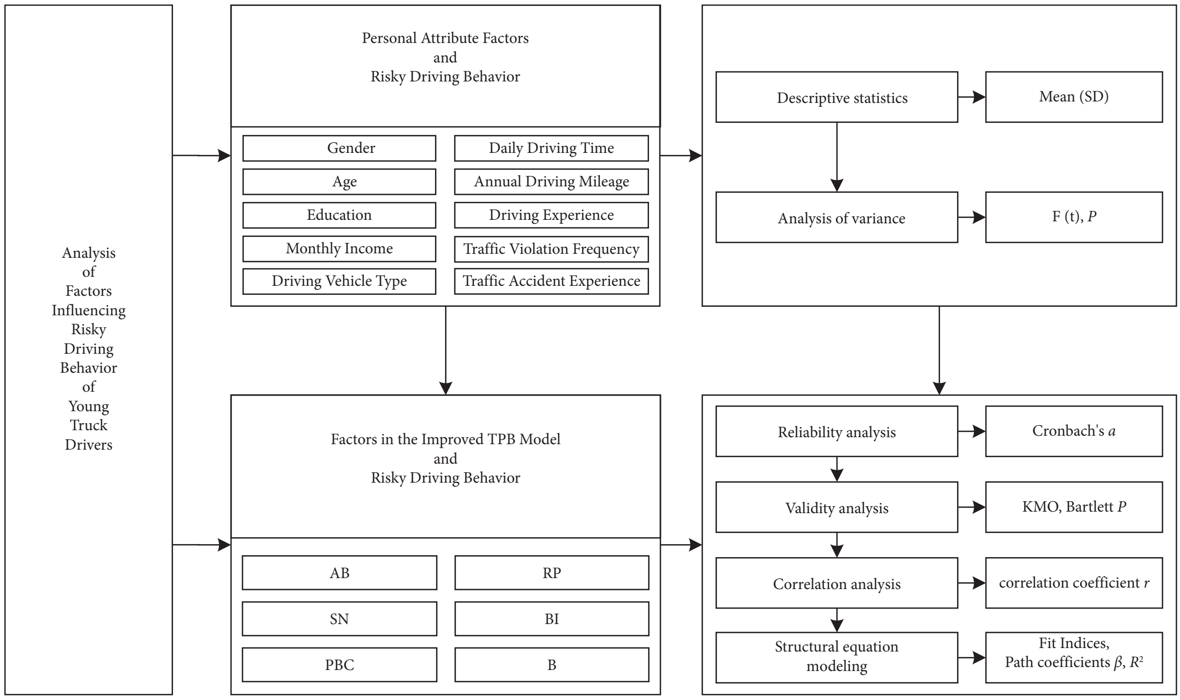

Figure 2: Data analysis procedures.

4. Results

4.1. Descriptive Statistics and Analysis of Variance. The descriptive statistics and analysis of variance results for personal demographic factors of young truck drivers are presented in Table 2. In the table, P indicates the significance level, where $P < 0.05$ indicates statistical significance, $P < 0.01$ indicates significant statistical significance, and $P < 0.001$ indicates extremely significant statistical significance. P values are output by the Amos software, with numeric values output when $P \geq 0.05$ and a numeric range output when $P < 0.05$.

Among the 330 respondents, there were 286 males (86.67%) and 44 females (13.33%), with ages ranging from 18 to 35 years old. The majority had an education level of high school or below (75.76%) and a monthly income of 5,000 to 10,000 yuan (49.39%). Regarding the type of driving vehicle, heavy-duty trucks accounted for the highest proportion, representing 37.58% of the total sample. The majority reported a daily driving time of 6 to 10 hours (47.58%) and an annual driving mileage of 0 to 50,000 kilometers (41.21%), with a driving experience of 6 to 10 years (42.73%), indicating that most young truck drivers arrange their work hours within a reasonable range. About 52.73% of the respondents reported a moderate frequency of traffic violations, indicating that more than half of young truck drivers sometimes violate traffic rules, while 85.45% stated that they had experienced relatively few traffic accidents, indicating that the majority of young truck drivers currently have a good record in terms of traffic accidents.

Using risky driving behavior as the dependent variable, independent sample t-tests were conducted for binary variables such as gender and age, while analysis of variance was conducted for multicategory variables including education level, monthly income, type of driving vehicle, daily driving time, annual driving mileage, driving experience, frequency of traffic violations, and traffic accident experience. The results showed that there were no significant differences in risky driving behavior with respect to gender, age, education level, monthly income, type of driving vehicle, daily driving time, and annual driving mileage ($P > 0.05$). This is consistent with some conclusions drawn by Li et al. [13], indicating that personal demographic factors such as gender, age, education level, and region do not significantly influence risky driving behavior among truck drivers. The results also revealed significant differences in risky driving behavior based on driving experience ($P < 0.05$), with the group of young truck drivers with 6–10 years of driving experience being more prone to risky driving behavior. Furthermore, the frequency of traffic violations ($P < 0.001$) and traffic accident experience ($P < 0.05$) were found to significantly influence risky driving behavior, with higher scores in risky driving behavior observed with increased frequency of traffic violations and traffic accident experiences. Similar conclusions have been drawn in related studies conducted among other occupational and nonoccupational driving groups [17–19].

4.2. Reliability Analysis. Reliability is an examination of the scale's reliability and internal consistency, primarily assessed using Cronbach's alpha. The standardized Cronbach's alpha values range from 0 to 1, with values closer to 1 indicating higher internal consistency and greater reliability of the scale. Generally, a Cronbach's alpha coefficient greater than 0.7 for subscales indicates a high reliability, while values

Table 2: Descriptive statistics and analysis of variance ($N = 330$).

Personal attribute factors	Category	Number	Proportion (%)	Mean (SD)	F (t)	P value
Gender	Male	286	86.67	2.99 (0.67)	1.580	0.120
	Female	44	13.33	2.78 (0.84)		
Age	18–30 years old	76	23.03	3.07 (0.53)	1.965	0.051
	30–35 years old	254	76.97	2.92 (0.74)		
Education	Primary or middle school	126	38.18	2.86 (0.70)	1.972	0.118
	High school or vocational school	124	37.58	3.05 (0.66)		
	Associate degree	56	16.97	2.91 (0.76)		
	Bachelor's degree and above	24	7.27	3.11 (0.65)		
Monthly income	0–5 thousand RMB	93	28.18	2.94 (0.71)	0.336	0.799
	5–10 thousand RMB	163	49.39	3.00 (0.72)		
	10–15 thousand RMB	62	18.79	2.90 (0.64)		
	Above 15 thousand RMB	12	3.64	2.93 (0.62)		
Driving vehicle type	Light-duty truck	100	30.30	2.89 (0.75)	0.688	0.560
	Medium-duty truck	34	10.30	3.07 (0.70)		
	Heavy-duty truck	72	21.82	2.94 (0.62)		
	Very heavy-duty truck	124	37.58	2.99 (0.70)		
Daily driving time	0 to 5 hours	106	32.12	2.94 (0.72)	0.349	0.844
	6 to 10 hours	157	47.58	3.00 (0.69)		
	11 to 15 hours	51	15.45	2.87 (0.70)		
	16 to 20 hours	12	3.64	2.94 (0.70)		
	More than 20 hours	4	1.21	2.95 (0.75)		
Annual driving mileage	0 to 50 thousand kilometers	136	41.21	2.99 (0.58)	2.476	0.061
	51 to 100 thousand kilometers	128	38.79	3.01 (0.78)		
	101 to 150 thousand kilometers	34	10.30	2.66 (0.75)		
	151 to 200 thousand kilometers	32	9.70	2.90 (0.71)		
Driving experience (license years)	0 to 5 years	116	35.15	2.87 (0.67)	3.227	<0.05
	6 to 10 years	141	42.73	3.05 (0.73)		
	11 to 15 years	58	17.58	3.04 (0.58)		
	16 to 20 years	15	4.55	2.54 (0.93)		
Traffic violation frequency	Few	138	41.82	2.79 (0.64)	10.001	<0.001
	Moderate	174	52.73	3.04 (0.70)		
	Many	18	5.45	3.43 (0.78)		
Traffic accident experience	Few	282	85.45	2.91 (0.65)	4.435	<0.05
	Moderate	46	13.94	3.23 (0.92)		
	Many	2	0.61	3.25 (0.35)		

between 0.6 and 0.7 are considered acceptable. For the total scale, a Cronbach's alpha coefficient of greater than 0.8 indicates a high reliability, while values between 0.7 and 0.8 are considered acceptable [36]. The formula for Cronbach's alpha is

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum S_i^2}{S^2}\right), \tag{1}$$

where k is the total number of items in the scale, S_i^2 is the variance of items i in the scale, and S^2 is the variance of total items in the scale.

The reliability of each subscale and the total scale were analyzed using SPSS 25.0, and the results are presented in Table 3. The Cronbach's alpha coefficients for all six subscales are greater than 0.7, and the Cronbach's alpha coefficient for the total scale is 0.900, exceeding 0.8, indicating good reliability and a high internal consistency of the scale.

Table 3: Reliability analysis.

Scale	Items	Cronbach's alpha
AB	3	0.844
SN	3	0.979
PBC	3	0.912
RP	3	0.869
BI	3	0.881
B	6	0.956
Overall scale	21	0.900

4.3. Validity Analysis. Validity is an examination of the effectiveness and correctness of the items in the scale, generally including content validity and structural validity. Higher validity indicates that the measurement results more accurately represent the true situation of the measured objects, making the scale more effective and accurate. Content validity is mainly examined by analyzing and judging whether the measurement items can effectively represent the measurement content by relevant experts. Since the survey questionnaire designed in this study drew from previous relevant research and was modified and adjusted multiple times based on the actual situation of young truck drivers, it can be considered to have a good content validity. In addition, structural validity is generally examined using a factor analysis. First, it is necessary to determine whether the scale is suitable for factor analysis. When the Kaiser–Meyer–Olkin (KMO) measure is higher than 0.8 and the significance of Bartlett's sphericity test is $P < 0.05$, factor analysis can be conducted [37]. The test results are shown in Table 4, with KMO = 0.883, and the Bartlett's sphericity test result reaches a significance of $P < 0.001$, indicating the presence of common factors among the item correlations, allowing for factor analysis. Then, the exploratory factor analysis was performed on the 21 items, using principal component analysis and varimax rotation. To ensure the quality of the factor analysis, items were removed based on the following principles [38]: the communality of items should be greater than 0.45; factor loadings should be at least greater than 0.5; the same item should not be included in multiple factors, each factor should have at least 3 items; and the cumulative variance contribution rate should be greater than 60%. The analysis results are shown in Table 5, which extracted 6 factors, with all item communalities greater than 0.45, factor loadings all greater than 0.5, and a cumulative variance contribution rate of 83.48%, significantly exceeding 60%, indicating good effectiveness of the factor analysis.

Table 4: KMO and Bartlett's sphericity test.

Test value	Result	Applicability of factor analysis
KMO	0.883	Applicable
Bartlett P	<0.001	Applicable

4.4. Correlation Analysis. Before conducting SEM analysis, it is necessary to analyze the Pearson correlation coefficients (r) among the factors of the improved TPB model. The results, as shown in Table 6, indicate that there is a significant correlation among all factors, with a moderate to low degree of correlation ($r_{\max} < 0.6$). Specifically, RP is significantly correlated with AB, SN, and PBC, with correlation coefficients of 0.088 ($P < 0.05$), 0.111 ($P < 0.05$), and 0.098 ($P < 0.05$), respectively. This validates the rationale of considering the mutual influence between RP and AB, SN, and PBC in the improved TPB model. Therefore, further SEM analysis can be conducted.

Regarding the frequency of risky driving behavior among respondents, corresponding items were designed in the survey questionnaire. Each item was evaluated using a Likert scale [32] ranging from 1 (never) to 5 (often), with an average score of 2.5. The mean (SD) of risky driving behavior (B) in Table 6 is 2.96 (0.70). This suggests that the frequency of risky driving behavior among respondents is moderately high, indicating that the surveyed group of young truck drivers tends to engage in more frequent risky driving behavior. This could significantly impact road safety levels, emphasizing the importance of studying the influencing factors of risky driving behavior.

4.5. Structural Equation Modeling. SEM was established using Amos 26.0. SEM consists of two parts: a measurement model comprising 6 latent variables and their corresponding 21 observed variables and a structural model representing the relationships among the 6 latent variables. First, 8 internationally recognized fit indices [39] and fit standards [39] were selected to evaluate the overall fit of the model. The evaluation results of the fit indices are shown in Table 7, indicating that all fit indices meet the ideal values, suggesting a good overall fit of the model. This indicates that the assumed model fits well with the sample data, and the model is acceptable, enabling further analysis of the relationships among latent variables based on the fitted SEM.

Then, the maximum likelihood estimation method was used to estimate the path coefficients. The sign (positive or negative) of the standardized path coefficients (β) indicates the direction of influence between latent variables, where larger absolute values of β indicate greater influence. The standardized path coefficients and the results of hypothesis testing are shown in Table 8, and the SEM path diagram is shown in Figure 3. The results indicate that all error variances (e) in the SEM are positive and significant ($t > 1.96$, $P < 0.05$). The parameter estimates' standard deviations (SE) are all very small, and the standardized factor loadings are all between 0.5 and 0.95, with no estimation violations, indicating that the model's intrinsic fit is ideal [40]. Further hypothesis testing reveals that the effects of AB ($\beta = 0.27$, $P < 0.001$), SN ($\beta = 0.14$, $P < 0.05$), PBC ($\beta = 0.34$, $P < 0.001$), and RP ($\beta = -0.25$, $P < 0.001$) on BI are statistically significant, supporting hypotheses H1, H2, H3, and H6; while the effects of BI ($\beta = 0.49$, $P < 0.001$), PBC ($\beta = 0.25$, $P < 0.001$), and RP ($\beta = -0.19$, $P < 0.001$) on B are statistically significant, supporting hypotheses H4, H5, and H7.

Regarding the analysis of the effects of AB, SN, PBC, and BI, similar conclusions have been drawn in some studies. For example, Hussain et al. [23] demonstrated significant positive effects of attitude toward behavior and subjective norms on behavioral intention, Baikejuli et al. [24] showed significant positive effects of attitude toward behavior and perceived behavioral control on behavioral intention, and Li et al. [13] demonstrated significant positive effects of perceived behavioral control on behavior. In addition, Hussain et al. [23], Baikejuli et al. [24], and Li et al. [13] all found that behavioral intention has the greatest direct impact on behavior. This also demonstrates the mediating role of behavioral intention in the improved TPB model, where attitude toward behavior, subjective norms, and perceived behavioral control influence the behavior of young truck drivers through their impact on behavioral intention, consistent with previous research findings by Yang et al. [25] and Li et al. [13], which demonstrated that attitude toward behavior, subjective norms, perceived behavioral control, and risk perception influence behavior through behavioral intention. As for the analysis of the impact of RP, similar conclusions have been drawn in some studies, such as those by Yang et al. [25] and Li et al.

Table 5: Factor variance contribution rate and item loadings.

Factors	Variance contribution rate (%)	Items (loadings)	Items (loadings)	Items (loadings)	Items (loadings)	Items (loadings)	Items (loadings)
AB	23.701	AB1 (0.898)	AB2 (0.843)	AB3 (0.756)	—	—	—
SN	37.569	SN1 (0.956)	SN2 (0.967)	SN3 (0.944)	—	—	—
PBC	49.953	PBC1 (0.890)	PBC2 (0.882)	PBC3 (0.868)	—	—	—
RP	61.493	RP1 (0.867)	RP2 (0.870)	RP3 (0.867)	—	—	—
BI	72.658	BI1 (0.795)	BI2 (0.776)	BI3 (0.801)	—	—	—
B	83.484	B1 (0.807)	B2 (0.834)	B3 (0.830)	B4 (0.871)	B5 (0.883)	B6 (0.859)

Table 6: Correlation analysis.

Factors	Mean (SD)	AB	SN	PBC	RP	BI	B
AB	1.78 (1.03)	1					
SN	1.46 (0.96)	0.365 ($p < 0.01$)	1				
PBC	2.43 (1.23)	0.210 ($p < 0.01$)	0.108 ($p < 0.05$)	1			
RP	2.63 (1.10)	0.088 ($p < 0.05$)	0.111 ($p < 0.05$)	0.098 ($p < 0.05$)	1		
BI	2.48 (1.10)	0.384 ($p < 0.01$)	0.284 ($p < 0.01$)	0.403 ($p < 0.01$)	0.288 ($p < 0.01$)	1	
B	2.96 (0.70)	0.353 ($p < 0.01$)	0.210 ($p < 0.01$)	0.456 ($p < 0.01$)	0.353 ($p < 0.01$)	0.509 ($p < 0.01$)	1

Table 7: Fit indices evaluation.

Fit indices	Standard	Improved TPB model		Traditional TPB model	
		Model results	Evaluation	Model results	Evaluation
CMIN/DF	1~3	1.637	Good	1.953	Excellent
RMSEA	<0.08	0.044	Good	0.054	Excellent
SRMR	<0.08	0.037	Good	0.040	Good
GFI	>0.9	0.926	Good	0.925	Good
AGFI	>0.9	0.913	Good	0.899	Excellent
CFI	>0.9	0.982	Good	0.979	Good
NFI	>0.9	0.955	Good	0.958	Good
IFI	>0.9	0.982	Good	0.979	Good

Table 8: Standardized path coefficients, hypothesis testing results, and R^2.

Hypotheses	Path	Estimate	P value	SE	CR	Results	R^2	
							BI	B
Improved TPB model							0.39	0.52
H1	AB—>BI	0.27	<0.001	0.076	4.508	Supported		
H2	SN—>BI	0.14	<0.05	0.058	2.538	Supported		
H3	PBC—>BI	0.34	<0.001	0.050	6.250	Supported		
H4	BI—>B	0.49	<0.001	0.040	8.141	Supported		
H5	PBC—>B	0.25	<0.001	0.031	4.806	Supported		
H6	RP—>BI	0.25 (−0.25)	<0.001	0.052	4.586	Supported		
H7	RP—>B	0.19 (−0.19)	<0.001	0.031	3.938	Supported		
Traditional TPB model							0.33	0.47
H1	AB—>BI	0.29	<0.001	0.079	4.589	Supported		
H2	SN—>BI	0.16	<0.01	0.059	2.888	Supported		
H3	PBC—>BI	0.36	<0.001	0.052	6.422	Supported		
H4	BI—>B	0.56	<0.001	0.040	9.264	Supported		
H5	PBC—>B	0.24	<0.001	0.032	4.494	Supported		

Note. The scores of the risk perception scale have been reversed, so the path coefficients (β) between risk perception and other variables are presented as negative values here.

[13], which found that risk perception has a negative impact on behavioral intention. However, the abovementioned studies only considered the indirect effects of risk perception on behavior and did not examine the direct impact of risk perception on behavior. By examining both indirect and direct effects, we discovered that young truck drivers, due to their own characteristics and lack of experience, have lower risk perception abilities, making it difficult for them to perceive the potential risks of risky driving behavior, thereby generating intentions for risky driving behavior or even directly engaging in risky driving behavior.

Through SEM, we can further evaluate R^2, which represents the proportion of variance in the dependent variable that is explained by the independent variables. This indicator reflects the degree of model's fitness. R^2 ranges between 0 and 1, with values closer to 1 indicating a better model fit, while lower values suggest a poorer fit. It is generally considered that when R^2 is greater than 0.45 [41], the explanatory power of the independent variables on the dependent variable is good. The results show that the improved TPB model explains 52% of the variance in behavior ($R^2 = 0.52$), indicating that the improved TPB model can effectively explain the occurrence of risky driving behavior among young truck drivers. Compared with other studies, Li et al. [13] combined TPB, sensation seeking, and risk perception to explain the adventurous driving behavior of truck drivers, and their model had an explanatory power of 64.3% ($R^2 = 0.643$) for behavioral variance. However, the model fit was poor, for instance, CMIN/DF = 3.455, RMSEA = 0.072, and SRMR = 0.065. Although the explanatory power of our model for behavior is slightly lower, the model fit is better, for example, CMIN/DF = 1.637, RMSEA = 0.044, and SRMR = 0.037. This

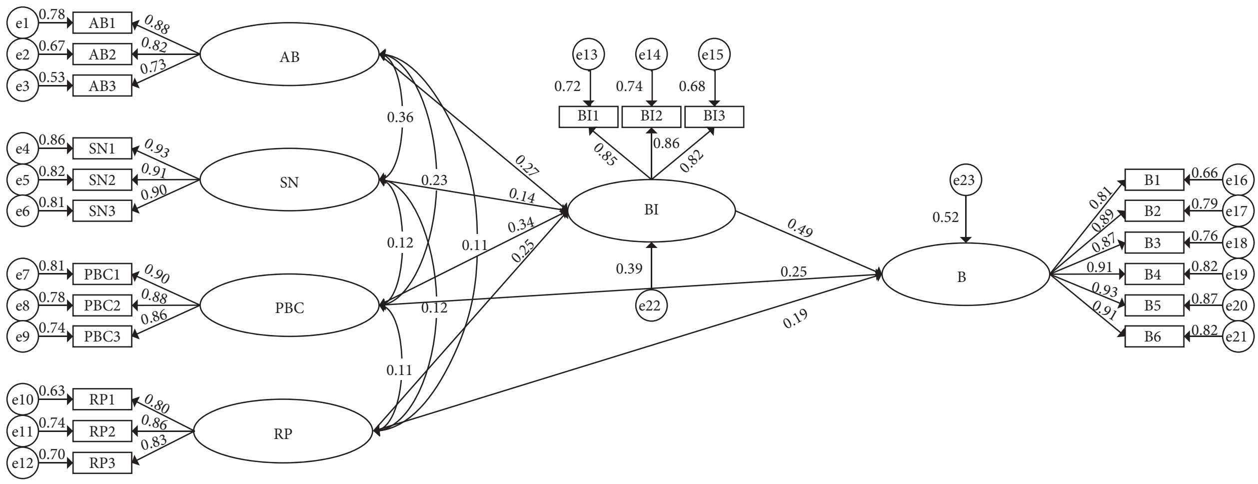

Figure 3: Path diagram of the SEM for the improved TPB model.

indicates that our model, considering the direct impact of risk perception on behavior, more accurately reflects the characteristics of actual data from young truck drivers.

Furthermore, a further analysis of the traditional TPB model is conducted. The model fit indices evaluation results are shown in Table 7, and the standardized path coefficients, hypothesis testing results, and R^2 are shown in Table 8, and the SEM path diagram is shown in Figure 4. Comparing the improved TPB model with the traditional TPB model, the results indicate that the fit indices of the traditional TPB model pass the test, and the analysis conclusions regarding the significant effects of various factors on behavior are basically consistent, with an explanatory power for behavior variance of 47% ($R^2 = 0.47$). The improved TPB model has better-fit indices, with CMIN/DF, RMSEA, and AGFI optimized by 16%, 18%, and 1.5% respectively, indicating that considering the indirect and direct effects of risk perception on behavior, the assumed model fits better with the sample data of young truck drivers. Moreover, it performs better in explaining variance, with an explanatory power for behavior variance of 52% ($R^2 = 0.52$), which is a 5% increase. This not only validates the rationality of the improved TPB model but also indicates that considering the direct impact of risk perception on behavioral intention and behavior enhances the model's explanatory power for risky driving behavior among young truck drivers. However, Li et al. [13] did not compare the improved model with the traditional model, and its rationality needs further verification. In addition, adding the risk perception factor can comprehensively consider the influence of environmental and psychological factors on risky driving behavior, enabling a more comprehensive analysis of its impact mechanism on risky driving behavior, thereby formulating more comprehensive intervention measures, which can further enhance the level of traffic safety.

5. Discussion

5.1. Discussion of Analysis of Variance Results. Through the analysis of variance of individual attribute factors, the results show that there are no significant differences in risky driving behavior among young truck drivers based on gender, age, education level, monthly income, type of vehicle driven, daily driving time, and annual driving mileage ($P > 0.05$). This is consistent with the findings of Li et al. [13] on risky driving among truck drivers. The results also indicate that there are significant differences in risky driving behavior among different driving experience groups ($P < 0.05$), with young truck drivers with 6–10 years of driving experience being more prone to risky driving behavior. There are significant differences in traffic violation frequency ($P < 0.001$) and traffic accident experience ($P < 0.05$) regarding risky driving behavior, with young truck drivers who have higher frequencies of traffic violations and traffic accident experiences being more likely to engage in risky driving behavior. Similar conclusions have been drawn in studies on other occupational and nonoccupational driving groups [17–19]. Based on these research findings, relevant suggestions and measures are proposed for young truck drivers. First, for young truck drivers with shorter driving experience, especially those with 6–10 years of experience, it is recommended to enhance driving experience training to improve their awareness of potential risks while driving and their ability to handle them, thereby reducing the likelihood of risky driving behavior. Second, for young truck drivers with higher frequencies of traffic violations, efforts should be made to educate them on traffic regulations and safety awareness, guiding them to develop good driving habits and reduce the occurrence of violations. Third, for young truck drivers with higher rates of traffic accident experiences, psychological counseling should be provided to help them cope with psychological pressure and anxiety while driving, promoting mental health and reducing the likelihood of risky driving behavior. Lastly, establishing effective supervision and feedback mechanisms to monitor and assess the driving behavior of young truck drivers in a timely manner, identifying and correcting unsafe driving behaviors promptly, can help improve their awareness and level of driving safety.

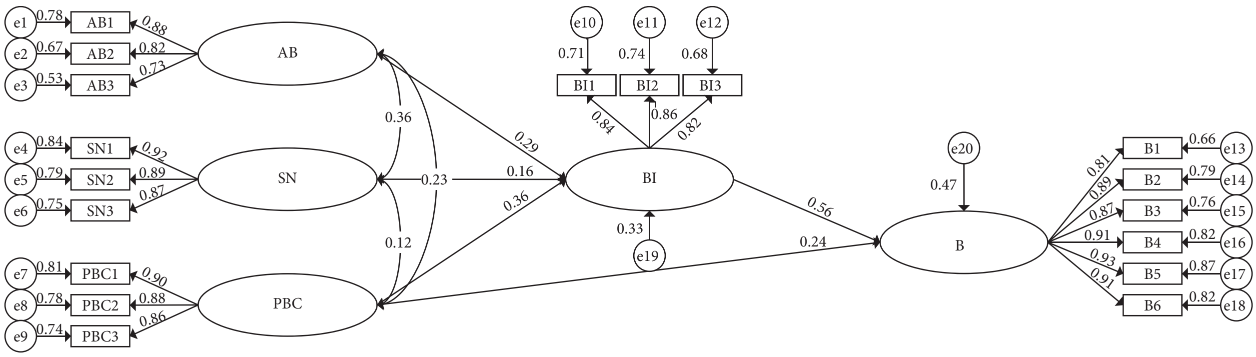

Figure 4: Path diagram of the SEM for the traditional TPB model.

5.2. Discussion of Analysis Results of the Model. Through the path coefficient analysis of SEM, the results indicate significant relationships between AB, SN, PBC, RP, BI, and B.

(1) AB ($\beta = 0.27$, $P < 0.001$) has a significant positive effect on BI. This is consistent with the findings of Hussain et al. [23] and Baikejuli et al. [24], suggesting that the attitude towards risky driving behavior among truck drivers has a significant positive impact on their intention to engage in such behavior. This implies that holding a negative attitude towards risky driving behavior can reduce the likelihood of its occurrence among truck drivers. Given that the attitudes of young truck drivers are relatively easier to shape and change, altering attitudes is considered crucial. Therefore, widespread publicity and education can be employed to enhance their awareness of safe driving. Television, mobile phones, and other online media platforms are effective channels for disseminating information on safe driving. Through vivid promotional videos and case analyses, young truck drivers can be made acutely aware of the consequences of risky driving, thereby fostering their willingness to conscientiously adhere to traffic rules.

(2) SN ($\beta = 0.14$, $P < 0.05$) has a significant positive impact on BI. This aligns with the findings of Hussain et al. [23], indicating that subjective norms have a significant positive influence on the intention of truck drivers to engage in risky driving behavior. This suggests that the opinions of family members, friends, and social experts have a significant influence on young drivers. Therefore, encouraging these social forces to actively intervene and guide young drivers can help instill correct traffic safety concepts and cultivate the habit of conscientiously obeying traffic rules.

(3) PBC ($\beta = 0.34$, $P < 0.001$) has a significant positive impact on BI and ($\beta = 0.25$, $P < 0.001$) a significant positive impact on B. This is consistent with some research findings, such as those of Baikejuli et al. [24], indicating that perceived behavioral control has a significant positive impact on the intention of truck drivers to engage in risky driving behavior, while Li et al. [13] suggest that perceived behavioral control has a significant positive impact on risky driving behavior among truck drivers. This implies that if young truck drivers perceive it as easy to engage in risky driving behavior, they will be more inclined or directly engage in such behavior. Therefore, efforts should be made to intensify the investigation and punishment of traffic violations, as well as timely disclosure of penalty cases and outcomes to convey a signal of rigorous law enforcement to society, thereby effectively deterring illegal behavior and reducing the economic costs and legal liabilities of traffic violations among young truck drivers.

(4) RP has a significant negative impact on BI ($\beta = -0.25$, $P < 0.001$) and a significant negative impact on B ($\beta = -0.19$, $P < 0.001$). This is similar to some research conclusions, such as that of Yang et al. [25], who found that risk perception has a negative impact on the intention of novice drivers to engage in risky driving, and Li et al. [13], found that risk perception has a negative impact on the intention of truck drivers to engage in risky driving. This suggests that young truck drivers, due to their lack of driving experience, may have weaker perception abilities regarding risk during risky driving, making them more prone to engaging in such behavior. Therefore, immersive virtual reality (VR) and other advanced technologies can be used for scenario-based, interactive driving training and education, allowing young drivers to personally experience various risk scenarios during virtual driving and gain a more intuitive understanding of potential dangers. This can help them learn how to respond correctly, enhance their perception of the risks associated with risky driving behavior, and make them more vigilant and cautious during actual driving, thus effectively reducing the occurrence of risky driving behavior among young truck drivers.

(5) BI has a significant positive impact on B ($\beta = 0.49$, $P < 0.001$), with BI being the most direct and important influencing factor on B. Similar conclusions have been drawn in previous studies, such as those of Hussain et al. [23], Baikejuli et al. [24], and Li et al. [13], all of which found that intention has the greatest direct impact on risky driving behavior among truck drivers. This indicates that inhibiting behavioral intention can directly reduce the likelihood of risky driving behavior. Therefore, traffic management departments should regularly investigate and identify individuals with higher intentions of engaging in risky driving behavior and provide targeted safety driving education to effectively reduce the likelihood of risky driving behavior.

These suggestions can provide decision-making support for subsequent interventions targeting risky driving behavior among young truck drivers, which is of great significance for regulating their safe driving behavior and improving road traffic safety levels.

6. Conclusion

The current research status on risky driving behavior among truck drivers has been analyzed. An overview of the TPB and its improved model's application in studying risky driving behavior is provided, along with a discussion on the advantages of integrating risk perception factors with TPB to enhance explanatory power. This provides a new perspective for studying risky driving behaviors among young truck drivers.

The direct impact of risk perception on behavior has been innovatively considered by establishing the improved TPB model and conducting a study on risky driving behavior among young truck drivers. A survey questionnaire incorporating risk perception factors suitable for the young truck driver population was designed, and valid data from 330 young truck drivers in China were collected. The improved TPB model was validated through SEM, and the influence mechanisms of various factors on risky driving behavior among young truck drivers were quantitatively analyzed. The results show that the improved TPB model can effectively explain risky driving behavior among young truck drivers, with an explanatory power of 52% for behavior variance. Specifically, AB, SN, PBC, and RP significantly influence BI, with effect values of 0.27, 0.14, 0.34, and −0.25, respectively. BI, PBC, and RP significantly influence B with effect values of 0.49, 0.25, and −0.19, respectively. Furthermore, a comparison with the traditional TPB model reveals that the improved TPB model performs better in terms of fit and explanatory power. Fit indices CMIN/DF, RMSEA, and AGFI were optimized by 16%, 18%, and 1.5%, respectively, and there was a 5% increase in explanatory power for behavior variance, validating the rationality and effectiveness of the improved TPB model. Finally, based on the analysis results, relevant suggestions and measures are proposed. This is of significant importance for developing targeted intervention measures for the young truck driver population to reduce the occurrence of risky driving behavior and improve road traffic safety levels.

The survey targeted young truck drivers in certain regions of China, with relatively limited scope and sample size, which limits the persuasiveness of the research findings. Therefore, future research should aim to conduct more comprehensive surveys on young truck drivers in other regions. In addition, other important influencing factors such as driving experience and safety incentives should be considered comprehensively to further explain risky driving behavior among young truck drivers.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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