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Formation Mechanisms and Clustering Differences in Risky Riding Behaviors of Electric Bike Riders

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ABSTRACT Individual differences between various riders cause risky riding behaviors such as violations, taking the lead, negligence and error, and pushing the limits, resulting in a high incidence and high number of road accidents for the vulnerable road use group of electric bike riders. Therefore, the subcluster differential characteristics among riders were analyzed in terms of their riding confidence, risk perception, safety attitude, and basic attributes. The influences and formation mechanisms of risky riding behaviors among the subclusters of riders were also explored. First, the 573 riders were clustered into 4 types, action type, anxiety type, introversion type, and negative type, based on the E-bike Risky Riding Behavior Questionnaire (E-RBQ), factor analysis method, and K-means clustering. Second, a structural equation model of e-bike risky riding behavior (E-SEM) was established to explore the main influencing factors for the risky riding behavior of the 4 types of riders and the differences among them. Finally, risky riding behavior avoidance strategies for various types of riders were proposed. The findings showed that negligence and error (0.48) and take the lead behavior (0.44) of action types were significantly and positively influenced by judgment ability; violation behavior (−0.52) and take the lead behavior (−0.41) of anxiety types were significantly and negatively influenced by traffic rules; pushing the limits (−0.29) and take the lead behaviors (−0.31) of introversion types were significantly and negatively influenced by probability evaluation; and negligence and error (−0.43) and violation (0.37) of negative types were negatively and positively influenced by herd mentality. In particular, the overconfidence of the action and anxiety types in their own techniques and judgment ability may cause misjudgment of the surrounding area; the worry degree of the introversion type must be balanced effectively; and the negative type must control the degree of confidence in their judgment ability.

INDEX TERMS Risky riding behavior, e-bike, SEM, K-means clustering, traffic safety.

I. INTRODUCTION

E-bikes are receiving increasing attention worldwide due to their small spatial footprint, high mobility and accessibility, and low cost of ownership and maintenance [1]. They are widely considered environmentally friendly [3], healthy, and highly economically cost-effective modes of transportation [4]. Compared to conventional bicycles, e-bikes can improve travel distance, speed, and overall performance and are better equipped for challenging terrain, travel distances, high temperatures, poor air quality, and other adverse factors associated with manual exertion [5], [6]. Additionally, the usage of e-bikes is viewed as an attractive way to reduce greenhouse gas emissions and is one of the factors

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contributing to the decline in the share of vehicles [7]. However, with the increase in the usage of e-bikes, new security issues also arise. According to estimates from the Centers for Disease Control and Prevention (CDC), there are 20 crashes resulting in injuries every 100,000 trips [8]. Similarly, during a pilot study in Multnomah County, Oregon, the injury rate for e-bikes was 2.2 per 10,000 miles and 2.5 per 10,000 trips [9]. Between 2013 and 2017, there were 56,200 accidents caused by e-bikes in China, resulting in 8431 deaths, 63,500 injuries, and 111 million yuan of direct property damage, where risky riding behaviors such as illegal lane occupation, running red lights, retrograde traffic, and speeding were the main causes of e-bike accidents [10].

E-bikes are an essential component of vulnerable road users and can be defined as road users that are most prone to road crashes [11]. Scholars have begun to explore the characteristics of the risky riding behavior of e-bike riders based on their traffic accidents in an attempt to take appropriate measures to reduce the risk of their accidents. Wang *et al.* [12] investigated the risk factors affecting the severity of e-bike collision injuries based on a logistic regression model with a classification tree, considering rider attributions, opposition vehicles, rider misbehavior, road, and environmental characteristics. Hu *et al.* [13] employed a logistic regression model to investigate the serious injury risk degree of e-bike riders, considering factors such as speed and age. Vlakveld *et al.* [14] analyzed traffic conflicts such as near-collisions and minor accidents in the Netherlands to explore potential crash companions, crash patterns, and factors that increased crash risk. However, particular risk factors may have different degrees or even opposite directions of injury consequences, since there are differences in the characteristics and risky riding behaviors among e-bike riders [15]. As artificial factors have been a major contributor to crashes, it is crucial to explore the relationship between riders and risky riding behaviors. Luu *et al.* [16] analyzed the relationship between young riders' risky riding behaviors and their attitudes toward road safety and proposed targeted guidelines for safe riding. James *et al.* [17] also investigated 181 e-bike riders and nonriders with questionnaires concerning riding behaviors and safety perceptions. Harms *et al.* [18] reviewed studies that correlated riders' riding behaviors and their traffic cognitive psychology by considering route familiarity. However, the differences in riders' individual characteristics were ignored in these studies, and the influence of riders' abilities, perceptions, and attitudes on risky riding behavior when interacting with other riders was also not addressed. In fact, **there is significant heterogeneity in the causes of risky riding behavior among rider groups with different attributes (as demonstrated in this paper), and ignoring such heterogeneity makes it difficult to propose targeted prevention strategies to regulate riding behavior**.

Therefore, there is a crucial necessity to explore the inter-rider differences and their internal associations with various risky riding behaviors in an investigation of the risky riding behaviors of e-bike riders. The Manchester Driver Behavior Questionnaire (DBQ), an important method for anatomizing the intrinsic formation mechanisms of risky riding behaviors [19], is the method of choice for this work. Structural equation modeling (SEM), another major approach that will be applied in this work, is an effective tool to address the relationship of latent variants that has been widely used to explore the path relationships between drivers' potential influences (including safety attitudes, subjective regulations, perceptual behavior control, personality traits, and traffic safety atmosphere) and riding behavior [20]–[22]; however, it ignores the important factor of riders' riding confidence. In contrast, the correlation between riding confidence and risky riding behavior has been well established for experienced riders [23].

Based on the inadequacies of the abovementioned findings, we investigate the formation mechanism of risky riding behavior and the differences among various e-bike riding groups based on the four dimensions of riding confidence, risk perception, safety attitude, and risky riding behavior using the DBQ survey and SEM method to provide scientific evidence for relevant surveys and departments to formulate effective and targeted safety strategies.

The paper's framework is as follows: **In the next section, Methodology**, we designed an e-bike risky riding behavior questionnaire consisting of the following five components: individual information, riding confidence, risk perception, safety attitude, and risky riding behavior, and performed a reliability test and factor analysis. Then, the e-bike riders were divided into 4 types based on the factor scores, and the e-bike risky riding behavior SEM model (E-SEM) was established. **In the third section, Results**, the matching degree of the E-SEM was measured, and the impact factors of risky riding behaviors and their differences were analyzed in the 4 clusters. Then, targeted risk avoidance strategies are proposed based on the characteristics of the 4 clusters. **In the final section, Conclusions**, the research objectives, main findings, limitations, and future research directions of this paper are summarized.

II. MATERIALS AND METHODS

A. STRUCTURE AND DATA OF E-RBQ

An initial E-RBQ was prepared based on theoretical analysis, literature review, and expert interviews. The initial E-RBQ was administered to a group of e-bike violators in Guilin city to test, adjust, and formulate an effective E-RBQ. The E-RBQ consists of the five parts of individual information, safety attitude, risk perception, riding confidence, and risky riding behavior, with a total of 81 questions. Among them, individual information included gender, age, marital status, education level, profession, and riding age, with a total of 11 questions. The remaining 4 sections are the main content, which primarily use 5-point Likert scales to record the answers to a total of 70 items.

The investigation mainly included riders with e-bike riding experiences in Guilin and Nanning (the questionnaires were completed with the consent of the respondents and were used only for this study to protect the privacy of their personal information). There were 632 questionnaires obtained, of which 573 were effective, for an effectiveness rate of 90.7%; 33.51% of the effective questionnaires were intended for accident patients. The number of samples required was verified to be at least 385 based on the simple random sample size calculation method shown in Equation (1) (considering the very large size of e-bike ownership and treating the matrix of the study as infinity without violating reason); thus, 573 samples met the requirement.

$$n = \frac{0.5Z_a^2 P(1-P)}{e^2} \tag{1}$$

where n is the number of samples, e is the allowable range of sampling error, Z is the standard normal distribution look-up table value at the confidence level, and P is the probability of occurrence of the matrix realization.

After the questionnaire was analyzed and revised, the Cronbach's α of each factor structure in the questionnaire was more than 0.7, and the KMO was more than 0.6, which met the reliability and validity test and were suitable for factor analysis.

TABLE 1. The results of the reliability and validity test and factor analysis.

Dimensions	Factor structure	Cronbach's α (>0.7)	KMO (>60%)
Riding confidence (A)	Technical ability (A1)	0.827	90.60%
	Judgment ability (A2)	0.853	83.58%
Risk perception (B)	Risk level (B1)	0.911	85.42%
	Worry degree (B2)	0.814	77.27%
	Probability evaluation (B3)	0.831	75.03%
Safe attitude (C)	Safe responsibility (C1)	0.932	88.52%
	Traffic rules (C2)	0.960	77.34%
	Crowd psychology (C3)	0.844	74.95%
Risky riding behavior (D)	Negligence and error (D1)	0.776	67.18%
	Violation behavior (D2)	0.866	79.20%
	Pushing the limits (D3)	0.791	63.86%
	Risk level (B1)	0.911	85.42%

The results of factor analysis indicated that the riding confidence (A) dimension consisted of two low-rank factors: technical ability (A1) and judgment ability (A2). The risk perception (B) dimension consisted of three low-rank factors: risk level (B1), worry degree (B2), and probability evaluation (B3). The safety attitude (C) dimension consisted of three low-rank factors: safety responsibility (C1), traffic rules (C2), and crowd psychology (C3). The risky riding behavior dimension (D) consisted of 4 low-rank factors: negligence and error (D1), violation behavior (D2), pushing the limits (D3), and take the lead behavior (D4), which represent 4 types of general risky riding behaviors of e-bike riders, as shown in Table 1.

B. CLUSTERING OF FACTOR SCORES AND E-SEM

1) CLUSTERING OF FACTOR SCORES

The riders' data specimens were clustered with K-means clustering based on the results of factor analysis. The results of the standardized factor scores of the riding confidence, risk perception, and safety attitude dimensions among the riders were taken as the clustering objects, and the optimal number of clusters was obtained with the values of Calinski-Harabaz (CH). A higher CH value represents a tighter cluster and more dispersion between clusters, which denotes a better clustering result. As shown in Figure 1, when k = 4, the CH value is at its maximum. The CH value decreases rapidly thereafter, so the e-bike riders can be divided into 4 clusters.

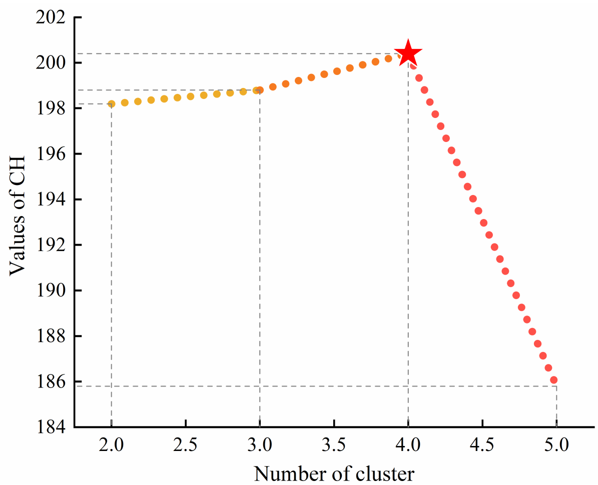

FIGURE 1. Optimal number of clusters was determined.

The 4 clusters were categorized as action type, anxiety type, introversion type, and negative type based on their characteristics of factor scores in the 3 dimensions of riding confidence, risk perception, and safety attitude, as shown in Figure 2. The basis of their categorization follows.

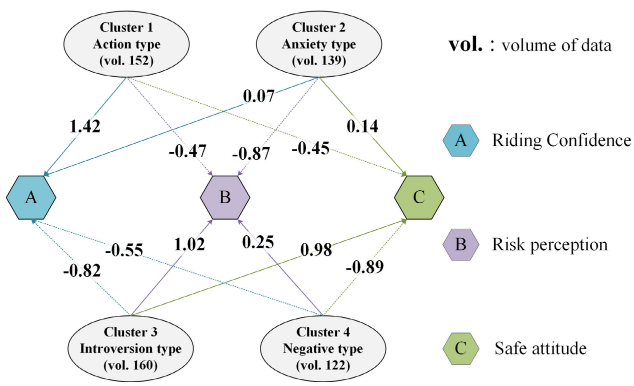

FIGURE 2. Normalization factor score results of 4 clusters in 3 dimensions.

Action type: In Cluster 1, the riders' riding confidence scores were the highest and their risk perception and safety attitude scores were low. Since this cluster was very confident in their riding ability, they tended to neglect risks due to overconfidence; they were the high-frequency cluster for risky riding behaviors such as negligence and error.

Anxiety type: In Cluster 2, the riders' riding confidence and safety attitude scores are medium and their risk perception scores are lowest. Since this cluster has lower perception awareness and the ability for risk, it is the cluster with the higher frequency of risky riding behaviors such as the take the lead behavior.

Introversion type: In Cluster 3, the lowest scores of riding confidence and the highest scores of both risk perception and safety attitude were observed among riders. This cluster has the most sensitive perception toward risk and the most positive attitude toward traffic safety but is prone to errors caused by an extreme lack of riding confidence. It shows unstable behavior in road safety and is a lower frequency cluster for risky riding behaviors such as negligence and errors.

Negative type: In Cluster 4, riders have lower riding confidence scores, medium risk perception scores, and the lowest safety attitude scores. The negative attitude of this cluster toward traffic safety is the most negative, and they tend to exhibit the take the lead behavior under the assumption of their security but infrequently push the limits and exhibit negligence and errors. Overall, the cluster is a low-frequency cluster for risky riding behaviors.

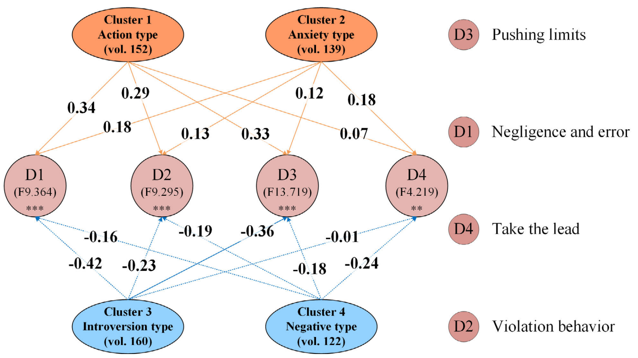

FIGURE 3. Standardized differences analysis of risk riding behavior of 4 clusters.

The four groups were classified into risk-tending and risk-avoiding categories based on the probability of risky riding behaviors. Of these, **the risk-tending category** included both the action and anxiety types, which had higher risky riding behavior scores than the standard values. Only the anxiety type was higher than the action type in the take the lead behavior. **The risk-avoiding category** contained both the introversion and negative types. Their risky riding behavior scores were lower than the standard value, and the negative type was just slightly higher than the introversion type in the take the lead behavior.

The results of the difference analysis (see Figure 3, where $**$ indicates P<0.01, $***$ indicates P<0.001) showed that each of the 4 clusters had significant differences in risky riding behavior factor scores. Thus, e-bike riders should be treated as a heterogeneous group and subcluster studies are required.

2) MODEL CONSTRUCTION OF E-SEM

The E-SEM model was established based on the factor analysis results, which is made up of the four dimensions of riding confidence, safety attitude, risk perception, and risky riding behavior, to explore the formation mechanism and differences of risky riding behavior in different e-bike riding clusters. The structural equation model consists of a measurement model and a structural model. The measurement model indicates the relationship between the measurement variables and latent variables. It specifies the associations between the endogenous latent variable η and the endogenous explicit variable Y (Equation 2) and between the exogenous latent variable ξ and the exogenous explicit variable X (Equation 3). The structural model, which indicates the associations between latent variables, specifies the causal relationships between hypothesized exogenous latent variable ξ and endogenous latent variable η (Equation 4).

$$Y = \Lambda_y \eta + \epsilon \tag{2}$$
$$X = \Lambda_x \xi + \delta \tag{3}$$
$$\eta = B\eta + \Gamma\xi + \varsigma \tag{4}$$

where $Y(p\times 1)$ is the vector constructed from the explicit variables of the endogenous latent variable η. $X(q\times 1)$ is the vector constructed from the explicit variables of the exogenous latent variable ξ. $\eta(m\times 1)$ is the vector constructed from the endogenous latent variable. $\xi(n\times 1)$ is the vector constructed from the exogenous latent variable. $\Lambda_y(p\times m)$ is the factor loading matrix of Y on η. $\Lambda_x(q\times n)$ is the factor loading matrix of X on ξ. $\delta(q\times 1)$ and $\epsilon(p\times 1)$ are both measurement error vectors. $\Gamma(m\times n)$ is the coefficient parameter matrix of the vector of the exogenous latent variables. $\varsigma(m\times 1)$ is the residual vector.

The observed variables for each low-rank factor were not shown in the theoretical model to simplify the model description. The factor paths of the high-rank latent variables set to 1 were treated as reference indicators to enable high-rank latent variables to be estimated.

III. RESULTS AND DISCUSSIONS

A. E-SEM MODEL VERIFICATION

First, under the assumption of the full path relationship among the factors, the paths with insignificant path coefficients were eliminated based on the model results, and then the model was rectified with the correction indices. All the inspection indices of the eventually established E-SEM model (as shown in Figure 5) meet the standard criteria, which means that the model adopts the inspection and the model calculation results are qualified. The results of the model inspection indices are shown in Table 2.

After model validation and correction, the path hypotheses were verified, and the results are shown in Table 3. The results show that after removing the riding confidence with risky

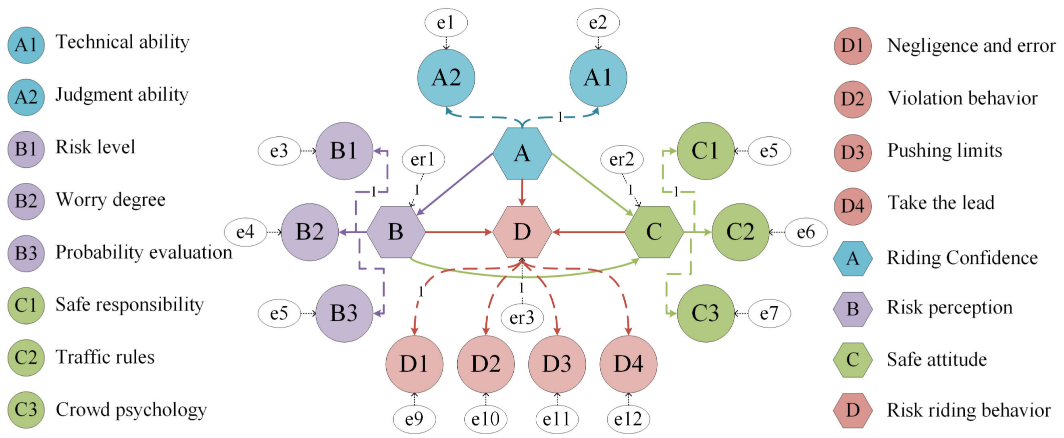

FIGURE 4. The construction diagram of E-SEM theoretical model.

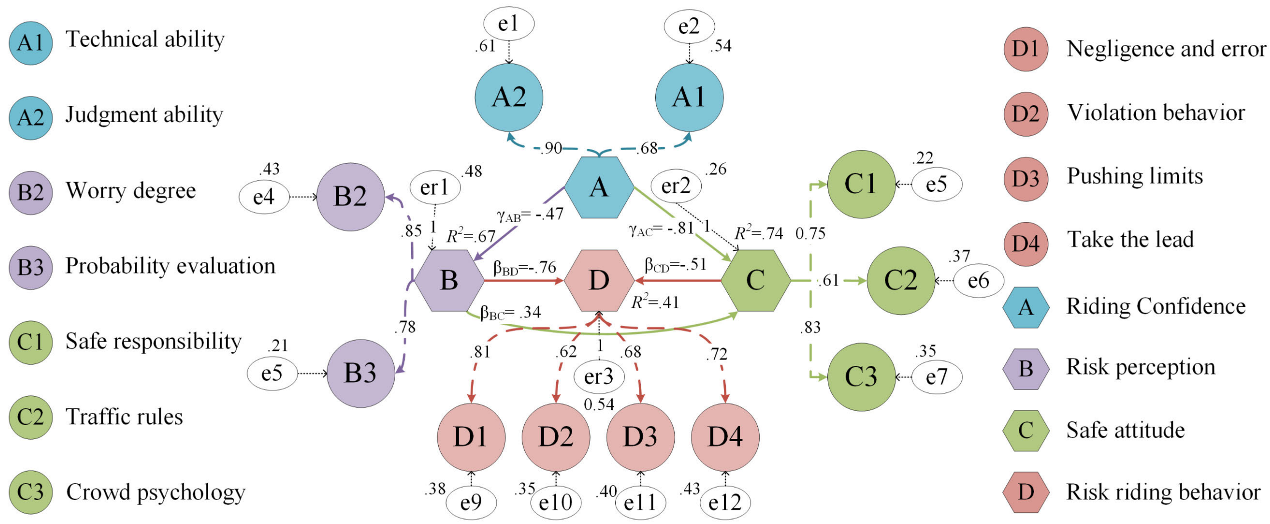

FIGURE 5. The fitting results of E-SEM model.

TABLE 2. The results of the E-SEM model fitness test.

Model	Descriptions	Model Values	Measurement criteria
χ^2/df	chi-square/degrees of freedom	2.251	1-5
RMSEA	root mean square of approximation error	0.028	<0.050
CFI	comparative fit index	0.922	>0.900
GFI	goodness of fitting	0.948	>0.900
NFI	Standard fitting index	0.913	>0.900
IFI	Incremental fitting index	0.925	>0.900

TABLE 3. The test results of the path coefficient.

Path	Standardized path coefficient	C.R.	Values of P
A→B	-0.472	-2.101	0.032
B→C	-0.342	-2.173	0.041
A→C	-0.807	-10.614	0.000
C→D	0.513	2.615	0.006
B→D	-0.764	-2.289	0.007

riding behavior paths, all paths achieved a 95% significance level.

B. ANALYSIS OF THE INFLUENCING FACTORS OF RISKY RIDING BEHAVIOR BY THE 4 CLUSTERS

Based on the fitting results of the E-SEM model for the 4 clusters, the characteristics of the influencing factors of risky riding behaviors were observed for each cluster, as shown in Figure 6.

1) NEGLIGENCE AND ERROR

For the **action type**, negligence and error are directly negatively influenced by worry degree (−0.36), directly positively influenced by judgment ability (0.48), and indirectly positively influenced by technical ability (0.21). For the **anxiety type**, negligence and error are directly negatively

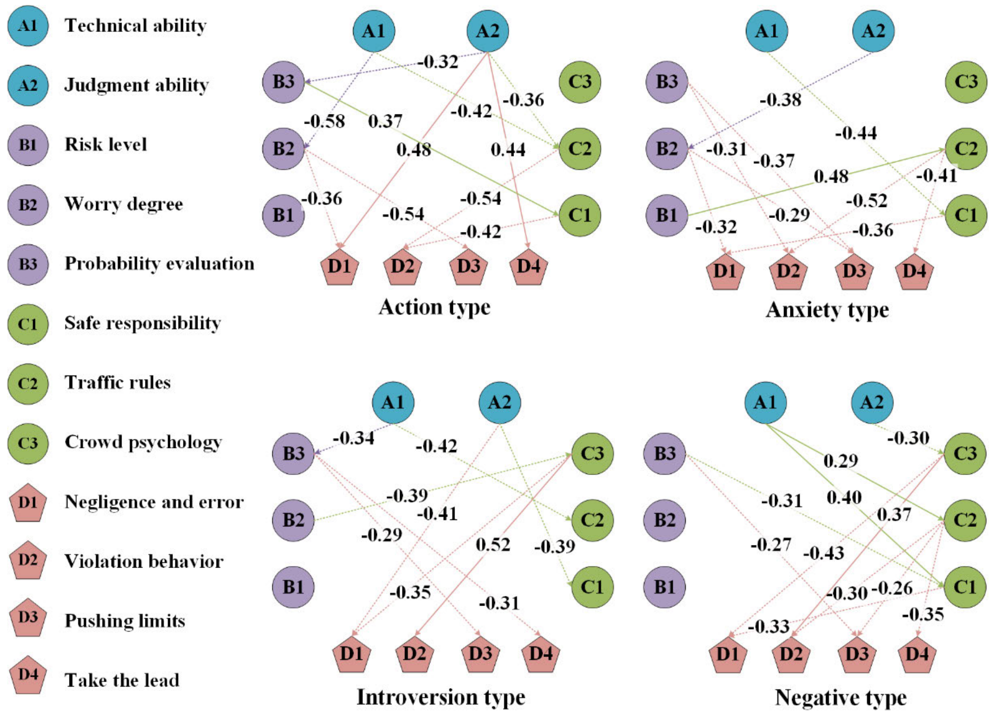

FIGURE 6. The E-SEM model results for the 4 clusters. The numbers are the standardized path coefficients among the factors, which indicate the influential effective relationships among the factors.

influenced by safety responsibility (−0.36) and worry degree (−0.32) and indirectly positively influenced by technical ability (0.16) and judgment ability (0.12). For the **introversion type**, negligence and error are directly negatively influenced by judgment ability (−0.41) and crowd psychology (−0.35) and indirectly positively influenced by worry degree (0.14). For the **negative type**, negligence and error are directly negatively influenced by safety responsibility (−0.33) and crowd psychology (−0.43), indirectly negatively influenced by technical ability (−0.13), and indirectly positively influenced by probability evaluation (0.10) and judgment ability (0.13). Among the influencing factors of negligence and error, the most influencing factors on the 4 clusters of action type, anxiety type, introversion type, and negative type are judgment ability (0.48), safety responsibility (−0.36), judgment ability (−0.41), and crowd psychology (−0.43), respectively.

2) VIOLATION BEHAVIOR

For the action type, violation behavior is directly negatively influenced by safety responsibility (−0.42) and traffic rules (−0.54) and indirectly positively influenced by technical ability (0.23) and judgment ability (0.24). For the anxiety type, violation behavior is directly negatively influenced by traffic rules (−0.52) and probability evaluation (−0.31) and indirectly negatively influenced by risk level (−0.25). For the introversion type, violation behavior is directly and positively influenced by crowd psychology (0.52) and indirectly and negatively influenced by worry degree (−0.20). For the negative type, violation behavior is directly and negatively influenced by traffic rules (−0.30), directly and positively influenced by crowd psychology (0.37), and indirectly and negatively influenced by technical ability (−0.09) and judgment ability (−0.11). Among the influencing factors of violation behavior, the most influencing factors on the 4 clusters of action type, anxiety type, introversion type, and negative type are traffic rules (−0.54), traffic rules (−0.52), crowd psychology (0.52), and crowd psychology (0.37), respectively.

3) PUSHING THE LIMITS

For the action type, pushing the limits is directly and negatively influenced by worry degree (−0.54) and indirectly and positively influenced by technical ability (0.31). For the anxiety type, pushing the limits is directly negatively influenced by worry degree (−0.29) and probability evaluation (−0.37) and indirectly positively influenced by judgment ability (0.11). For the introversion type, pushing the limits is directly negatively influenced by probability evaluation (−0.29) and indirectly positively influenced by technical ability (0.10). For the negative type, pushing the limits is directly and negatively influenced by probability evaluation (−0.27) and traffic rules (−0.26) and indirectly and negatively influenced by technical ability (−0.08). Among the influencing factors of pushing the limits, the most influencing factors on the 4 clusters of action type, anxiety type, introversion type, and negative type were worry degree (−0.54), probability evaluation (−0.37), probability evaluation (−0.29), and probability evaluation (−0.27), respectively.

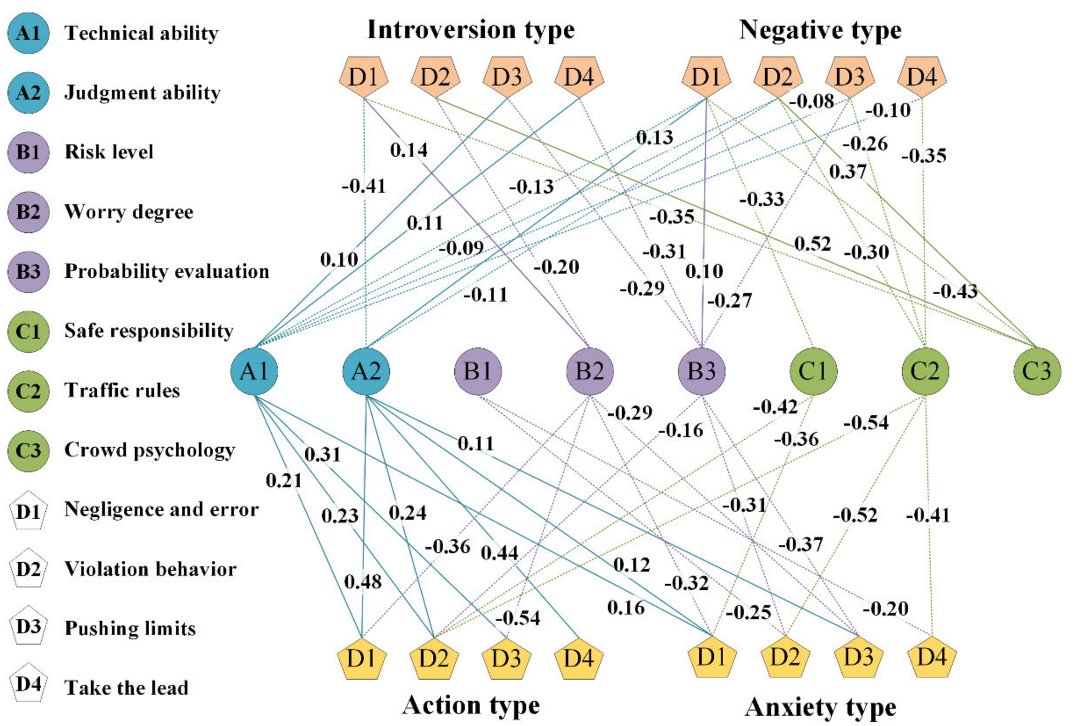

FIGURE 7. The E-SEM model results for 4 clusters (eliminating high-rank factors).

4) TAKE THE LEAD

For the action type, take the lead behavior is directly and positively influenced by judgment ability (0.44) only. For the anxiety type, take the lead behavior is directly and negatively influenced by traffic rules (−0.41) and indirectly and negatively influenced by risk level (−0.20). For the introversion type, take the lead behavior is influenced by the direct negative influence of probability evaluation (−0.31) and the indirect positive influence of technical ability (0.11). For the negative type, take the lead behavior is influenced by the direct negative influence of traffic rules (−0.35) and the indirect negative influence of technical ability (−0.10). Among the influencing factors of take the lead behavior, the most influencing factors for the 4 clusters of action type, anxiety type, introversion type, and negative type were judgment ability (0.44), traffic rules (−0.41), probability evaluation (−0.31), and traffic rules (−0.35), respectively.

C. DIFFERENCE ANALYSIS OF INFLUENCING FACTORS FOR RISKY RIDING BEHAVIOR IN THE 4 CLUSTERS

1) DOMINANT INFLUENCING FACTORS FOR EACH CLUSTER

The results of the influence of each factor on the four risky riding behaviors of each cluster based on Section III.B indicated significant differences in the risky riding behaviors of the 4 clusters as influenced by each factor.

The risky riding behaviors of the action type were most influenced by judgment ability (A2). This was primarily caused by the fact that this cluster had the highest riding confidence score, but overconfidence tended to cause misjudgment of the surrounding environment and lower concern about the latent risk of road traffic, which triggered various types of risky riding behaviors. The risky riding behaviors of the anxiety type group were most influenced by traffic rules (C2). This was primarily caused by the lack of sensitivity to risk in this cluster, which tended to occasionally disregard traffic safety and violated traffic rules, causing risky riding behaviors.

The risky riding behaviors of the introversion type were most influenced by the probability evaluation (B3), which revealed that for the risk-avoiding category, the failure of the probability evaluation and excessive crowd psychology tended to cause risky riding behaviors. The risky riding behaviors of the negative type were most influenced by crowd psychology (C3). Although this cluster behaved well in terms of riding behaviors, their own negative safety attitudes and disregard for road traffic rules tended to trigger crowd psychology, which caused their riding to be influenced by others to perform extremely risky riding behaviors.

2) DIFFERENCES IN INFLUENCING FACTORS ON RISKY RIDING BEHAVIOR FOR DIFFERENT DIMENSIONS

For the purpose of promoting cross-cluster comparisons, the parameters were table-transformed with common cross-cluster measurement scales when the parameters were estimated in the multicluster structural model. To further define the structural differences and influencing factors of various risky riding behaviors among the four clusters, the high-rank factors were no longer extracted from each construct when the structural analysis of various types of clusters' behaviors was performed. Rather, confirmatory factor analysis of 12 factors was directly employed as the measurement model to obtain the structural relationships among the 12 factors, as shown in Figure 7.

The risk level, worry degree, safety responsibility, and traffic rules in the 4 clusters all negatively influenced risky riding behavior, which is consistent with the findings of previous scholars. However, there were some differences in the influence orientation of probability evaluation, crowd psychology, technical ability, and judgment ability in different clusters. The influence differences of the 3 dimensions of riding confidence, risk perception, and safety attitude on the risky riding behavior of the 4 clusters were analyzed as follows.

3) RIDING CONFIDENCE (A)

Technical ability (A1) and judgment ability (A2) had direct and indirect positive influences on specific risky riding behaviors for the action and anxiety types, indicating that higher riding confidence tended to cause riders to ignore traffic safety and trigger various risky riding behaviors. In contrast, judgment ability (A2) had a negative influence (−0.41) on the negligence and error behavior (D1) of the introversion type, which indicated that appropriate confidence in judgmental ability was beneficial to reduce negligence and error behavior. The negative influence of technical ability (A1) on all types of risky riding behaviors for the negative type indicated that appropriate confidence in technical ability could regulate riding behaviors. Notably, judgment ability of the negative type had the opposite influence on their negligence and error behavior (0.13) and violation behavior (−0.11), which indicated that understanding the degree of confidence in their judgment ability is critical to promoting beneficial riding.

4) RISK PERCEPTION (B)

The risk level (B1) had an indirect negative influence on the anxiety type via traffic rules and crowd psychology. The worry degree (B2) had a significantly negative influence on the action and anxiety types and the opposite influence on negligence and error behavior (D1, 0.14) and violation behavior (D2, −0.20) of the introversion type. The indication was that for the introversion type, which lacked sufficient riding confidence, there was a requirement to balance their own worrying attitude toward traffic safety to avoid excessive negligence and errors and violation behaviors.

The probability evaluation (B3) had a significant negative influence on the risky riding behavior of the action, anxiety, and introversion types, which indicated that under certain scenarios, when the rider regarded the higher probability of being in danger, the risk perception ability of the rider was higher and the risky riding behavior was more effectively avoided. The probability evaluation (B3), in addition to having a directly negative influence (−0.27) on pushing the limit behavior (D3) of the negative type, also had an indirect positive influence (0.10) on negligence and error behavior (D1) via the intermediate factor of safety responsibility (C1). This result indicated a negative attitude toward traffic safety when the cluster regarded a higher probability of being in danger, which tended to cause errors in riding and negligence and error.

5) SAFE ATTITUDE (C)

The risky riding behaviors of both the action and anxiety types were not significantly influenced by crowd psychology (C3). The crowd psychology of both the introversion and negativity types had a significantly negative influence (−0.35, −0.43) on negligence and error (D1) and a positive influence (0.52, 0.37) on violation behavior (D2). Analogously, the negative type had a negative safety attitude, so appropriate crowding could prevent negligence and error. However, both groups were influenced by crowd psychology and tended to exhibit crowd violation behaviors.

D. RIDING RISK AVOIDANCE STRATEGIES FOR THE 4 HETEROGENEOUS CLUSTERS

For the four types of riders with significant differences, targeted measures could be taken to ensure their riding safety. Ibrahim *et al.* [24] suggested that relevant training modules such as work preparation and risk perception training should be implemented for e-bike riders. This is especially true for riders who have a history of risky traffic behaviors such as driving through red lights and riding on motorways [25]. Therefore, we provide some proposals and strategies that would be beneficial to avoid risky riding behaviors based on the different characteristics of risky riding behaviors in the 4 types.

For the action and anxiety types, we should enhance safety education and training, promote safety awareness, correct riding attitudes, and regulate riding behavior with penalty point policies for violations. For the introversion and negative types, we should upgrade the traffic infrastructure to optimize the riding environment, increase positive riding confidence, and prevent risky riding behavior. Negligence and error behavior arising from misjudgment of road conditions should be avoided by raising the rational awareness of riding in a crowd via crowd psychology education, while avoiding violations arising from implicit crowd riding.

The trend direction of the same influencing factor on specific risky riding behaviors in various clusters was different. Owing to the nature of the risk-trending category, the overconfidence of the action and anxiety types in their technical and judgment abilities can directly or indirectly cause risky riding behaviors. Hence, the assessment mechanism of the technical ability for the action and anxiety types and the correction mechanism of their judgment ability should be strengthened to avoid unnecessary riding risks caused by their overconfidence. Owing to the nature of the risk-avoiding category, negligence and error behavior could be prevented effectively by the judgment confidence and crowd psychology of the introversion type, but the worry degree could have the opposite influence on the negligence and error behavior and violation behavior. Therefore, the introversion type should be assisted with a suitable psychological adjustment mechanism to improve their excessive worry about road safety. The negative types' confidence in their technical ability could prevent all kinds of risky riding behavior, but their confidence in their judgment ability had the opposite influence on negligence and error behavior and violation behavior. Thus, the degree of confidence in their judgment ability should be rationally controlled.

The effective management of the above proposed auxiliary improvement mechanism strength depends on the values of the influence degree coefficients obtained in this paper. For this purpose, the relative weights of the mechanism regulation can be better determined to achieve an effective riding risk prevention strategy.

IV. CONCLUSION

With the aim of investigating the formation mechanism and the differences in risky riding behaviors of various e-bike riding clusters, E-RBQ data from Guilin and Nanning cities were obtained in this paper. The riders were divided into four different clusters based on K-means clustering and factor analysis, and an E-SEM model was established to investigate the characteristics of risky riding behavior subclusters of e-bikes and the characteristics of different influencing factors.

First, the E-RBQ questionnaire was designed employing a 5-point Likert scale in the five dimensions of individual information, safety attitude, risk perception, riding confidence, and risky riding behavior. The 4 dimensions of riding confidence (A), risk perception (B), safety attitude (C), and risky riding behavior (D) and the associated 12 low-rank factors were extracted by reliability and validity tests and factor analysis. Next, e-bike riders were clustered into the following 4 clusters based on CH evaluation indices: action type, anxiety type, introversion type, and negative type by employing K-means clustering based on the factor score results. The 4 clusters were categorized into the risk-tending and risk-avoiding categories based on the probability of risky riding behavior. Then, the E-SEM model was established based on the 4 heterogeneous clusters, and this was checked by the model fitness test. Finally, the characteristics of the influencing factors of negligence and error, violation behavior, pushing the limits, and take the lead behavior of each cluster were explored based on the model results. The differences between the influencing factors of risky riding behaviors of each cluster were analyzed in the 3 dimensions of riding confidence (A), risk perception (B), and safety attitude (C). Risk prevention strategies for riding for the 4 heterogeneous cluster characteristics were recommended. The main findings are as follows:

(1) The riders were clustered into 4 clusters based on their characteristics, and the influencing factors of risky riding behaviors for each cluster had significant differences. For the 4 clusters of action type, anxiety type, introversion type, and negative type, the most influential factors on negligence and error behavior were judgment ability (0.48), safety responsibility (−0.36), judgment ability (−0.41), and crowd psychology (−0.43), respectively; the most influential factors on violation behavior were traffic rules (−0.54), traffic rules (−0.52), crowd psychology (0.52), and crowd psychology (0.37), respectively; the most influential factors on pushing the limits behavior were worry degree (−0.54), probability evaluation (−0.37), probability evaluation (−0.29), and probability evaluation (−0.27), respectively; and the most influential factors on take the lead behavior were judgment ability (0.44), traffic rules (−0.41), probability evaluation (−0.31), and traffic rules (−0.35), respectively. Overall, the most influential factors on risky riding behavior in the 4 clusters of action type, anxiety type, introversion type, and negative type were judgment ability (A2; negligence and error: 0.48; take the lead: 0.44), traffic rules (C2; violation behavior: −0.52; take the lead: −0.41), probability evaluation (B3; pushing the limits: −0.29; take the lead: −0.31), and crowd psychology (C3; negligence and error: −0.43; violation behavior: 0.37).

(2) For the risk-tending category, the action and anxiety types have overconfidence in their technical and judgment abilities. The assessment mechanism of the technical ability for the action and anxiety types and the correction mechanism of their judgment ability should be strengthened to avoid unnecessary riding risks caused by their overconfidence. For the risk-avoiding category, the judgment ability confidence and crowd psychology of the introversion type could effectively prevent the occurrence of negligence and error behavior, but the worry level requires effective balancing. The negative types' confidence in their technical ability could prevent all kinds of risky riding behavior, but the degree of their judgment ability confidence must be regulated.

The prevalent groups of e-bike riders were investigated by clustering their risky riding behaviors; differences between e-bike styles were not considered for this paper. For further investigations at a later stage, we will focus on investigating the effects of the diversity of e-bike styles (e.g., pure electric bikes, power-assisted bicycles, and electric bikes that combine pure and power-assisted modes [2]) on risky riding behaviors to more comprehensively understand the mechanisms of risky riding behaviors.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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