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Cell Phone Usage Among Chinese Delivery Riders During Rides: An Analysis Using an Extended Theory of Planned Behavior

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Abstract
China's online food delivery industry has grown rapidly, leading to a significant increase in the number of food delivery riders. However, a worrying trend is the frequent use of mobile phones while riding, which endangers riders themselves and poses risks to traffic safety. Our study aims to explore the reasons behind this behavior, including work demands, personal habits, and technological dependence, to inform safer traffic policies, improve rider efficiency, and ensure overall safety. In this study, we employed structural equation modeling to examine the factors influencing cell phone usage while riding among delivery riders. A total of 504 delivery riders participated in interviews, with 501 successfully completing the questionnaires. Based on the theory of planned behavior, we analyzed the behavior of cell phone usage while riding. The behavior of delivery riders using cell phones while riding is influenced by several psychological factors, either directly or indirectly. SN and law enforcement exerted a significant effect on intention, whereas attitudes, perceived behavioral control (PBC), and descriptive norms showed a negative correlation with intention. However, perceived danger, perceived severity, and perceptual barriers did not demonstrate a significant effect on behavioral intentions (BI). PBC significantly influences riding behavior, while BIs are negatively correlated with it. Strengthening enforcement efforts and raising awareness about the dangers of using cell phones while riding can be effective measures to reduce the prevalence of delivery riders using their phones while riding.

Keywords
freight systems, urban freight transportation, delivery, bicycles, human factors, bicycle transportation, electric bicycles

The rise of online food delivery services has created numerous job opportunities for delivery riders worldwide, heavily reliant on internet-enabled smartphones for efficient management (*1*). In China, the food delivery and courier industry has witnessed significant growth, driven by the popularity of online-to-offline (O2O) food delivery services, further fueled by the expansion of the internet and e-commerce (*2*). Serving as a third-party platform, O2O food delivery in China connects customers with restaurants, facilitating online ordering and offline delivery (*3*). A 2023 workforce survey by the All-China Federation of Trade Unions reported a surge in delivery riders to 13 million, constituting 15% of China's emerging employment forms (*4*). This growth, particularly during the COVID-19 pandemic, is exemplified by Meituan's rider increase from 4.7 million to 6.24 million between 2020 and 2022, a 32.8% rise (*5*).

There is an increasingly evident connection between e-bike riders and a spectrum of traffic violations, posing significant risks to road safety. Research has highlighted a myriad of concerning behaviors among e-bike riders, including riding in lanes designated for motor vehicles, disregarding the requirement to halt behind the white

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line at red lights, engaging in cell phone use while riding, carrying oversized cargo, unlawfully occupying lanes, running red lights, traveling against the flow of traffic, and making phone calls while riding (*6–9*). A recent study indicates that, by the end of 2022, approximately 4 billion individuals out of the total 4.6 billion users of mobile internet services would be accessing these services through smartphones, underscoring that many people use cell phones (*10*). In our fast-paced lives, an increasing number of individuals are resorting to their phones, even while driving or riding.

Food delivery riders often engage in risky riding behaviors and traffic violations, including riding against traffic, running red lights, and using cell phones while riding (*11–13*). Research conducted by Rusli et al. in Malaysia revealed that a significant number of delivery riders are involved in traffic infractions, particularly the use of mobile devices while operating their vehicles, as well as disregarding traffic signals and making unauthorized U-turns (*12*). The use of cell phones while operating a vehicle has been recognized as a substantial contributor to vehicular accidents. Despite legal prohibitions against cell phone usage while driving in many countries, the incidence of reported accidents attributable to this conduct has exhibited an upward trend (*14*). Another study by Useche et al. emphasizes that occupational crashes among food delivery riders are not solely attributed to mobile device usage; stress-related factors and work-related fatigue also play significant roles in these incidents (*15*).

Literature Review

Currently, there exists a significant amount of research dedicated to exploring the use of cell phones while driving. Drivers who use cell phones while driving face a four to five times greater likelihood of being in a traffic accident compared with those who refrain from using cell phones while driving (*16*, *17*). Using cell phones while driving results in delayed reactions to potential hazards, extended following distances, reduced visual attention to the surrounding environment, and sluggish response times to occurrences on the road (*18*). The findings imply an inverse correlation between risk perception and cell phone usage while driving, indicating that individuals with heightened awareness of associated hazards are less likely to engage in such behavior (*19*). Additionally, research underscores the influential role of societal factors, enforcement of distracted driving laws, and overall quality of life in shaping attitudes toward distracted driving, thus significantly affecting individuals' decisions about cell phone use while driving (*20*, *21*). According to the World Health Organization, the propensity for road traffic accidents escalates significantly—ranging between 2% to 9%—when drivers engage in texting or calling via cell phones while operating a vehicle (*22*). Despite widespread awareness among motorists about the dangers of cell phone usage while driving, research indicates that 72% of them remain reluctant to cease this behavior (*23*).

While extensive research by both domestic and international scholars has explored the use of cell phones while driving, there remains a significant gap in the academic literature concerning the behavior of using cell phones while riding e-bicycles, particularly among food delivery riders. Recent studies have highlighted the prevalence of risky riding behaviors among delivery riders, particularly in the context of Vietnam. A significant factor contributing to these behaviors is the use of mobile phones while riding, which has been identified as a major source of distraction. Nguyen's study emphasizes that food delivery riders frequently use their phones for essential tasks such as confirming orders and navigating, which increases the likelihood of accidents resulting from distraction (*24*). This aligns with findings from Wu et al., who noted that delivery workers are particularly prone to technology-based distractions, including manually operating their phones while riding (*25*). The implications of these distractions are critical, as they can lead to severe traffic incidents, particularly in urban environments where the risk is heightened (*26*). Bertenshaw et al. found that using cell phones while riding and disregarding traffic signals have been identified as common self-reported violations among delivery riders (*13*). Multiple factors, such as weather conditions, the quantity and kind of lanes, the length of red light intervals, and the presence of law enforcement officials, all influence the use of cell phones while riding (*27*). Utilizing a cell phone during riding can result in distracted riding, diminished spatial awareness, or compromised balance (*28*). Furthermore, the use of cell phones while riding imposes significant cognitive and physical demands, resulting in diminished performance and narrower safety margins (*29*). Additionally, it can reduce drivers' awareness of their immediate surroundings, which in turn impairs their driving capabilities and ultimately increases the risk of accidents (*27*). Factors influencing cell phone use while riding include risk perception, riding habits, and perceived benefits such as increased work efficiency and access to immediate information associated with such behaviors (*30*). A study by Nguyen-Phuoc et al. emphasizes that working conditions also significantly influence food delivery riders' behavior, highlighting the delivery industry and regulators' responsibility for their safety, reveals that personal resources and risk perceptions play a pivotal role in determining risky riding behaviors, and ultimately confirms that addressing organizational factors and enhancing riders' quality of life are essential steps toward improving road safety (*31*).

Current Study

Because of the substantial number of food delivery riders in China, who also occupy a significant portion of the roads and often utilize cell phones for order reception, customer communication, or navigation while riding their bicycles, there is a need to explore the influencing factors of cell phone use behavior in this context. These riders travel through urban streets, sharing road space with other traffic such as cars, bicycles, and pedestrians, which directly affects traffic flow and safety. In-depth research into the traffic behaviors of food delivery riders can provide insights into their patterns of behavior, frequency of traffic violations, and the resulting traffic safety hazards, as well as potential solutions. Such research can inform the development of more targeted traffic management policies and safety measures to reduce the occurrence of traffic accidents and enhance the overall traffic efficiency and safety of urban roads. Additionally, studying the traffic behaviors of food delivery riders can also facilitate the provision of relevant training and education to enhance their traffic safety awareness, further reducing accident risks.

Researchers have employed socioecology or social-cognitive models in the analysis of individual behavior (*32*, *33*). The theory of planned behavior (TPB, as shown in Figure 1) has been thoroughly investigated and widely applied across diverse domains including health, business, psychology, and environmental research. Since TPB only asserts that individuals' inclinations toward certain behaviors are shaped by their attitudes, subjective norms (SN), and perceived behavioral control (PBC), many scholars have further developed TPB to bolster its predictive capabilities in comprehension and modulation of behaviors (*34*, *35*). Factors influencing the riding behavior of delivery riders, particularly on e-bikes (in this study, we focus on electric two-wheelers, commonly referred to as "e-bikes" in China, which are equipped with electric motors to assist with riding), are multifaceted and encompass various psychological, social, and environmental aspects. Research has highlighted several key factors that play a significant role in shaping the riding behavior of delivery riders. Risk perception and riding habits have been identified as crucial factors of delivery riders' riding behavior (*36*). Psychological factors, such as attitudes and behavior, and road conditions have been found to affect riding behavior (*37*, *38*). Studies have shown that risk perception and positive outcomes of risky riding behavior significantly influence a rider's decision-making process (*39*, *40*). Additionally, the relationship between riding confidence and risky riding behavior is mediated by risk perception and safety attitudes (*41*). Environmental factors, including weather conditions, traffic situations, and infrastructure, also play a role in influencing riding behavior (*37*). Furthermore, the social context of riding, such as peer behaviors and attitudes toward protective equipment, can affect safety behavior. Gender differences have been observed in the factors influencing riding behavior, with men and women showing variations in the effects of certain factors such as health motivation and PBC (*40*).

Although several studies have analyzed the riding behaviors of delivery riders, most have not examined the psychological aspects of these behaviors. These research results are worth further investigation. Few studies have extended TPB to explain the variance in riding behaviors among delivery riders. Therefore, the purpose of this study is to analyze riding behaviors among Chinese delivery riders through an extended TPB model.

Method

Framework

The Theory of Planned Behavior (TPB). TPB posits that individual behavior is influenced by two key factors: behavioral intentions (BI) and PBC. BI is shaped by SN, attitudes, and PBC. "Attitudes" reflects an individual's inclination toward a specific behavior, SN gauges social approval or disapproval, and PBC clarifies the individual's perceived ability to control the behavior (*32*, *33*, *42*, *43*).

TPB has been widely employed in studies concerning traffic behaviors, effectively predicting safe traffic behaviors across various groups, including high school students, motorcycle riders, cyclists, and novice drivers (*44*–*47*). It has also been applied to understand factors influencing intentions to engage in unsafe driving acts, risky driving behaviors, and cell phone use while driving or cycling (*47*–*49*). Additionally, TPB has been applied to assess community-based programs promoting safe road crossing behaviors in youth (*50*).

Furthermore, TPB has seen widespread application and expansion across diverse fields, providing a deeper understanding and prediction of human behavior. Research conducted by Godin and Kok, and Armitage and Conner, highlights that the TPB is an extension of the earlier theory of reasoned action, incorporating additional factors such as PBC (*35*, *51*). Extended TPB models, as demonstrated by Chan et al., exhibit higher predictive abilities in explaining behaviors related to environmental practices among companies (*52*). Studies by Sabina del Castillo et al. and Pierron et al. extend TPB, incorporating structural equation modeling (SEM) and behavioral economics, improving its prediction of wine consumption, and reducing anthropogenic stocks (*53*, *54*).

Studies have revealed that, alongside attitudes, SN, and PBC within the framework of TPB, risk perception and law enforcement elements are also significant in

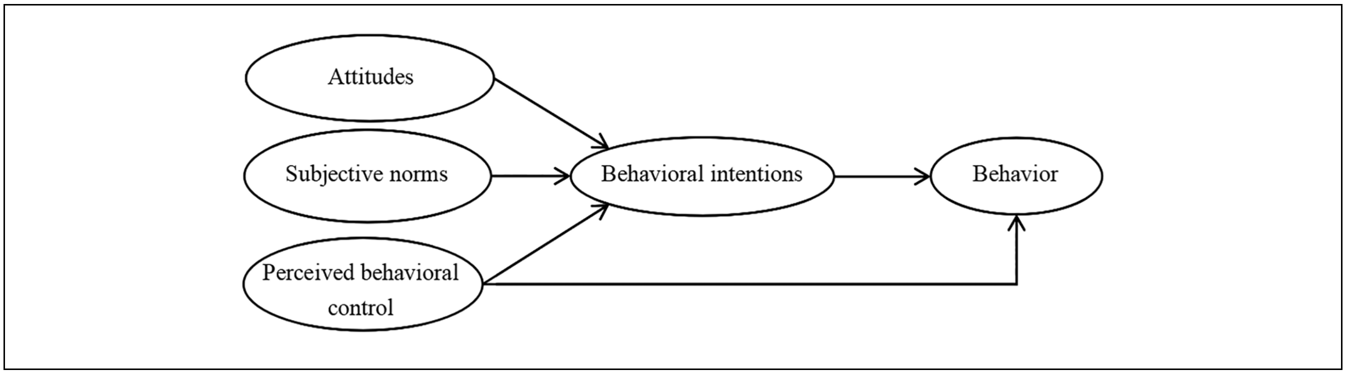

Figure 1. The theory of planned behavior.

shaping behavior and intentions (*55–57*). Although TPB has been extensively utilized in various fields to analyze BI, including the context of illegal phone usage, the integration of external constructs such as perceived benefits and risk perception into this framework remains insufficiently explored, particularly with regard to their influence on attitudes and subsequent BI. Given this gap, attention has been directed toward the dynamic nature of human behavior and the inherent limitations of established theories when selecting social and psychological constructs for this study. Recognizing that TPB, despite its influence in numerous research domains, might not adequately address the complexities of recently emerged phenomena such as technological engagement and occupational distractions—phenomena that were not prominent in the literature 40 years ago—a thorough examination of existing research was conducted.

This examination aims to identify constructs that not only align closely with the core tenets of TPB but also offer enhanced explanatory power within the specific context of this study. The chosen variables were determined based on their theoretical significance, empirical support from related studies, and their capacity to provide deeper insights into the multifaceted nature of technological engagement, occupational distractions, and their relationship with BI. By incorporating these constructs into the study's framework, the intention is to broaden the applicability of TPB, enhance its explanatory capacity, and contribute to a more comprehensive understanding of these contemporary phenomena.

Perceived benefits play a crucial role in shaping attitudes toward behaviors. Research indicates that individuals are more likely to develop positive attitudes toward adopting new technologies when they perceive significant benefits from their use (*58*). This is particularly relevant in the context of illegal phone usage, where individuals may weigh the perceived benefits of using their devices against the potential risks involved. Studies have shown that perceived usefulness significantly affects BI across various domains, including technology acceptance (*59*). This suggests that enhancing the perceived benefits associated with legal phone usage could potentially mitigate illegal usage patterns. Moreover, the relationship between perceived risks and benefits is complex and often influences individuals' decision-making processes. For example, Hubert et al. highlight that consumers often compare perceived risks against perceived benefits when making purchasing decisions (*60*). This comparative analysis can extend to illegal phone usage, where individuals may rationalize their behavior based on the perceived advantages of accessing certain services illegally versus the risks of potential consequences. Additionally, the integration of perceived risk into the TPB framework can provide a more nuanced understanding of how these external constructs interact with core constructs such as attitude and BI (*61*). Building on the aforementioned background, the proposed framework of this article unfolds as follows.

In this study, a thorough investigation was conducted into various factors that may potentially influence food delivery riders' usage of cell phones while riding. Several new items were also introduced. These new items encompass risk perception, descriptive norms, perceived severity, perceived benefits, and law enforcement. "Risk perception" refers to riders' recognition and assessment of the potential risks associated with using cell phones while riding. "Descriptive norms" reflect the prevalent behavioral patterns of cell phone usage among food delivery riders, which may influence individual behavioral choices. "Perceived severity" concerns riders' understanding of the potential serious consequences of using cell phones while riding. "Perceived benefits," on the other hand, refer to the convenience or advantages that riders believe they can derive from using cell phones. Lastly, while our primary focus is on psychological factors, we also acknowledge the crucial role of "law enforcement factors," which encompass the implementation of relevant laws and regulations and riders' compliance with them, as they may indirectly influence the psychological dynamics and outcomes of our study. By comprehensively considering these factors, we aim to provide a more comprehensive analysis of food delivery riders' cell phone usage while riding, and propose corresponding suggestions and measures. The target behavior of general cell phone use was defined as the "frequency of cell phone use while riding in the last month, frequency of checking cell phone messages or making calls while riding in the last month." All items related to TPB and other constructs were assessed using 5-point Likert scales.

Participants and Procedure

The survey was conducted in Tianhe District of Guangzhou, China, from January to March, 2024. Tianhe District, located in the eastern part of the city, is a major urban center renowned for its bustling commercial and financial sectors, towering skyscrapers, shopping centers, and prominent business districts such as Tiyuxilu and Zhujiang New Town CBD. Given its dense population and central role in education, transportation, and cultural activities, Tianhe District was selected as the study site to ensure a diverse and representative sample of food delivery riders across various demographics, including age, gender groups, educational background, and work experience.

Data collection occurred at large commercial complexes and designated rest stations for food delivery riders within Tianhe District. Participants were recruited through a combination of convenience sampling and targeted approaches. Specifically, rest areas within these complexes and rider rest stations were selected based on their high traffic of food delivery riders during both morning and afternoon idle periods. These stations were carefully chosen to ensure that the sample included riders from various routes and different work schedules. To further validate the diversity of the data, an expert panel was consulted to confirm that the selection process was appropriate and covered a wide range of food delivery riders with regard to geographical location and work conditions within the district. Additionally, to ensure the survey's appropriateness and minimize any potential adverse effects, participants' consent was obtained before their participation, and the questionnaire was carefully assessed.

The survey was administered through face-to-face interviews or self-administered questionnaires, with respondents having the option to complete the survey independently or with assistance from investigators for those with reading or writing difficulties. Participants were informed that the survey was for academic research purposes only and that it would take approximately 20 min to complete.

A total of 520 food delivery riders were approached, with 504 questionnaires collected. After excluding incomplete or invalid responses, 501 questionnaires were deemed valid for analysis. The age distribution of the sample was as follows: 190 respondents (37.9%) were aged 18–29 years, 232 (46.3%) were aged 30–39 years, 75 (14.9%) were aged 40–49 years, and 4 (0.7%) were aged 50–59 years. No respondents were aged 60 years or above. The sample was predominantly male, with 485 males (96.8%) and 16 females (3.2%). Concerning marital status, 65.4% of the respondents were married. As far as education was concerned, 71.5% had a high school education or lower, while approximately one-third (28.5%) held an associate degree or higher.

To enhance the representativeness and credibility of the study, it is important to note that the sample may not be entirely random and may be subject to certain biases. For example, the high proportion of male participants reflects the gender imbalance in the food delivery industry. Additionally, the sample's educational background may not be fully representative of all food delivery riders in Tianhe District or broader populations. These limitations will be considered in the interpretation and generalization of the study findings.

Measures and Questionnaire

The constructs of TPB are latent variables, so they cannot be directly measured but are instead reflected through observable and measurable manifested variables. SEM is employed to study the behavior of cell phone usage while riding among delivery riders. In SEM, two fundamental models are commonly utilized: the measurement model and the structural model. The measurement model evaluates the causal relationship between the latent variable and the observable indicators, while the structural model validates the causal and correlated relationships among latent constructs (*62*). The maximum likelihood estimation method is employed to estimate the parameters inherent within the SEM (*63*).

Based on the above analysis, the behavior of cell phone usage while riding was explored through extended TPB models (which integrate TPB and some social constructs and descriptive norms). Figure 2 depicts the conceptual structure of the extended TPB model applied in our study. The specific manifest indicators for the latent variables will be discussed in the next section.

The questionnaire comprised standard TPB items which evaluated attitude, SN, PBC, and intention to use a cell phone while riding (*42*). These standard TPB measures, along with the additional items, evaluated cell phone usage while riding. Background information on participants was also collected (e.g., gender, age, education). General intention to use a cell phone while riding

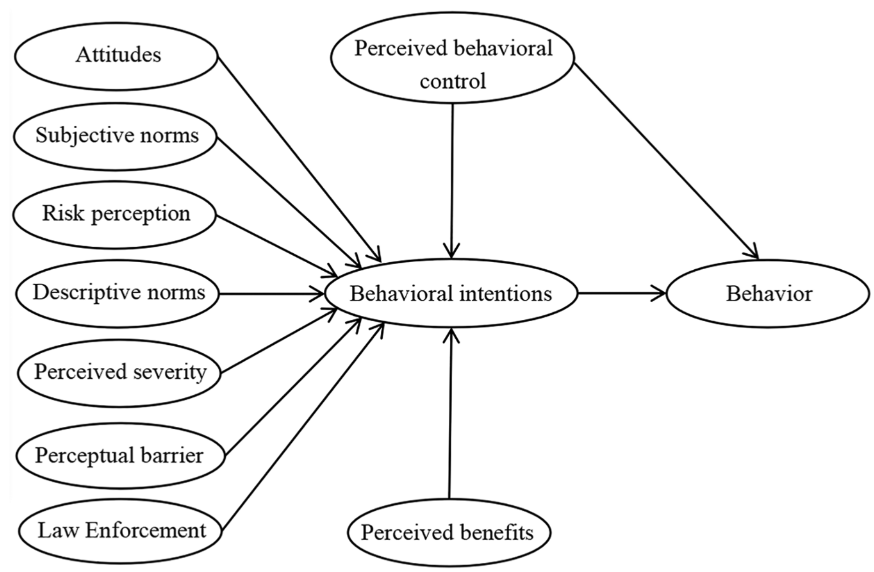

Figure 2. The model construct.

was assessed using three items, for example, "In the future, I will definitely not use my cell phone while riding." (1 = strongly disagree, 5 = strongly agree). Attitude toward using a cell phone while riding was gauged with three items, for example, "Using a cell phone while riding can save time." (1 = strongly disagree, 5 = strongly agree). SN, PBC, perceived likelihood of accidents, perceived severity, descriptive norm, law enforcement, perceived benefits, and perceptual barrier were each measured with three items. For example, "My company often urges me not to look at my cell phone while riding" (1 = strongly disagree, 5 = strongly agree), and "How often do your colleagues check their cell phones while riding?" (1 = never, 5 = always). The appendix contains a comprehensive list of questionnaire items representing these constructs.

Results

Measurement Model Analysis

Before assessing the structural model of the SEM, the reliability and convergent validity of the measurement model must first be evaluated. This ensures a proper understanding of how accurately the manifest indicators describe the latent variables (*64*). Therefore, a confirmatory factor analysis was conducted to evaluate the manifest indicators of the constructs depicted (in Figure 2) individually. The outcomes are presented in Table 1.

Standardized factor loadings are deemed acceptable when they exceed 0.6 (*65*). Composite reliability, also referred to as construct reliability, assesses the internal consistency of scale items and is considered acceptable if it exceeds 0.7 (*66*). The average variance extracted (AVE) is a measure indicating the extent to which variance in observed indicators is accounted for by the underlying construct, typically regarded as satisfactory when surpassing 0.5 (*67*). Table 1 shows the reliability and convergent validity of the latent variables in the current study. The convergent validity of these latent variables is deemed acceptable.

Discriminant validity assesses whether constructs are distinct from one another. Inter-construct correlations should be lower than the square root of AVE (*68*). In Table 2, the diagonal entries represent the square root of AVE, while the entries in the lower triangle depict the correlations between corresponding constructs. As demonstrated in Table 2, the values on the diagonal surpass those within the corresponding column and row, thus confirming discriminant validity.

Structural Model Analysis

We analyzed the delivery riders' riding behaviors using the extended TPB model. To assess the model's adequacy, we employed a variety of widely used fit indices in conjunction with the root mean square error of approximation (RMSEA). Specifically, we evaluated the model based on the chi-square/degrees of freedom ratio (χ^2/DF), comparative fit index (CFI) (CFI > 0.9), Tucker-Lewis index (TLI) (TLI > 0.9), RMSEA (< 0.08), and standardized root mean square residual (SRMR < 0.08) (*69*, *70*). These indices serve as critical benchmarks for assessing the fit of the model to the observed data.

Table 1. The Reliability and Convergence Validity of the Latent Variables

Item	Parameters of significant test		Composite reliability	Convergence validity (AVE)
	Estimate	*p*-value		
Behavior				
BEHA1	0.956	***	0.935	0.829
BEHA2	0.948	***		
BEHA3	0.821	***		
Attitude				
ATT1	0.853	***	0.917	0.786
ATT2	0.971	***		
ATT3	0.830	***		
Subjective norms				
SN1	0.734	***	0.865	0.683
SN2	0.887	***		
SN3	0.850	***		
Behavioral intention				
BI1	0.959	***	0.956	0.878
BI2	0.963	***		
BI3	0.887	***		
Perceived behavioral control				
PBC1	0.969	***	0.967	0.906
PBC2	0.980	***		
PBC3	0.905	***		
Risk perception				
SUS1	0.974	***	0.986	0.960
SUS2	0.981	***		
SUS3	0.984	***		
Perceived severity				
SEV1	0.918	***	0.960	0.890
SEV2	0.942	***		
SEV3	0.969	***		
Descriptive norms				
DN1	0.977	***	0.917	0.789
DN2	0.934	***		
DN3	0.735	***		
Law enforcement				
LAW ENFORCE1	0.965	***	0.913	0.781
LAW ENFORCE2	0.963	***		
LAW ENFORCE3	0.695	***		
Perceived benefits				
BEN1	0.942	***	0.973	0.924
BEN2	0.981	***		
BEN3	0.960	***		
Perceptual barrier				
BAR1	0.793	***	0.857	0.670
BAR2	0.962	***		
BAR3	0.676	***		

Note: AVE = average variance extracted.
***$p < 0.001$.

The model fit indices, presented in Table 3, indicate that the extended TPB model achieved acceptable levels of fit. However, it is important to delve deeper into the implications of these values for understanding the model's robustness. The CFI and TLI values exceeding 0.9 suggest a strong correspondence between the model and the data, indicating that the model captures a substantial portion of the variance in the observed variables. The RMSEA value below 0.08 indicates a good approximation of the true population covariance matrix, while the SRMR value below 0.08 further supports the model's fit by indicating that the residuals are small and randomly distributed.

The results of our SEM are presented in Table 4 and Figure 3, providing a clear overview of the relationships among the variables. To delve deeper into the model's fitness, it is essential to examine the key findings in the context of our research theme, which explores the factors

Table 2. Discriminant Validity of Constructs

DIM	Discriminant validity										
	1	2	3	4	5	6	7	8	9	10	11
1	0.910										
2	0.652	0.887									
3	−0.211	−0.204	0.826								
4	−0.651	−0.632	0.297	0.937							
5	0.518	0.598	−0.186	−0.534	0.952						
6	−0.184	−0.376	0.196	0.314	−0.334	0.980					
7	−0.203	−0.265	0.235	0.288	−0.230	0.547	0.943				
8	0.669	0.339	−0.314	−0.439	0.364	−0.058	−0.160	0.888			
9	−0.175	−0.162	0.151	0.317	−0.079	0.150	0.181	−0.200	0.884		
10	0.006	−0.072	0.002	0.094	−0.157	0.188	0.164	0.102	0.000	0.961	
11	0.355	0.537	−0.145	−0.368	0.430	−0.255	−0.151	0.111	−0.033	−0.099	0.819

Note: 1 = behavior; 2 = attitude; 3 = subjective norm; 4 = behavioral intention; 5 = perceived behavioral control; 6 = risk perception; 7 = perceived severity; 8 = descriptive norm; 9 = law enforcement; 10 = perceived benefits; 11 = perceptual barrier; DIM = Dimensions.

influencing delivery riders' use of cell phones while riding.

Table 4 reveals that several constructs are significantly associated with BI. Notably, attitude ($\beta = -0.496$, $p < 0.001$) emerges as a strong negative predictor, suggesting that a negative attitude toward using cell phones while riding significantly reduces the intention to do so. Similarly, PBC ($\beta = -0.165$, $p < 0.001$) and descriptive norms ($\beta = -0.245$, $p < 0.001$) also exhibit negative influences. It is noteworthy that perceived difficulty in controlling the behavior and observing others not using cell phones while riding contribute to lower intentional use. Conversely, law enforcement ($\beta = 0.552$, $p < 0.001$) positively influences BI, highlighting the importance of legal regulations in shaping riders' behaviors.

It is also noteworthy that factors such as SN, perceived likelihood of accidents, perceived severity, perceived benefits, and perceptual barrier did not reach statistical significance in predicting BI, suggesting that these constructs may not play a crucial role in this particular context.

When it comes to actual riding behavior, the results are equally insightful. BI ($\beta = -0.526$, $p < 0.001$) has a strong negative impact, reinforcing the notion that intentions directly translate into actions. Furthermore, PBC ($\beta = 0.234$, $p < 0.001$) positively influences riding behavior.

The model's explanatory power is further demonstrated by its ability to account for 53.8% of the variability in BI and 47.8% of the variability in actual riding behavior. These findings not only demonstrate the robustness of our model but also provide practical insights into the factors that can be targeted to reduce cell phone use among delivery riders while riding, thus enhancing road safety.

In conclusion, integrating these key findings with our research theme underscores the importance of considering multiple factors in understanding and addressing cell phone use among delivery riders. Our model serves as a valuable tool for policymakers, safety advocates, and delivery companies in developing effective interventions at aimed promoting safe riding practices.

Mediation Effect Analysis

A mediation effect denotes the mechanism through which an independent variable affects a dependent variable by traversing one or more intermediary variables, termed as mediators. The analysis of mediation holds pivotal significance in elucidating the underlying mechanisms governing the associations among variables, delineating the total effect into direct and indirect pathways (*71*). Mediation analysis occupies a crucial position in research methodology, providing a means to enhance understanding of how a particular exposure affects an outcome through intervening factors. This analytical framework allows researchers to evaluate the significance of various pathways and mechanisms that are intertwined in the complex interactions between variables (*72*). Remarkably, mediation may transpire even without an overarching effect, emphasizing the essentiality of exploring mediation effects regardless of the existence of a notable direct effect (*73*).

Table 5 displays the analysis of the indirect effects of the proposed model, based on data collected from Guangzhou City. The results in Table 5 show a significant indirect effect of attitudes, SN, law enforcement, and PBC on actual behavior. They indirectly influence behavior by shaping an individual's cognition, beliefs, intentions, or decision-making processes. These findings

Table 3. The Goodness-of-fit Indices

Fit index	Criterion	Model index
ML χ^2	Smaller is better	1,328.108
DF	Larger is better	448
χ^2/DF	$1 < \chi^2/DF < 3$	2.965
CFI	> 0.90	0.954
TLI	> 0.90	0.945
RMSEA	< 0.08	0.063
SRMR	< 0.08	0.056

Note: CFI = comparative fit index; DF = degrees of freedom; ML = maximum likelihood; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; TLI = Tucker-Lewis index; χ^2 = chi-square.

bear significant implications for guiding the development of effective behavioral intervention measures, such as promoting positive behavior through altering individual attitudes, enhancing SN, reinforcing law enforcement, or improving PBC.

Discussion

Attitudes strongly affect cell phone usage intention while riding, followed by descriptive norms and law enforcement. The significant effect of attitude was also verified by the findings of Ma et al. (*27*). Understanding the power of attitudes is crucial for developing effective

Table 4. Research Model Regression Weight

Independent variable	Estimate	SE	Est./SE	*p*-value
Behavioral intention				
Attitude	−0.496	0.065	−7.662	0.000
Subjective norm	0.108	0.05	2.141	0.032
Perceived behavioral control	−0.165	0.044	−3.714	0.000
Risk perception	0.022	0.061	0.361	0.718
Perceived severity	0.078	0.071	1.101	0.271
Descriptive norms	−0.245	0.05	−4.852	0.000
Law enforcement	0.246	0.047	5.206	0.000
Perceived benefits	0.091	0.071	1.272	0.203
Perceptual barrier	−0.044	0.051	−0.869	0.385
Behavior				
Behavioral intention	−0.526	0.042	−12.509	0.000
Perceived behavioral control	0.234	0.041	5.752	0.000

Note: Est. = estimated; SE = standard error.

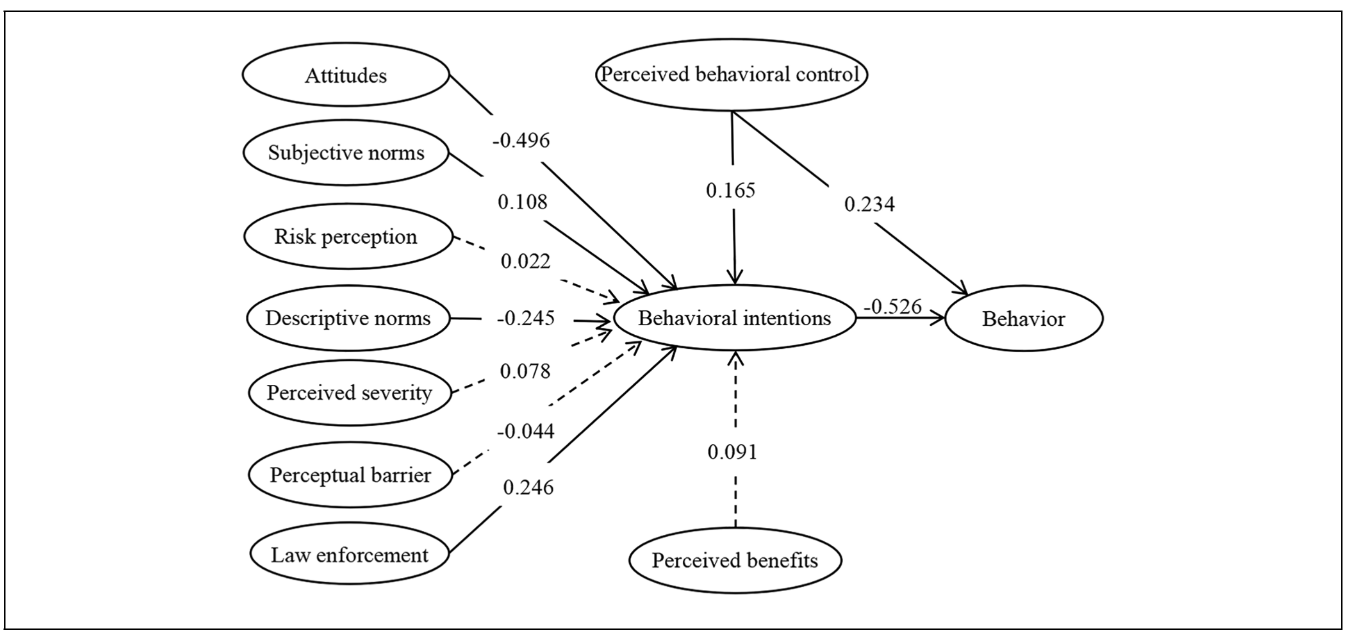

Figure 3. The result of the extended theory of planned behaviour model.
Note: dashed line = non-significance at the 95% confidence level; solid line = significance at the same level.

Table 5. Mediation Effect of Items on Behavior

Item	Direct	Indirect	Total
Perceived behavioral control	0.234**	0.087**	0.321**
Attitude	NA	0.261**	0.261**
Subjective norm	NA	−0.057	−0.057
Risk perception	NA	−0.012	−0.012
Perceived severity	NA	−0.041	−0.041
Descriptive norms	NA	0.129**	0.129**
Law enforcement	NA	−0.129**	−0.129**
Perceived benefits	NA	−0.048	−0.048
Perceptual barrier	NA	0.023	0.023

Note: NA = not available.
**$p < 0.05$.

strategies to promote safe riding practices and minimize distractions caused by cell phone usage.

Luo highlighted that PBC has emerged as a pivotal positive factor significantly influencing the behavior of using cell phones while riding (*74*). This underscores the crucial role of PBC in shaping actions related to cell phone usage, in alignment with our research. Dinh Vinh Man et al. emphasize the importance of enhancing riders' PBC and altering their intentions toward cell phone usage while riding (*75*). To achieve this goal, sustained public awareness campaigns and education programs are strongly recommended.

Our research has uncovered that descriptive norms significantly influence the intentions and behaviors related to cell phone use while riding, suggesting that the riding preferences of nearby individuals exert a substantial influence on delivery riders' choices. This assertion is supported by various empirical studies that highlight the role of social norms in shaping individual behaviors across different contexts.

For instance, Latkin et al. emphasize that social norms can lead to sustained behavior change, particularly in health-related contexts, indicating that the influence of peers can be a powerful motivator for altering behaviors (*76*). Similarly, Moran et al. argue that perceived social norms are specific to reference groups, reinforcing the idea that individuals are likely to adjust their behaviors based on the norms established within their immediate social circles (*77*). This aligns with the social identity theory, which posits that individuals align their behaviors with those of their reference groups to maintain a positive self-concept (*77*).

Furthermore, Waterman et al. highlight that perceptions of peer behaviors significantly influence adolescents' intentions to engage in specific actions, suggesting that peer-established norms can shape individual choices in various contexts (*78*). The phenomenon of selective perception, where individuals focus on information that aligns with their existing beliefs or behaviors, also plays a crucial role in understanding how descriptive norms influence behavior. This is echoed in the work of Geber et al., who note that communication among peers about risk-taking behaviors can reinforce pro-risk norms, thereby increasing the likelihood of engaging in such behaviors (*79*). This supports our findings that delivery riders may be influenced by the riding preferences of those around them, as they selectively attend to the behaviors of their peers.

Moreover, the interplay between descriptive and injunctive norms is critical in understanding behavior modification. Liang et al. note that, when descriptive norms conflict with injunctive norms, the former often have a stronger influence on behavior (*80*). This suggests that individuals may prioritize observed behaviors over perceived obligations, further reinforcing our assertion about the impact of nearby individuals on delivery riders' choices.

In conclusion, the evidence from various studies underscores the complexity of the relationship between descriptive norms and behavior, particularly in the context of cell phone use while riding. The interplay of social identity, selective perception, and normative influences provides a robust framework for understanding how social norms shape individual behaviors in specific contexts. Zhao et al. found that SN, particularly those stemming from peer influence, play a crucial role in shaping adolescents' cycling behaviors, although their impact on cell phone use while cycling is comparatively weaker (*81*). Wu et al. discovered an inverse link between descriptive norms, which represent individuals' perceptions of others' behavior, and cell phone usage behaviors, which is consistent with our study (*28*).

This connection may be attributed to selective perception, where individuals selectively attend to information that aligns with their existing beliefs or behaviors (*28*). However, the role of descriptive norms extends beyond mere perception; they intersect deeply with peer/social influence and cultural factors, as posited by TPB that we theoretically endorse. Descriptive norms not only reflect the perceived behaviors of others but also serve as powerful social cues, shaping individuals' actions through mechanisms such as peer pressure, social comparison, and the desire for social approval (*82*).

In the context of riding behavior, the presence of others who adhere to safe riding practices, such as not using their phones while riding, can create a norm that encourages similar behavior, especially among those who value social conformity and approval. Additionally, cultural factors play a pivotal role in shaping descriptive norms around cell phone use while riding. Different cultures have varying norms and expectations about mobile phone usage in public, including while engaging in activities such as riding. These cultural differences can influence riders' perceptions of what is considered acceptable or unacceptable behavior, thereby affecting their adherence to descriptive norms.

Our analysis reveals that law enforcement plays a crucial role in mitigating the intention of riders to use cell phones while driving. Consistent with Useche's findings, we observed that enforcement actions have a significant impact on behaviors linked to distracted riding, particularly the use of cell phones (*83*). The potential for severe consequences when caught using a cell phone while riding acts as a strong deterrent, effectively discouraging such risky behavior. Furthermore, law enforcement contributes not only to ensuring road safety but also to fostering responsible driving habits among all road users, thereby reducing the risk of accidents caused by distractions. Given the importance of law enforcement in influencing individuals' decision-making about cell phone use while driving, we propose that the government should consider introducing more stringent legislation to regulate this behavior. Such measures are vital for safeguarding the safety of riders, other road users, and maintaining overall traffic order. Additionally, imposing strict penalties on those who violate these regulations would serve as a powerful deterrent and send a clear message that using a cell phone while riding is unacceptable and will be severely punished.

Research conducted by Zhao et al. explores the influence of SN on aggressive riding behaviors, emphasizing that, while the impact may be slightly less pronounced, it remains noteworthy and substantial (*81*). This is consistent with the conclusions of our research. We found that, among the various factors considered, the influence of SN is slightly weaker compared with other projects. This finding suggests that, although SN do play a role, their impact is not as significant as some other factors under investigation. This observation provides valuable insights into the complex interactions between different variables and their relative contributions to the overall phenomenon under study.

Conclusions and Limitations

Research Findings

This study delved into the intricate psychological factors that influence delivery riders' cell phone usage while they are on the job. Through comprehensive analysis, we discovered that several key determinants—namely attitudes, PBC, SN, descriptive norms, and law enforcement—play pivotal roles in shaping their BI. Our findings revealed a robust and significant relationship between these psychological constructs and the riders' intentions to use their cell phones while riding.

Furthermore, our research highlighted a strong negative correlation between behavioral intention and actual behavior. In simpler terms, riders who harbored negative intentions toward using their cell phones while riding were indeed less likely to engage in such behavior. This underscores the importance of addressing these psychological determinants to promote safer riding practices and reduce the potential risks associated with cell phone usage while on the road. By understanding and targeting these factors, policymakers, educators, and stakeholders can work together to foster a culture of responsible and safe riding among delivery riders.

Policy Implications

Attitude and PBC are significantly associated with delivery riders' intention to use cell phones while riding. To effectively encourage delivery riders to refrain from using cell phones while riding, it is crucial to implement a multifaceted approach. Firstly, raising awareness of the potential life-threatening risks associated with using cell phones while riding is imperative. Companies should conduct comprehensive safety training sessions and publicity campaigns specifically tailored to delivery riders. These campaigns should include real-life case studies and statistics highlighting the dangers of distracted riding. Additionally, riding safety awareness should be promoted in key locations frequented by delivery riders, such as restaurants, delivery hubs, and rider rest stations, through engaging television programs, online videos, and interactive workshops. Furthermore, to alter delivery riders' attitudes and behaviors, companies and local authorities should collaborate on the following specific initiatives:

1) Technological interventions: Explore and implement technological solutions that can automatically restrict or limit cell phone usage while riding. These could include smartphone applications with "ride mode" features that disable non-essential notifications and functions, or integrated bike systems that detect and warn riders about distracted behavior.
2) Peer influence programs: Leverage the power of peer influence by establishing mentorship programs where experienced riders act as role models and mentors to newcomers. Organize regular meetings and workshops where riders can share their experiences and strategies for staying focused while riding.
3) Strategic poster placement: Strategically place eye-catching posters and signage in high-traffic areas for delivery riders, such as restaurant entrances, delivery hub walls, and rider rest stations. These posters should vividly illustrate the dangers of using cell phones during rides and provide clear, actionable tips for staying safe.

4) Law enforcement and penalties: Local authorities should enforce stricter laws and penalties for using cell phones while riding. Traffic police should conduct targeted patrols in areas with high delivery activity and issue fines to riders caught violating the law. Simultaneously, authorities should launch awareness campaigns to inform riders about the new regulations and penalties.

Descriptive norms play a significant role in shaping delivery riders' behavior. To foster a norm against cell phone use while riding, companies and authorities should publicly recognize and reward riders who demonstrate exemplary safe riding practices. This could include social media shout-outs, awards, or incentives such as discounts on riding gear or insurance.

SN is also crucial. Therefore, authorities and companies should actively engage with the delivery rider community to create a supportive environment where safe riding is the expected and encouraged behavior. This could involve organizing community events, workshops, and forums where riders can discuss and share their experiences with safe riding practices.

Finally, PBC can be influenced by the availability of practical tools and resources. Besides technological interventions, companies could provide riders with hands-free devices or other alternatives that facilitate communication without compromising safety.

In conclusion, a comprehensive and multifaceted approach that combines awareness-raising, technological interventions, peer influence programs, strategic poster placement, law enforcement, and positive reinforcement is essential to effectively reduce delivery riders' use of cell phones while riding. By addressing the underlying attitudes, PBC, and social norms, we can work toward creating a safer riding environment for all.

Limitations and Future Work

Limitations

1) Self-reporting bias: As a questionnaire-based study, we relied on self-reported data from delivery riders. This approach may be subject to bias, as riders might have provided inaccurate or misleading information for various reasons, such as protecting their privacy, avoiding potential consequences, or social desirability bias. To mitigate this limitation in future studies, a combination of methods, such as direct observations, interviews, and possibly the use of technology to track cell phone usage, could be employed to validate self-reported data.
2) Sample selection and generalization: While this study provides valuable insights into the behavior of delivery riders within a specific cultural and regulatory framework, it is important to acknowledge its limitations in sample selection and the generalization of findings. The relatively small sample size may limit the statistical robustness of the results, suggesting that they should be interpreted with caution and may not universally represent all delivery riders. Furthermore, the study's localized context, encompassing unique traffic conditions, regulatory policies, and cultural norms, may have influenced the observed behaviors, thereby restricting the extrapolation of findings to broader or differing settings. Additionally, the absence of direct comparisons with similar research conducted in other environments hinders a comprehensive understanding of the universal versus context-specific aspects of delivery rider behavior. Despite these limitations, this study makes a significant contribution to the existing literature and lays a foundation for future research. For future studies, incorporating a more diverse and representative sample of delivery riders from various regions, age groups, and gender groups would enhance the external validity of the results.
3) Unconsidered factors: This study focused primarily on cell phone usage while riding. However, there are likely other factors that could influence riders' behavior while riding, such as road conditions, weather conditions, traffic density, and the specific demands of their delivery tasks. These factors were not fully considered in our study and could potentially affect our findings. Future research should explore the interplay between these various factors and their influence on delivery riders' behavior.
4) Model assumptions: The models and frameworks used in this study were based on certain assumptions that may not fully capture the complexity of real-world situations. The reasonableness of these assumptions should be critically evaluated, and alternative models or frameworks could be explored in future research to provide a more comprehensive understanding of the phenomenon.

Future Work. Based on the limitations identified above, several directions for future research are proposed:

1) Multi-method studies: Future research should employ a combination of qualitative and quantitative methods, including direct observations, interviews, and possibly the use of technology to track cell phone usage, to provide a more comprehensive and reliable understanding of delivery riders' behavior.

2) Expanded sample and context: Studies should aim to include a more diverse and representative sample of delivery riders from different regions, age groups, gender groups, and employment statuses to enhance the generalizability of the findings. Additionally, exploring the impact of environmental and social contexts on riders' behavior could provide deeper insights into the phenomenon.
3) Comprehensive factor analysis: Future research should investigate the interplay between various factors, such as road conditions, weather conditions, traffic density, and delivery task demands, and their influence on delivery riders' behavior. This could help to identify the most significant factors affecting riders' safety and behavior on the road.
4) Refining models and frameworks: Critical evaluation and refinement of existing models and frameworks are necessary to more accurately capture the complexity of real-world situations. Alternative models or frameworks should be explored to provide a more accurate and comprehensive understanding of the phenomenon.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Jianrong Liu. Author, Xu Liu. Author; data collection: Chen Wang. Author, Xin Shu. Author; analysis and interpretation of results: Xu Liu. Author, Jianrong Liu. Author; draft manuscript preparation: Xu Liu. Author, Jianrong Liu. Author. All authors reviewed the results and approved the final version of the manuscript.

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