Peer Influence, Face-Saving, and Safe-Driving Behaviors: A Bayesian GITT Analysis of Chinese Drivers

Minh-Hoang Nguyen [1], Dan Li [2,*], Thi Mai Anh Tran [3], Thien-Vu Tran [4], Quan- Hoang Vuong [1, 5]

[1] Centre for Interdisciplinary Social Research, Phenikaa University, Hanoi 100803, Vietnam

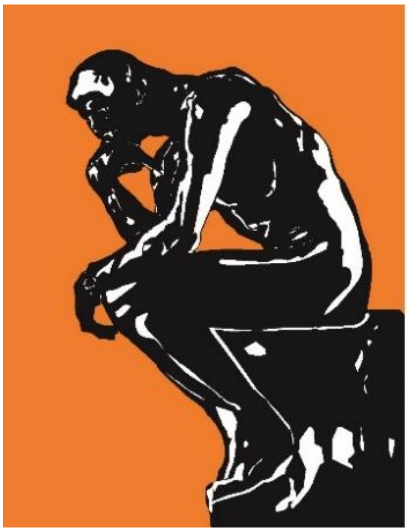
[2] College of Educational Science, Yan'an University, Yan'an, China

[3] College of Forest Resources and Environmental Science, Michigan Technological University, Houghton, MI 49931 USA

[4] The University of Danang - Vietnam-Korea University of Information and Communication Technology, Danang City, Vietnam

[5] Professor, University College, Korea University. 145 Anam-ro, Seongbuk-Gu, Seoul 02841, South Korea

*Corresponding Email: dellelee103@gmail.com (Dan Li)



February 25, 2025

[*Original working draft v1 / Un-peer-reviewed*]

* * * * *

"At the time, Kingfisher was of glorious fame. His name reminded all birds of his great wisdom. When they met him, all were soft-spoken and did not even dare to compliment him."

In "The Great Master"; *Wild Wise Weird* (2024)

Abstract

This study examines the dynamic relationship between face-saving mechanisms—proxied by age, income, and gender—and the peers' safe-driving information on the driving behaviors of Chinese drivers. Using the Bayesian Mindsponge Framework (BMF) and Granular Interaction Thinking Theory (GITT) to analyze data from 1,039 Chinese drivers, we uncover a complex interplay of factors. Our findings suggest that peers serving as role models and actively supporting careful driving positively influence drivers' safe driving behaviors. The effect of role-model peers is strengthened among drivers with higher age and income levels. In contrast, the impact of actively engaged peers is lower among these groups and male drivers (though the gender's negative moderation effect is weakly reliable). These results highlight the crucial role of peer influence in promoting safe driving and underscore the dynamic effects of cultural values, particularly face-saving concerns, on drivers' cognitive and behavioral processes in China.

Keywords: peers' role model; active support; safe-driving behaviors; the socio-cultural values; Granular Interaction Thinking Theory (GITT); Confucianism; face value

1. Introduction

Road traffic crashes pose a critical challenge for global public health, with far-reaching consequences for individuals, families, and economies worldwide. According to the World Health Organization (WHO, 2023a), these incidents cause the deaths of approximately 1.19 million people and leave up to 50 million more with non-fatal injuries annually (WHO, 2023a). More than 90% of road traffic deaths occur in low- and middle-income countries (WHO, 2023a). Road traffic accidents are the second leading cause of death for children aged 5 to 14 years (WHO, 2022). Beyond the immediate human cost, they also impose substantial economic burdens on societies, with estimates indicating that road traffic accidents cost most countries 3% of their gross domestic product (WHO, 2023b).

China, as the world's largest automotive market, faces escalating challenges due to rapid motorization. Between 2019 and 2023, the country witnessed a substantial increase from 418 million to 530 million drivers, presenting critical challenges for effective road safety strategies (Xinhua, 2024). In 2023, China reported 60,028 fatalities due to road traffic accidents, which translates to one death every eight minutes (Zhang, 2024). The direct economic loss from these accidents was estimated at around 490.1 billion yuan (72.6 billion USD), reflecting the significant financial burden on the healthcare system, emergency services, and the broader economy (Tan et al., 2020).

In response to this challenge, the Chinese government has implemented a series of strategic plans, such as the "14th Five-Year Plan for National Road Traffic Safety," which outlines comprehensive measures to improve traffic management, enforce safety regulations, and upgrade infrastructure (Fan, 2022). However, China's average road traffic mortality rate (17.4) remains higher than that of many developed countries (9.2), suggesting the need for continued efforts to improve road safety (WHO, 2023b). Targeted interventions that focus on human behavior remain a crucial determinant and directly impact the effectiveness of these strategies (Guggenheim et al., 2020; McCarty & Kim, 2024; Pagomenos et al., 2023).

Research has shown that sociocultural factors significantly influence individual attitudes, perceptions, and driving behaviors (Lindstrom-Forneri et al., 2010; Simons-Morton et al., 2012; Wang et al., 2024; Yousaf & Wu, 2024; Zeyin et al., 2022). In the Chinese context, where Confucian values shape social interactions, the concept of "face" (面子, *mianzi*) plays a crucial role in how individuals process and respond to information from peers (Han, 2016). This cultural emphasis on face-saving, which affects how drivers interact with and learn from their peers, can create a complex dynamic in the relationship between peer influence and driving behavior.

Peer influence operates through two main mechanisms: role modeling and direct engagement (Curry et al., 2015; Rose et al., 2024). In role modeling, individuals observe and learn from their peers' safe driving practices, while direct engagement involves real-time interaction and feedback during driving situations (Bingham et al., 2016; Simons-Morton et al., 2012; Weston & Hellier, 2018). Previous research suggests that both mechanisms can affect driving behavior, with studies showing that when friends encourage safe driving, drivers are more likely to adopt safe driving practices (Jose-Luis Padilla et al., 2023; Yang et al., 2021; Zeyin et al., 2022). On the other hand, when peers engage in or encourage risky driving, it can normalize such behaviors and increase the likelihood of drivers taking risks on the road (Simons-Morton et al., 2012; Trógolo et al., 2022; Weston & Hellier, 2018).

However, the effectiveness of these influence mechanisms may vary significantly based on the cultural context and individual characteristics (Nordfjærn et al., 2014; Sagberg et al., 2015; Zhang, 2023). In Chinese society, where face-saving is highly placed, the processing of peer-provided information may differ between role modeling and direct engagement. For example, while role modeling primarily depends on the individual's information-processing capabilities, direct engagement might be heavily influenced by face-saving considerations, particularly among individuals of higher social status (Lewis, 2006).

Demographic factors such as age, gender, and income are also found to influence safe driving behaviors (Granié et al., 2021; McCarty & Kim, 2024; Shen et al., 2018; Wickens et al., 2012). Young drivers, for example, are more susceptible to the influence of their peers, both positively and negatively (Cassarino & Murphy, 2018). Gender differences also exist in driving behaviors, with female drivers tending to be more responsive to traffic rules and safety-oriented influences than males (Granié et al., 2021; Wickens et al., 2012). Income affects access to safe vehicles and driver education, influencing driving behaviors and safety outcomes (Metzger et al., 2020). However, Geng et al. (2024) found that high-income drivers are more likely to get distracted when driving, such as phone use and multitasking, influenced by social norms and user experiences (Geng et al., 2024).

Despite extensive research on peer influence in driving behavior, previous studies have not adequately examined how these demographic factors moderate the effectiveness of the two distinct influence mechanisms, role modeling and direct engagement, especially within the Chinese cultural context of face-saving (Guggenheim et al., 2020; Guggenheim & Taubman – Ben-Ari, 2015; Simons-Morton et al., 2012; Weston & Hellier, 2018). Understanding these moderation effects is crucial, as they may operate differently for role modeling versus direct engagement scenarios.

To address this research gap, our study employs the Bayesian Mindsponge Framework to analyze data from 1,039 Chinese drivers in 2022. This approach allows us to model the complex interactions between information processing mechanisms, cultural values, and demographic factors more effectively (Vuong et al., 2022a). We hypothesize that friends' safe-driving information positively influences Chinese drivers' safe-driving behaviors through both role modeling and direct engagement mechanisms, and demographic factors, including income, age, and gender, moderate this relationship.

Specifically, our research objectives are:

- Examine how friends' safe-driving information affects Chinese drivers' safe-driving behaviors.
- Examines how the socio-cultural factors affect the relationship between friends' safe-driving information and Chinese drivers' driving behaviors

By providing more nuanced insights into the interplay between peer influence mechanisms, cultural values, and demographic factors, we offer a comprehensive understanding of promoting safe driving behaviors in China's cultural context. Our findings can inform the development of more effective, culturally relevant strategies to improve road safety in China. Given the significant public health challenge posed by road traffic accidents worldwide, this research contributes to the broader effort to reduce traffic-related injuries and fatalities.

2. Methodology

2.1 Theoretical Foundation

This study adopts Granular Interaction Thinking Theory (GITT) as its theoretical framework to explain how drivers' gender, age, and income moderate the relationship between friends' safe-driving information and safe-driving behaviors (Vuong & Nguyen, 2024b, 2024c). GITT is an extension of the Mindsponge Theory, integrating principles from quantum mechanics and Shannon's information theory to explain how macroscopic behaviors in complex systems, such as human cognition, emerge from microscopic interactions of discrete information units (Hertog, 2023; Rovelli, 2018; Shannon, 1948). Since GITT builds upon the Mindsponge Theory, it retains its core capability of describing how individuals absorb, filter, and internalize information from their external environment (Vuong, 2023; Vuong & Napier, 2015)

GITT has two primary spectrums: the mind and the environment. The mind functions as an information collection-cum-processor, while the environment represents a broader information-processing system—such as a social or ecological system—that interacts with and encompasses the mind (Vuong & Nguyen, 2024a). The human mind constantly engages with its surroundings, restructuring itself to adapt and sustain existence. Only systems capable of efficiently managing this flow of information—by acquiring, storing, transmitting, and processing it—can survive, develop, and reproduce. In this sense, effective information management is crucial for adaptation, aligning closely with Charles Darwin's theory of evolution (Darwin, 2003; Darwin & Wallace, 1858).

Within the mind, information deemed essential for survival, development, and reproduction will be assigned a higher probability (i.e., given higher priorities) of being stored and utilized in subsequent cognitive processes. These prioritized information units are values that serve as guiding benchmarks for subsequent cognitive processes, including the multi-filtering process. Values play a central role in the mind's multi-layered filtering process, influencing how new information is integrated or differentiated. When new information aligns with pre-existing values, it is assimilated into the cognitive framework. Conversely, information that contradicts or deviates significantly from established values undergoes differentiation—a process in which the mind evaluates the costs and benefits of accepting or rejecting it (Vuong et al., 2025). If the new information is deemed beneficial, it is incorporated into future thinking, filtering, and behavioral processes. However, if the perceived costs outweigh the benefits, the information is discarded. When the costs and benefits are unclear, the information is temporarily stored in the mind, awaiting further contextual input for reassessment (Vuong et al., 2022b).

According to Goffman and Qi, "face" is a social representation of an individual that reflects the respect, esteem, or confidence others have in them. It is both something a person possesses and is aware of, as well as something recognized by others (Goffman, 1955; Qi, 2011). The evaluations that shape one's face state are inherently social rather than merely personal or subjective. In societies influenced by Protestant culture, individuals are typically viewed as autonomous, making decisions based on personal will (Fei et al., 1992). In this context, face is primarily determined by how individuals present themselves and behave to gain social respect or acceptance. In contrast, Chinese society emphasizes the embeddedness of individuals within social relationships, where roles in interpersonal and group interactions define obligations. Thus, face in Chinese society is not only a personal matter but also shaped by the actions of those closely connected to an individual, such as family members, teachers, employers, and other social ties (Qi, 2017). Additionally, in Chinese culture, face can be constructed as part of a self-conscious social strategy (Qi, 2011). Beyond seeking approval or avoiding disapproval, individuals engage in a "politics of face," where face value can be granted, lost, fought for, or even presented as a gift in social exchanges (Yutang, 1935).

From the perspective of Granular Interaction Thinking (Vuong & Nguyen, 2024c), we view a person's face value as the perceived social approval or disapproval they receive—encompassing respect, regard, confidence, or their opposites—emerging through interactions with others and connections to their social groups. As a dynamic psycho-social construct, face value is influenced by subjective factors such as expectations, past experiences, the behaviors and status of those involved, social norms, and broader social contexts. Because of this dynamic, even within the same context, changes in one of these factors can lead to shifts in face value. In Chinese society, the individual face is closely tied to the collective face, making face value even more complex, as the characteristics and reputation of one's social groups also shape the formation of an individual's face value. However, for those who consciously perceive themselves as excluded from the "politics of face," their thoughts and behaviors are less likely—if at all—to be influenced by social approval or disapproval (Vuong & Nguyen, 2024a).

Confucianism significantly influences the cultural underpinnings of the Chinese character. The emphasis on societal harmony within Confucian thought has historically driven individuals to seek their rightful place within the clan's social structure, which can manifest in two distinct behavioral patterns regarding face: a strong concern for maintaining social standing and a sense of powerlessness or lack of agency. In the context of daily interactions, face embodies the social standing that is highly regarded within Chinese culture. This status is deliberately cultivated through individual effort, accomplishments, and the resulting sense of pride over time (Hwang & Han, 2010). Male, high-income, and older people generally have higher social status within Chinese society, so they are more susceptible to face values. Thus, their thinking and behavioral processes are more likely to be influenced by face values.

For peer influence while driving, there are two main ways a peer can impact a driver: friends' support (engaging with the driver when he/she is driving) and friends' role model (acting as a role model and letting the driver observe and learn) (Bingham et al., 2016; Simons-Morton et al., 2012; Taubman-Ben-Ari & Katz-Ben-Ami, 2012; Taubman-Ben-Ari et al., 2014; Weston & Hellier, 2018). According to GITT, the desire to preserve face values is more likely to influence information absorption among males, high-income individuals, and older adults when they are directly urged by friends to adopt safe driving behaviors. In an effort to protect their face value, they may become less receptive to such direct advice, reducing the likelihood of transitioning to safer driving habits. However, when individuals observe their friends engaging in safe driving rather than being explicitly advised, the face-saving concern is not triggered. As a result, the absorption of safe driving information is expected to occur without interference from the face-saving mechanism.

2.2 Model Construction

2.2.1 Dataset

This study utilized a dataset of 1039 Chinese drivers' driving behavior conducted by (Jin et al., 2023). The dataset was collected through an online survey and organized into five key categories: (1) driving-related information, (2) aggressive driving behaviors, (3) peer and friend influence, (4) family influence, and (5) socio-demographic details. This dataset provides valuable insights for public health and transportation researchers, enabling the exploration of factors that shape driving behaviors and impact road safety in China.

Online interviews were initially conducted with 54 participants to identify their aggressive driving behaviors and explore the underlying reasons. Participants were specifically asked how their peers, friends, and parents influenced their driving behavior. All interviews took place via WeChat between April 10 and 25, 2022, with respondents drawn from a WeChat public group of drivers who had purchased insurance from the same provider that created the group. Each interview lasted approximately 15 to 30 minutes, and the insights gathered were used to develop questions for the subsequent survey.

To assess self-reported aggressive driving behavior, the study employed the Aggressive Driving Behavior Scale (Houston & Harris, 2003). However, based on interview findings, certain questions were modified and localized to better align with the Chinese context. The original scale comprised 11 items rated on a 6-point Likert scale (1 – never to 6 – always). The adapted version condensed the questionnaire to seven items, adopted a 5-point Likert scale (1 – strongly disagree to 5 – strongly agree), and reworded statements in a more positive tone to reduce resistance to potentially sensitive or face-losing questions in Chinese culture.

A convenience sampling approach was used for survey distribution. The survey was created on the WeChat mini-app "Survey Star," and group owners shared the survey link in four WeChat public groups from May 1 to 5, 2022. All group members were insured by the company that owned the groups, ensuring that all respondents were vehicle owners. Each group had a maximum of 500 members, totaling 2,000 potential participants. In the end, 1,039 drivers completed the survey, yielding a response rate of 51.95%. Before participating, all respondents provided informed consent. The survey questionnaire received the approval of the Institutional Review Board of the China University of Political Science and Law on March 18, 2022 (Jin et al., 2023). The Institutional Review Board ensures adherence to ethical standards, safeguarding participants' rights, welfare, and well-being throughout the study. All collected data have been anonymized and comply with applicable ethical guidelines and data protection regulations.

2.2.2 Variable Selection and Rationale

This study utilizes six variables for analysis. The outcome variable, *SafeDriving*, was derived by averaging seven self-reported variables measuring safe driving behavior, demonstrating high internal reliability (Cronbach's alpha = 0.943). The original dataset includes eight variables assessing peer influence on respondents' safe driving behavior. Among them, six variables capture peers' active engagement in promoting safe driving, while the remaining two reflect peers serving as role models. Accordingly, *FriendsSupport* was created as a composite variable by averaging the six variables reflecting peers' active engagement (Cronbach's alpha = 0.826), and *FriendsRoleModel* was generated by averaging the two variables reflecting peers serving as a role model (Cronbach's alpha = 0.933). Additionally, three socio-demographic variables—*Gender*, *Age*, and *Income*—were also included in the analysis. Table 1 provides a detailed description of these variables.

Table 1: Description of variables

Variable's name	Description	Data type	Details
Gender	Self-identified gender	Binary	0. Female
			1. Male

Age	Driver's age range (years old)	Numerical	1. 18-25 2. 25-30 3. 30-40 4. 40-50 5. 50+
Income	Earnings per month per driver (in RMB)	Numerical	1. Below 3000 2. 3000 – 9000 3. 9000 – 15000 4. 15000 – 30000 5. Above 30000
SafeDriving	Speed: rarely exceed	Numerical	1. Strongly disagree. 2. Disagree. 3. Neutral 4. Agree 5. Strongly agree
	Normal speed, avoid weaving, reckless overtaking		
	Safe distance, no tailgating		
	No retaliation: flashing high beams, changing lanes abruptly		
	Use the turn signal, give a heads-up, don't change lanes abruptly		
	Allow other drivers to merge		
	Slow down, stop at the yellow light		
FriendsSupport	My friends support me in safe driving	Numerical	1. Strongly

	My friends always advocate for safe driving, even when in a hurry.		disagree. 2. Disagree. 3. Neutral 4. Agree 5. Strongly agree
	My friends caution me against driving under the influence of alcohol or drugs.		
	My friends respect my decision not to drink or use drugs before driving.		
	My friends praise me instead of ridicule me for being courteous and yielding to other vehicles.		
	I am more careful while driving when my friends are in the car.		
FriendsRoleModel	I have never seen my friends drink or use drugs and drive	Numerical	1. Strongly disagree. 2. Disagree. 3. Neutral 4. Agree 5. Strongly agree
	I rarely witness my friends engaging in uncivilized driving behaviors such as reckless lane changes, speeding, or flashing.		

2.2.3 Statistical Models

In this study, we examine how friends' support and role models influence safe driving behaviors among Chinese drivers. We developed a simple model in which safe driving is regressed on friends' support and role models, incorporating the moderation of three demographic variables associated with driving behavior. Model 1 below was constructed with the moderation of $Income$ variable.

$$SafeDriving \sim \text{normal}(\mu, \sigma) \quad (1.1)$$

$$\mu_i = \beta_0 + \beta_1 * FriendsSupport_i + \beta_2 * FriendsRoleModel_i + \beta_3 * Income_i + \beta_4 * Income_i * FriendsRoleModel_i + \beta_5 * Income_i * FriendsSupport_i \quad (1.2)$$

$$\beta \sim normal(M, S) \quad (1.3)$$

The probability around μ is determined by the form of normal distribution, whose width is specified by the standard deviation σ. The safe driving score of driver i is indicated by μ_i. $FriendsSupport_i$ and $FriendsRoleModel_i$ are the levels of driver i's friends' support and role models, respectively. The model has an intercept β_0 and five coefficients, β_1-β_5. The non-additive effect of $Income_i * FriendsSupport_i$ is reflected through the coefficient β_5. If the coefficient β_5 is negative, it supports our assumption that higher face value (as reflected through higher income) constrains the absorption of safe driving information when the driver's friends actively support safe driving.

The coefficients of the predictor variables are distributed as a normal distribution around the mean denoted M and with the standard deviation denoted S.

The second model was constructed with the moderation of Age variable.

$$SafeDriving \sim \mathrm{normal}(\mu, \sigma) \quad (2.1)$$

$$\mu_i = \beta_0 + \beta_1 * FriendsSupport_i + \beta_2 * FriendsRoleModel_i + \beta_3 * Age_i + \beta_4 * Age_i * FriendsRoleModel_i + \beta_5 * Age_i * FriendsSupport_i \quad (2.2)$$

$$\beta \sim normal(M, S) \quad (2.3)$$

In this model, the non-additive effect of $Age_i * FriendsSupport_i$ is reflected through the coefficient β_5. If the coefficient β_5 is negative, it supports our assumption that higher face value (as reflected through older age) constrains the absorption of safe driving information when the driver's friends actively support safe driving.

The third model was constructed with the moderation of $Gender$ variable.

$$SafeDriving \sim \mathrm{normal}(\mu, \sigma) \quad (3.1)$$

$$\mu_i = \beta_0 + \beta_1 * FriendsSupport_i + \beta_2 * FriendsRoleModel_i + \beta_3 * Gender_i + \beta_4 * Gender_i * FriendsRoleModel_i + \beta_5 * Gender_i * FriendsSupport_i \quad (3.2)$$

$$\beta \sim normal(M, S) \quad (3.3)$$

In this model, the non-additive effect of $Gender_i * FriendsSupport_i$ is reflected through the coefficient β_5. If the coefficient β_5 is negative, it supports our assumption that higher face value (as reflected through being male) constrains the absorption of safe driving information when the driver's friends actively support safe driving.

2.2.4 Analysis and Validation

The current study employs Bayesian Mindsponge Framework (BMF) analytics for several reasons. First, BMF combines Granular Interaction Thinking Theory for theoretical reasoning with Bayesian analysis for statistical investigation, providing a robust approach to studying cognitive, psychological, and social phenomena (Nguyen et al., 2022; Vuong et al., 2022b). GITT is inherently probabilistic, as it suggests that the likelihood of value formation depends on the preexisting information and values within the mind (Vuong et al., 2025; Vuong & Nguyen, 2024c). This aligns well with Bayesian modeling, which treats both known and unknown quantities—including uncertainties, unobserved data, and unknown parameters—probabilistically (Gill, 2015). Given the probabilistic nature of both the theory and the inference approach, BMF is particularly well-suited for analyzing survey data, which often contain noise and subjective biases.

Given the complexity of human psychological processes, we opted for parsimonious models to enhance predictability. Bayesian inference is well-suited for estimating such models, as it probabilistically accounts for all properties, including unknown parameters.

Additionally, Bayesian analysis, supported by the Markov Chain Monte Carlo (MCMC) algorithm, enables the estimation of highly complex models, such as those in this study, which involve non-linear relationships (Dunson, 2001). Estimating non-linear relationships increases model complexity and necessitates a larger sample size for reliable estimation (Blum & François, 2010). The stochastic processes of Markov chains generate a large number of iterative samples, effectively facilitating model fitting.

Science is currently grappling with a reproducibility crisis, particularly in psychology and the social sciences (Camerer et al., 2018; Open Science Collaboration, 2015), where many studies cannot be easily replicated due to technical limitations in analytical approaches. A key factor contributing to this crisis is the high sample-to-sample variability of p-values (Halsey et al., 2015). To address this issue, we adopted Bayesian linear analysis, which avoids reliance on p-values and instead interprets results using credible intervals. Bayesian credible intervals directly express the probability that the true value lies within a given range for a specific dataset. This provides a clearer, more intuitive representation of uncertainty (van Zyl, 2018; Wagenmakers et al., 2018).

In the Bayesian approach, the selection of prior knowledge is required for model estimation. In this study, we employed uninformative priors, which impose minimal prior influence on the model by specifying a flat prior distribution to avoid subjective biases.

The diagnosis of models' goodness of fit is estimated through the Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) (Vehtari et al., 2017; Vehtari A & Gabry J, 2024). LOO is calculated as follows:

$$LOO = -2LPPD_{LOO} = -2\sum_{i=1}^{n} log \int p(y_i|\theta)p_{post(-i)}(\theta)d\theta$$

The posterior distribution of $p_{post(-i)}(\theta)$ is the calculation of the data minus data point i. The R **loo** package provides the computation of the *k*-Pareto values in the PSIS method regarding the LOO cross-validation. In the case of *k*-Pareto reaching the values at a level of 0.7 or above, the model's goodness of fit is not good for accurately estimating LOO cross-validation. However, if models' k-Pareto values are less than 0.5, the model's goodness of fit meets the fitting requirements.

After assessing the model's goodness of fit, the next step is to evaluate convergence diagnostics and interpret the analytical results. The validity of the research is supported by statistical measures and visual assessments of Markov chain convergence. Specifically, two key indicators are used: the effective sample size (*n_eff*) and the Gelman-Rubin shrink factor (*Rhat*). The *n_eff* value represents the number of effectively independent samples generated without autocorrelated stochastic simulation, while Rhat measures scale reduction factors (Brooks & Gelman, 1998). A Markov chain is considered to have achieved convergence when n_eff exceeds the threshold of 1,000, ensuring reliable inference conditions (McElreath, 2020). Conversely, a Rhat value of 1.1 or higher suggests non-convergence, whereas a Rhat value close to 1 confirms that the chains have successfully converged. Graphical methods further illustrate convergence, i.e., trace plots, providing additional validation of the model's reliability.

The bayesvl R package is utilized for Bayesian analysis, offering high-quality visualizations and an intuitive user interface (La & Vuong, 2019). The analysis was conducted with four Markov chains, each containing 5,000 iterations. 2,000 of them were used for warm-up. To ensure transparency and cost-effectiveness, all code and data used in this study have been publicly deposited on the Open Science Framework for review and evaluation (Vuong, 2018): https://osf.io/d4xvr/

3. Results

3.1. Model 1

Before assessing the results, it is crucial to evaluate the goodness of fit for Model 1. As shown in Figure 1, although not all estimated *k*-values remain below the 0.5 threshold, only one count of k-value (accounting for 0.1% of the total counts) is located within the range $(0.5, 0.7]$, which is an ‘ok’ interval. Thus, the goodness of fit between Model 1 and the observed data is acceptable.

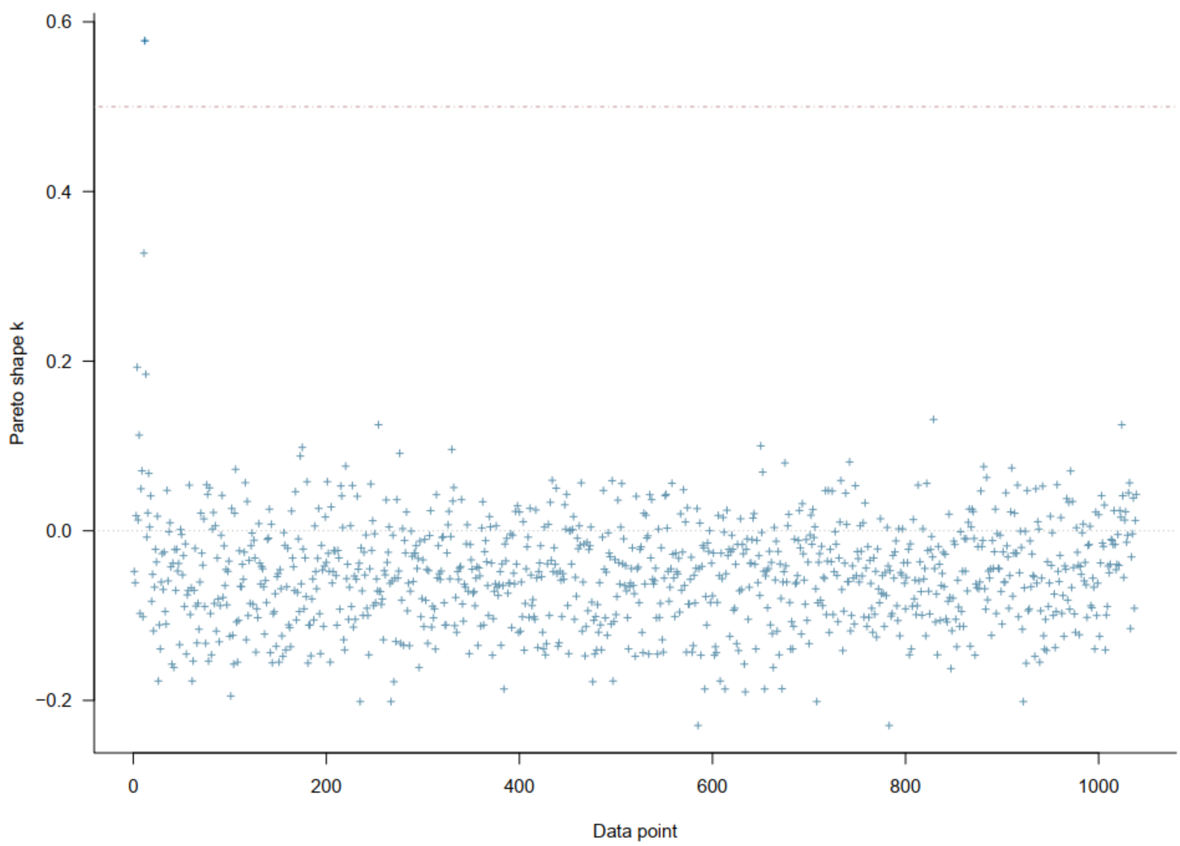


Figure 1. Model 1’s PSIS-LOO diagnosis

The posterior distributions of Model 1’s parameters are presented in Table 2. All effective sample size (*n_eff*) values exceed 1,000, and the *Rhat* statistics are exactly 1, confirming the successful convergence of the Markov chains. This convergence is further supported by the trace plots in Figure 2, which show all chains stabilizing around a central equilibrium after the 2,000th iteration (i.e., the warmup period).

Table 2: Estimated results of Model 1

Parameters	Mean	SD	*n_eff*	*Rhat*
Constant	0.12	0.13	4042	1
FriendsRoleModel	0.19	0.06	3779	1
*FriendsRoleModel*Income*	0.04	0.02	3754	1
FriendsSupport	0.77	0.06	3617	1
*FriendsSupport*Income*	-0.04	0.02	3571	1
Income	0.01	0.05	4042	1

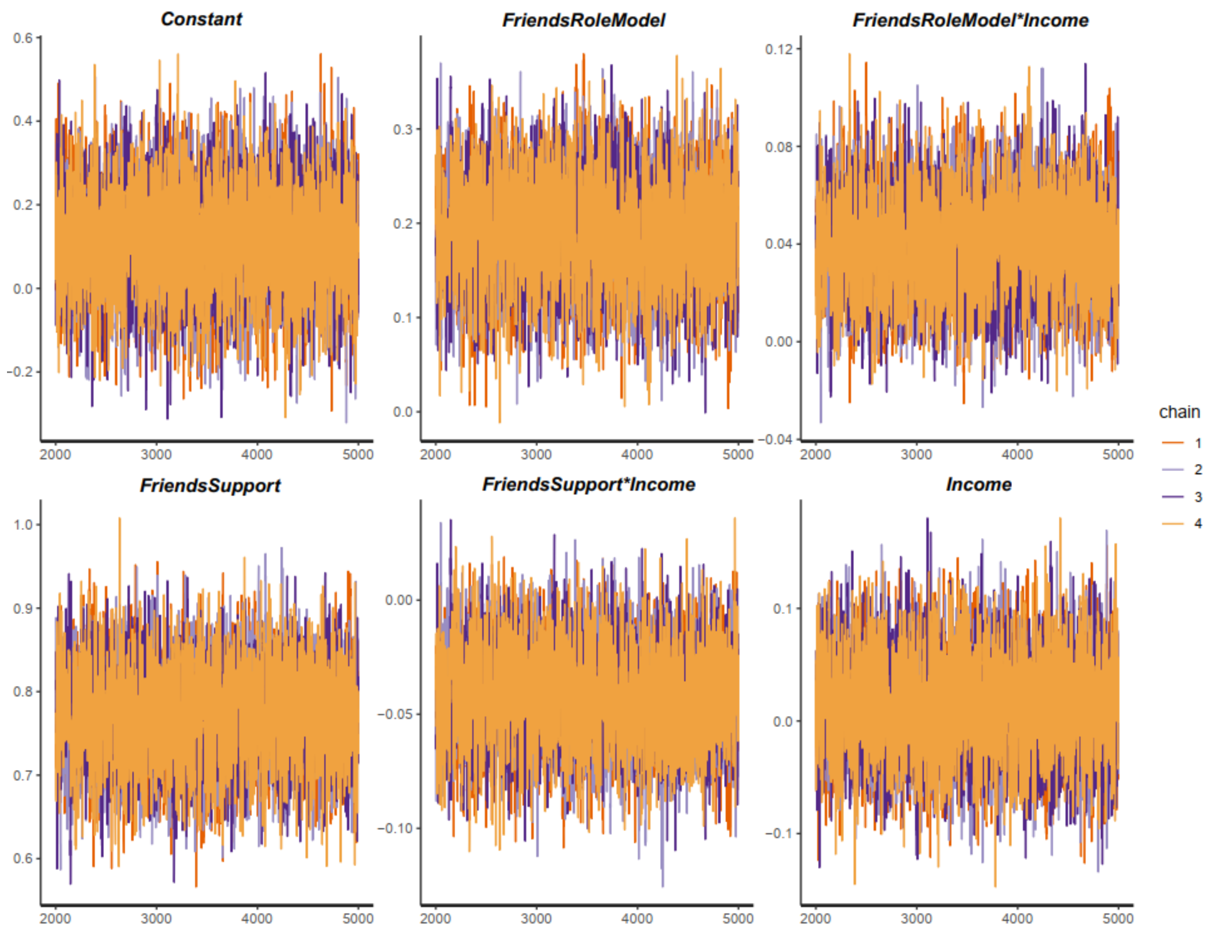


Figure 2. Model 1's trace plots

With all diagnostic assessments confirming the convergence of the Markov chains, the simulation results are deemed reliable for further interpretation. The estimated results of Model 1 suggest that friends serving as role models positively influence Chinese drivers' safe driving behaviors ($M_{FriendsRoleModel}$ = 0.19 and $S_{FriendsRoleModel}$ = 0.06), with this effect further enhanced by higher driver income ($M_{FriendsRoleModel*Income}$ = 0.04 and $S_{FriendsRoleModel*Income}$ = 0.02). Additionally, peer's active support positively influences safe driving behaviors ($M_{FriendsSupport}$ = 0.77 and $S_{FriendsSupport}$ = 0.06), although this relationship is negatively moderated by income ($M_{FriendsSupport*Income}$ = -0.04 and $S_{FriendsSupport*Income}$ = 0.02).

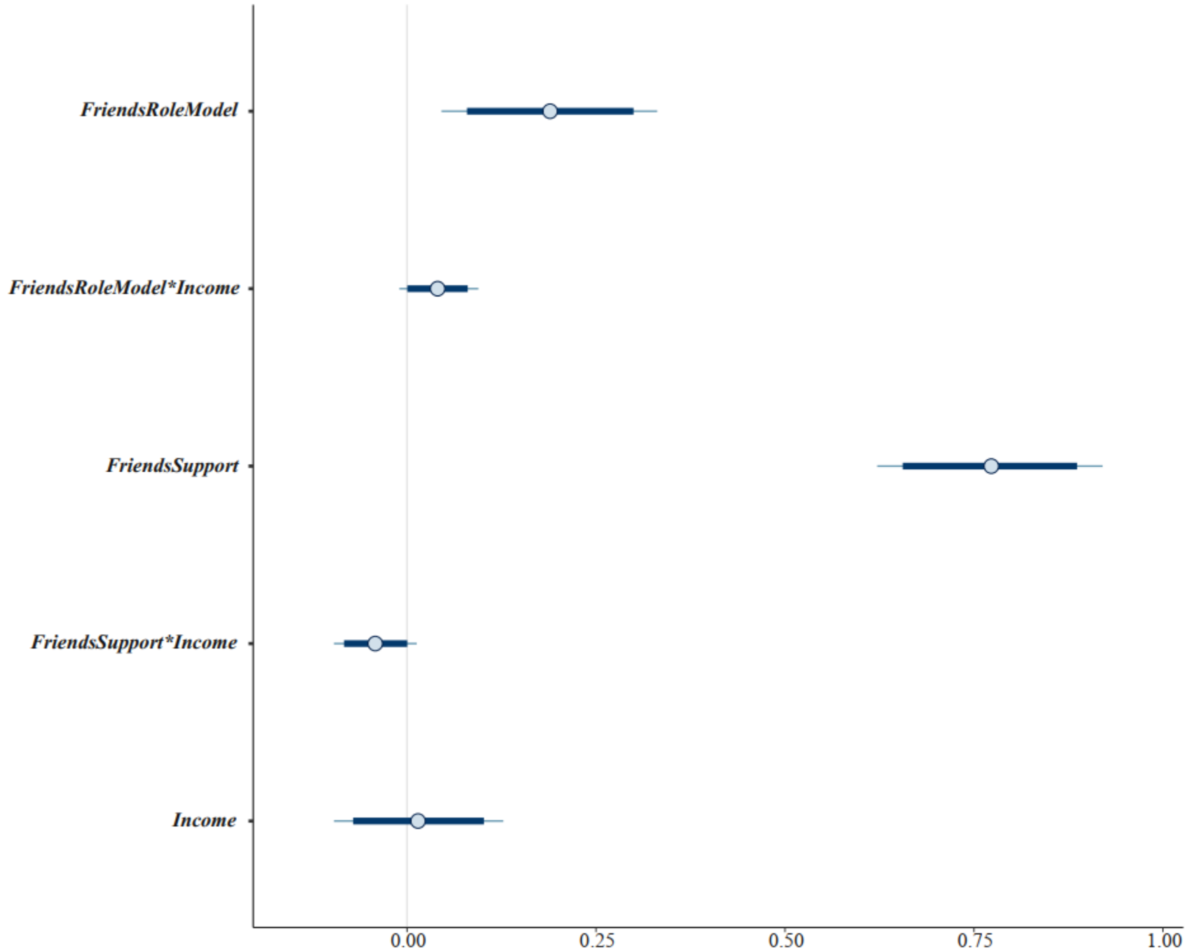


Figure 3. Model 1's posterior distributions

Figure 3 presents the posterior distributions of the coefficients, with the 95% Highest Posterior Density Intervals (HPDIs) shown as bold blue lines and the 99% HPDIs as thin blue parts of the lines. The posterior distributions' 95% HPDIs for $FriendsRoleModel$, $FriendsRoleModel * Income$, and $FriendsSupport$ fall entirely on the positive side of the x-axis, indicating high reliability of positive relationships. In contrast, the posterior distribution's 95% HPDI of $FriendsSupport * Income$ is entirely on the negative side, suggesting a highly reliable negative relationship. Meanwhile, the distribution of $Income$ falls within the neutral zone, indicating an unclear association.

3.2. Model 2

The result of the PSIS-LOO assessment for Model 2 is illustrated in Figure 4. All computed *k*-values remain below the 0.5 threshold, confirming a satisfactory goodness of fit with the observed data.

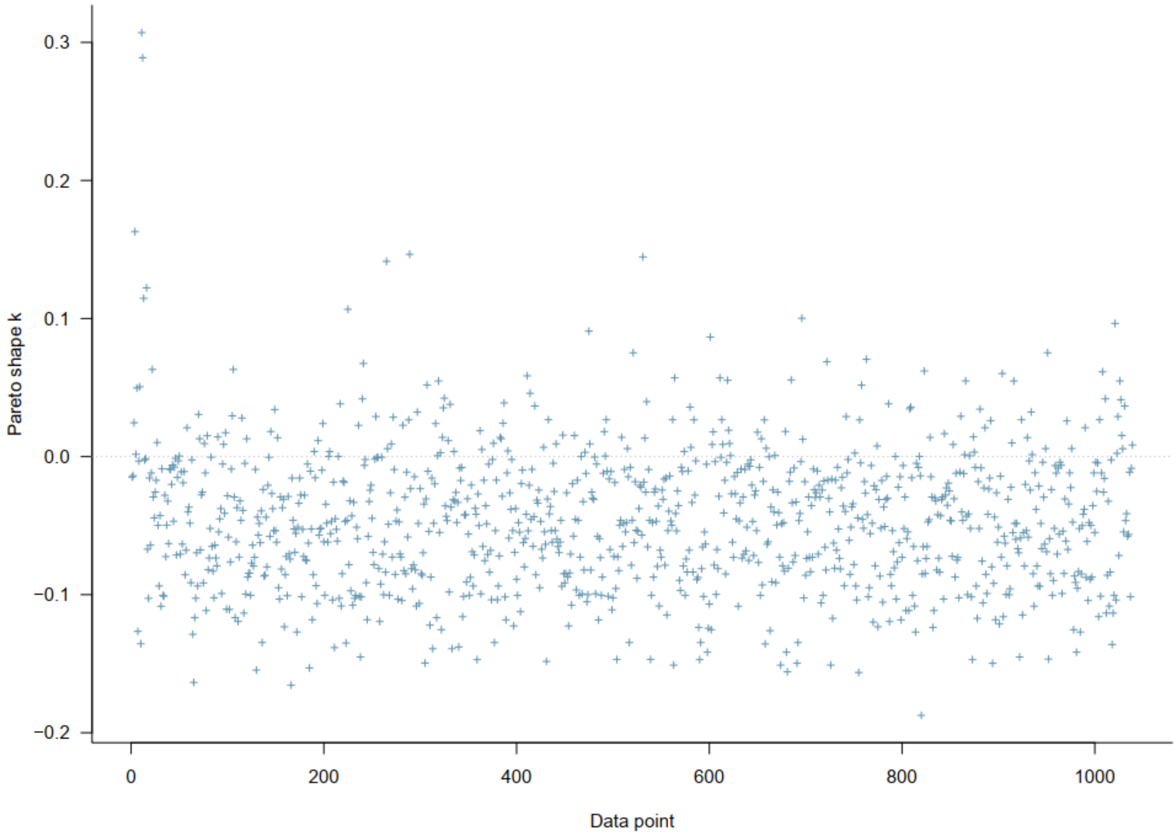


Figure 4. Model 2's PSIS-LOO diagnosis

As shown in Table 3, the statistical indicators *n_eff* (exceeding 1,000) and *Rhat* (equal to 1) confirm the convergence of the Markov chains in Model 2. This convergence is further supported by the trace plots illustrated in Figure 5. Therefore, the simulated results from Model 2 are considered eligible for further interpretation.

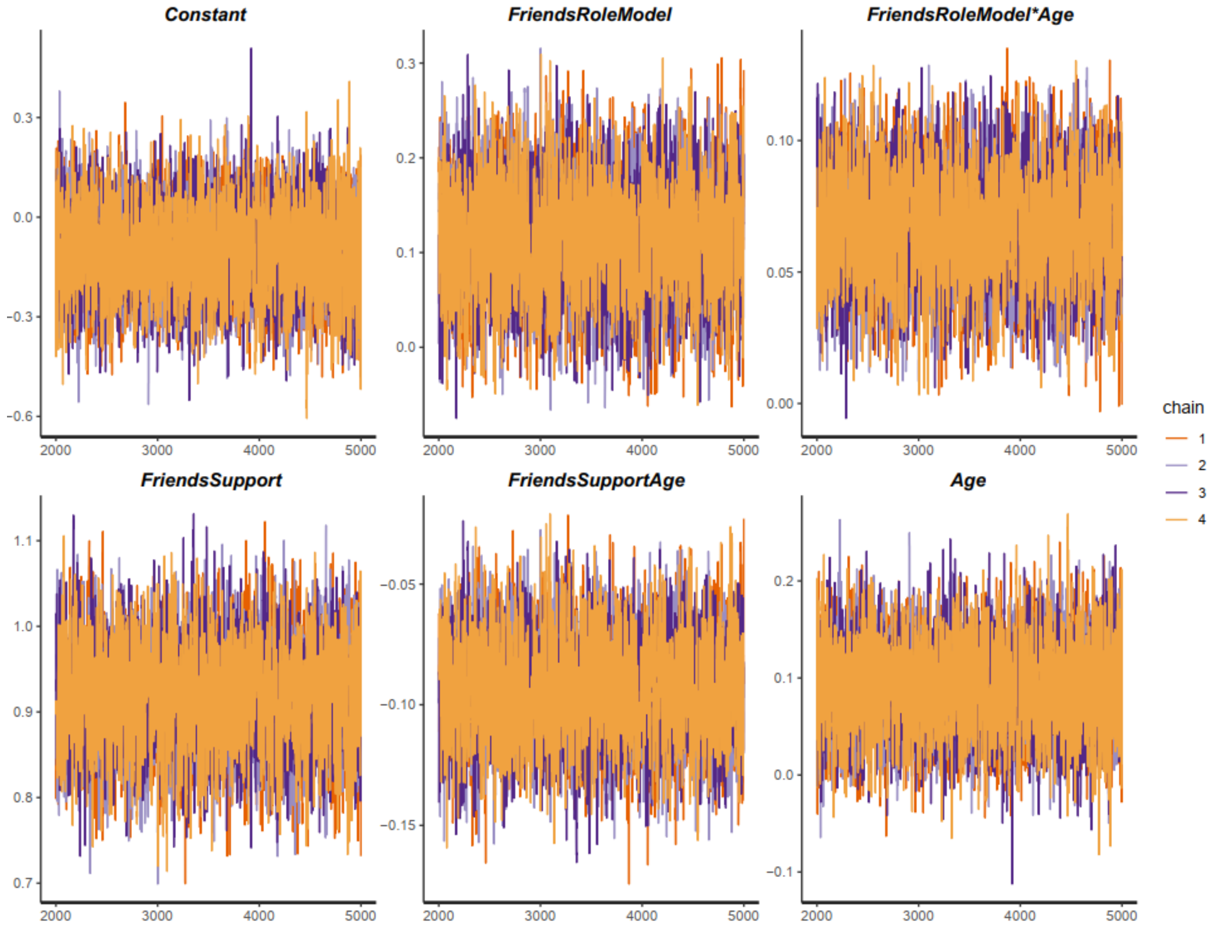


Figure 5. Model 2's trace plots

Table 3: Estimated results of Model 2

Parameters	Mean	SD	*n_eff*	*Rhat*
Constant	-0.10	0.13	4574	1
FriendsRoleModel	0.11	0.06	3955	1
*FriendsRoleModel*Age*	0.07	0.02	3951	1
FriendsSupport	0.92	0.06	3963	1
*FriendsSupport*Age*	-0.09	0.02	3953	1
Age	0.09	0.05	4544	1

The simulated results in Table 3 indicate that friends serving as role models positively influence Chinese drivers' safe driving behaviors ($M_{FriendsRoleModel}$ = 0.11 and $S_{FriendsRoleModel}$ = 0.06), with this effect being positively moderated by age ($M_{FriendsRoleModel*Age}$ = 0.07 and $S_{FriendsRoleModel*Age}$ = 0.02). Similar to Model 1, friends' active support also has a positive impact on safe driving behaviors ($M_{FriendsSupport}$ = 0.92 and $S_{FriendsSupport}$ = 0.06); however, this relationship is negatively moderated by age ($M_{FriendsSupport*Age}$ = -0.09 and $S_{FriendsSupport*Age}$ = 0.02). Additionally, age itself also has a direct positive effect on safe driving behaviors (M_{Age} = 0.09 and S_{Age} = 0.05). The posterior distributions' HPDIs of all the coefficients are entirely situated on either the positive or negative side of the axis, indicating the high reliability of all the associations (see Figure 6).

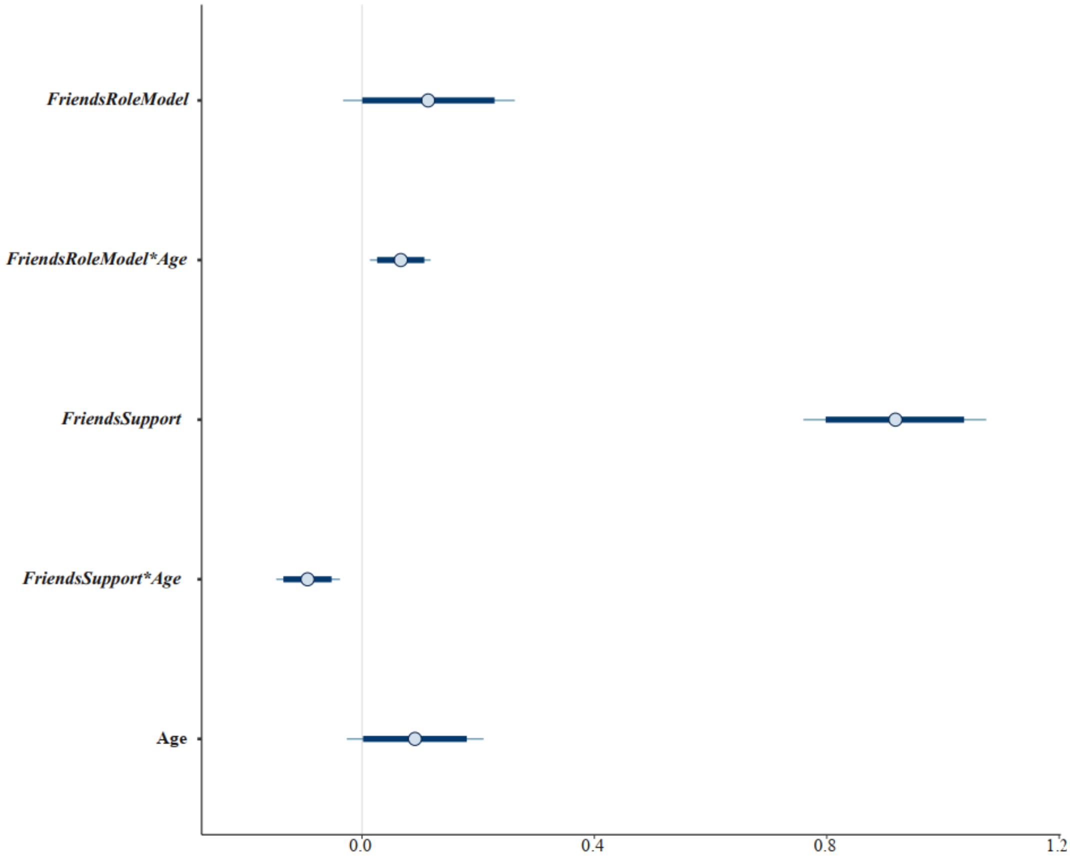


Figure 6: Model 2's posterior distributions

3.3. Model 3

The PSIS-LOO test results for Model 3 are displayed in Figure 7. All computed k-values remain below the 0.5 threshold, confirming a satisfactory goodness of fit with the dataset.

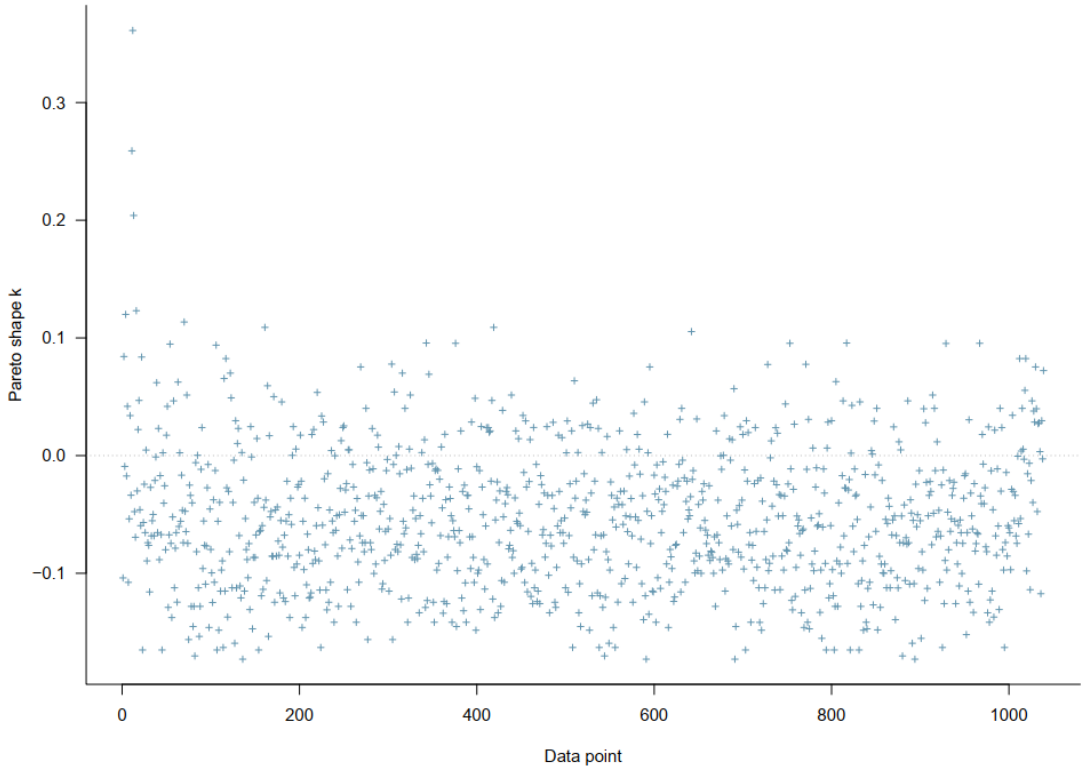


Figure 7. Model 3's PSIS-LOO diagnosis

The statistical indicators of *n_eff* (exceeding 1,000) and *Rhat* (equal to 1) in Table 4 confirm the convergence of the Markov chains in Model 3. The trace plots in Figure 8 further support this convergence. Therefore, the simulated results from Model 3 are eligible for interpretation.

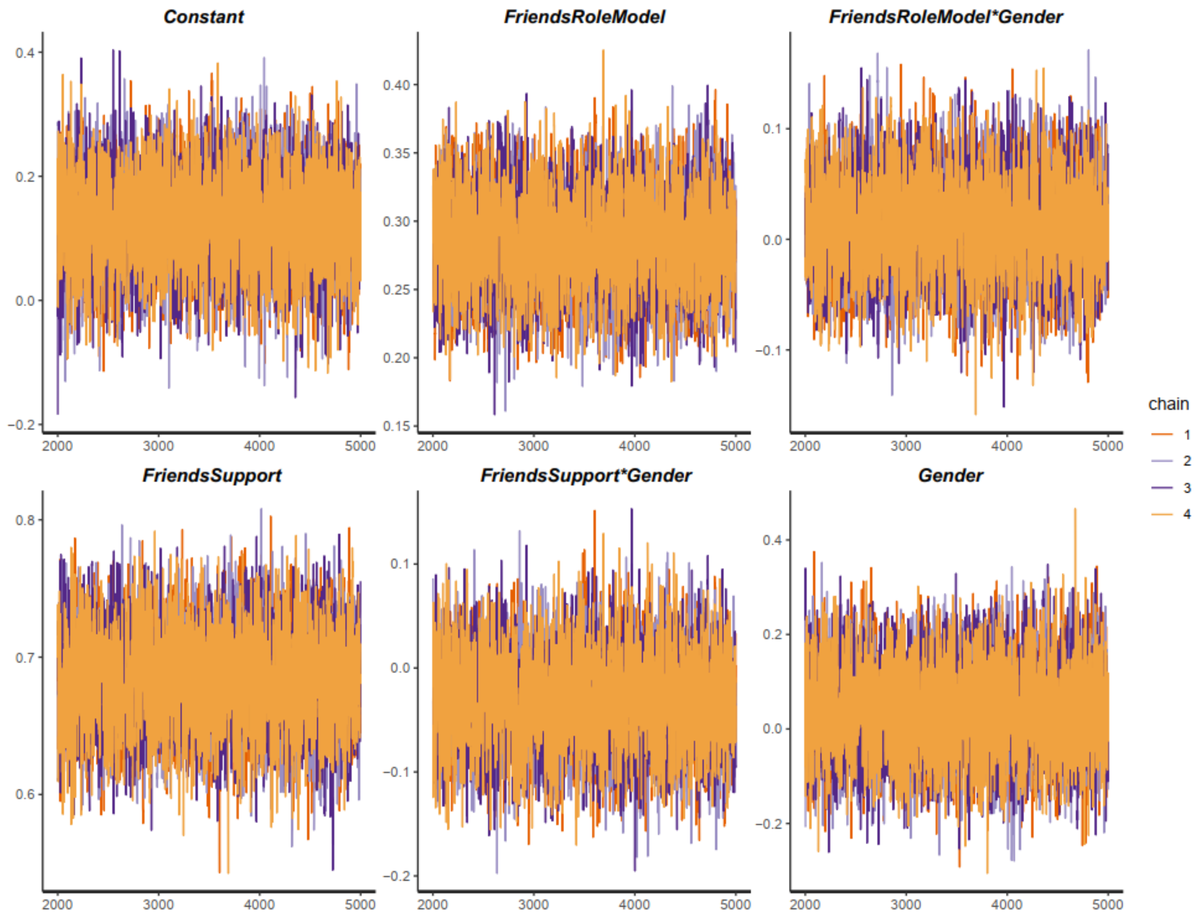


Figure 8. Model 3's trace plots

Table 4: Estimated results of Model 3

Parameters	**Mean**	**SD**	***n_eff***	***Rhat***
Constant	0.12	0.07	5169	1
FriendsRoleModel	0.28	0.03	4114	1
*FriendsRoleModel*Gender*	0.02	0.04	4069	1
FriendsSupport	0.69	0.03	4351	1
*FriendsSupport*Gender*	-0.03	0.04	4325	1
Gender	0.04	0.09	5134	1

The simulated results in Table 4 indicate that both friends serving as role models and friends' active support positively influence Chinese drivers' safe driving behaviors

($M_{FriendsRoleModel}$ = 0.28 and $S_{FriendsRoleModel}$ = 0.03; $M_{FriendsSupport}$ = 0.69 and $S_{FriendsSupport}$ = 0.03). However, $Gender$ also positively moderates the relationship between $FriendsRoleModel$ and $SafeDriving$ and negatively moderates the relationship between $FriendsSupport$ and $SafeDriving$. However, as their HPDIs in Figure 9 suggest, the moderation effects are weakly reliable.

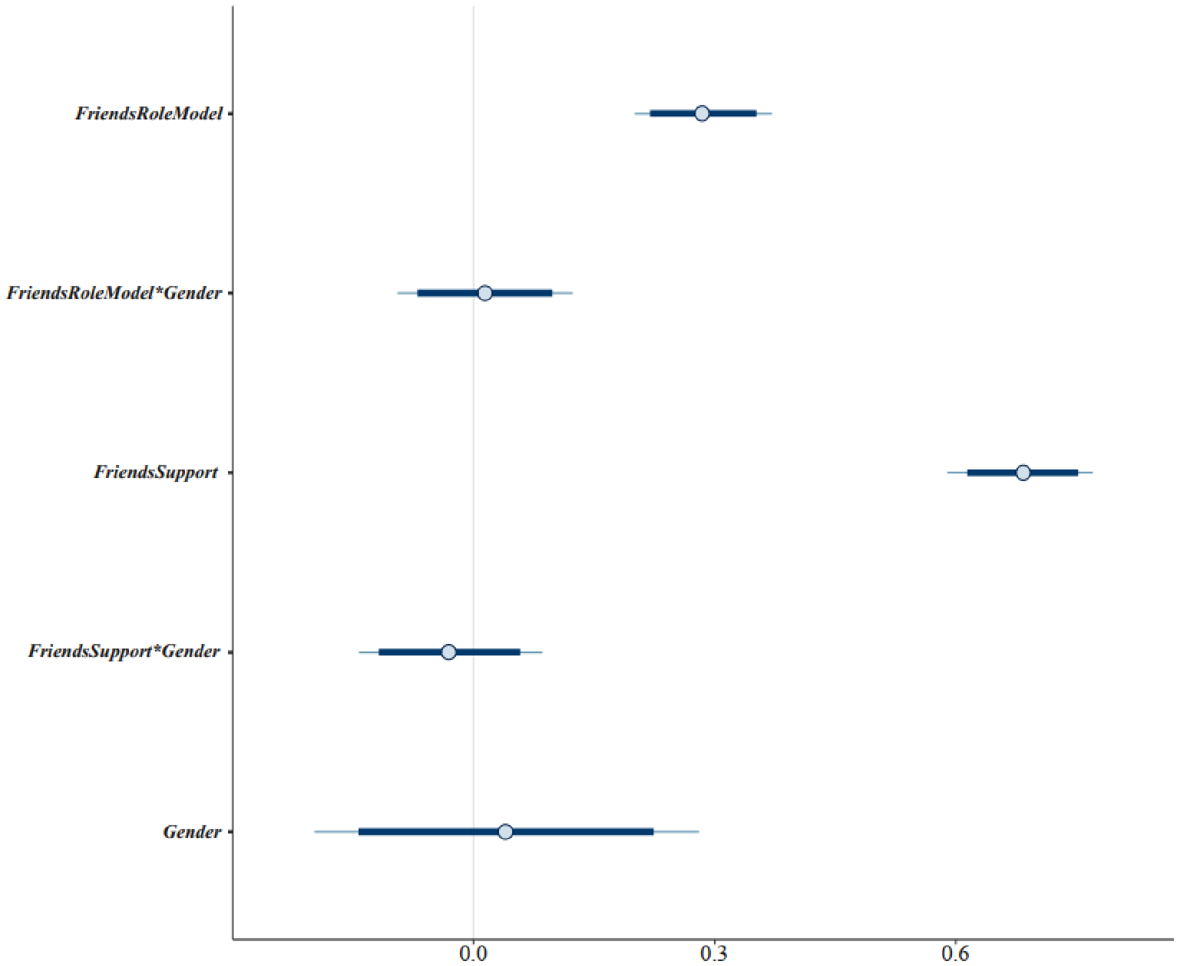


Figure 9: Model 3's posterior distributions

4. Discussion

This study utilized Bayesian Mindsponge Framework analytics to examine how peers' influence—through both role modeling and active support—shapes Chinese drivers' safe-driving behaviors while also exploring the moderating effects of demographic factors such as income, age, and gender (used as proxies for face value). Drawing from data on 1,039 Chinese drivers, the findings reveal a complex interplay among these factors. Both peers' role modeling and active support significantly contribute to drivers' safe driving behaviors. However, while drivers' income and age positively moderate the effect of peers as role models, they negatively moderate the impact of friends' active support, underscoring the nuanced role of face value in information processing and behavioral adaptation.

Our study highlights that peers' role modeling and supportive behaviors play a crucial role in fostering safe driving practices among Chinese drivers. These findings align with the research of José-Luis Padilla et al. (2023) and Yang et al. (2021), which demonstrate a negative correlation between reckless driving behaviors and traffic violations when friends share a commitment to safe driving and engage in discussions about responsible driving. Furthermore, both shared commitment and communication about safe driving are positively linked to non-aggressive driving behaviors and prosocial driving actions, such as courteous interactions on the road and measures that reduce traffic incidents (Zeyin et al., 2022). This underscores the positive influence of collective commitment to road safety, as well as the importance of discussions among friends in encouraging responsible driving habits. Within friendships, effective communication and mutual dedication to safe driving manifest in both role modeling (e.g., witnessing friends engage in unsafe driving behaviors, not seeing friends drinking/using drugs while driving) and supportive behaviors (e.g., advocating safe driving practices even when in a hurry, respecting the decision not drinking/using drug before driving, cautioning me against driving under the influence of alcohol or drugs, etc.)

When considering drivers' age and income, it is evident that age is positively associated with safe driving behaviors. Additionally, both age and income positively moderate the influence of friends as role models on safe driving behaviors. Reckless driving among younger individuals is a widespread issue and a significant contributor to traffic-related injuries and fatalities worldwide (Guggenheim et al., 2020). Prior research attributes this risk-taking tendency to factors such as underdeveloped driving skills and psychological influences, including feelings of empowerment, self-worth, and the pursuit of social validation (McKenna & Horswill, 2006; Steinberg, 2007; Upahita et al., 2018). As individuals mature, they typically develop stronger driving skills, greater financial stability, and a heightened sense of social responsibility. This progression often leads to an increased awareness of personal and public safety, reinforced by greater authority in family and professional settings and public recognition of their status or achievements—all of which contribute to safer driving behaviors.

Additionally, across all age groups, driving behaviors and norms are shaped by social interactions and peer influence (Guggenheim et al., 2020). Among mature drivers, peer groups tend to share similar levels of driving proficiency and psychological stability, making them less likely to engage in reckless driving or driving under the influence of alcohol or drugs. Furthermore, family responsibilities—such as ensuring the safety of children or elderly relatives—reinforce cautious driving practices. Consequently, peers serving as role models, particularly by embodying these responsible behaviors, have a stronger impact on shaping safe driving habits among mature drivers.

In contrast, age and income negatively moderate the relationship between peers' active support and Chinese drivers' safe driving behaviors. Additionally, being male also acts as a negative moderator, but its effect is weakly reliable and is therefore not discussed further. These findings align with the assumptions formulated by GITT. According to GITT, drivers' cognitive processing patterns—deeply shaped by their core cultural values—influence how they evaluate peer influence and support (Vuong, 2023; Vuong & Nguyen, 2024c). In the cultural context of China, face-saving plays a significant role in social interactions. When drivers engage with peers while driving, their ability to absorb and process information (i.e., learning) is strongly influenced by the ingrained value of face-saving. As a result, drivers with higher social status—determined by factors such as age, income, occupation, and social class—are more likely to reject or downplay peer input to maintain their social image. This leads to a diminished influence of peer support among higher-status drivers. Conversely, adolescents and young adults—who typically have lower social status—are more susceptible to peer influence. As a result, encouragement, criticism, or persuasion from friends can either amplify risk-taking behaviors or enhance safety awareness among young drivers (Banz et al., 2019; Weston & Hellier, 2018; Zhang et al., 2019). Research suggests that the social climate surrounding safe driving within peer groups impacts young drivers' behavior and crash risk (Guggenheim & Taubman–Ben-Ari, 2018; Yang et al., 2021).

These findings have significant implications for strengthening drivers' commitment to safe driving practices. The direct influence of both peer support and role modeling on safe driving behaviors suggests that fostering a safe driving environment among friends can encourage prosocial driving behaviors and reduce aggressive driving tendencies (Aktaş & Öztürk, 2024; Zeyin et al., 2022). To cultivate this positive driving culture, collaborative policies should be implemented at the government, community, and educational levels. Additionally, awareness campaigns—leveraging social media and mainstream media—should highlight both the benefits and risks of peer influence on driving behaviors. These initiatives can enhance peer-driven, safe-driving norms and reinforce prosocial driving attitudes and practices. Moreover, the impact of friends' role modeling and support is moderated by factors such as age and income (proxying face value in the Chinese context). To maximize the effectiveness of peer influence, it is crucial to consider socio-cultural aspects, particularly the face-saving mechanism that shapes how individuals absorb information and respond to peer-driven behavioral norms.

This study has several limitations, which we outline here for transparency (Vuong, 2020). Firstly, the analysis of drivers' perceptions regarding the influence of friends' safe-driving information on their safe-driving behaviors relies on self-reported survey data, which may be prone to subjective biases. Future research could address this limitation by incorporating experimental methodologies to validate findings. Moreover, the face values in this study were not directly measured but only proxied through age, income, and gender. Thus, future studies should be conducted to validate the findings by directly measuring the face value among drivers. Secondly, the dataset consists exclusively of participants from China, which may limit the generalizability of the results to other sociocultural settings. Consequently, caution is necessary when applying these findings to international contexts with significantly different driving norms and cultural influences. To enhance comparative insights, future studies should explore drivers' perspectives on the impact of safe-driving information using the Bayesian Mindsponge Framework (BMF) across a broader range of regions and nations. This would provide a more comprehensive understanding of how cultural and social factors shape safe driving behaviors globally.

Reference

Aktaş, A., & Öztürk, İ. (2024). “You are the company you keep”: A study of peer pressure on driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *106*, 244-256. https://doi.org/10.1016/j.trf.2024.08.017

Banz, B. C., Fell, J. C., & Vaca, F. E. (2019). Complexities of young driver injury and fatal motor vehicle crashes. *The Yale Journal of Biology and Medicine*, *92*(4), 725.

Bingham, C. R., Simons-Morton, B. G., Pradhan, A. K., Li, K., Almani, F., Falk, E. B., . . . Albert, P. S. (2016). Peer passenger norms and pressure: Experimental effects on simulated driving among teenage males. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 124-137. https://doi.org/https://doi.org/10.1016/j.trf.2016.06.007

Blum, M. G., & François, O. (2010). Non-linear regression models for Approximate Bayesian Computation. *Statistics and Computing*, *20*, 63-73. https://doi.org/10.1007/s11222-009-9116-0

Camerer, C. F., Dreber, A., Holzmeister, F., Ho, T.-H., Huber, J., Johannesson, M., . . . Pfeiffer, T. (2018). Evaluating the replicability of social science experiments in Nature and Science between 2010 and 2015. *Nature Human Behaviour*, *2*(9), 637-644. https://doi.org/10.1038/s41562-018-0399-z

Cassarino, M., & Murphy, G. (2018). Reducing young drivers’ crash risk: Are we there yet? An ecological systems-based review of the last decade of research. *Transportation Research Part F: Traffic Psychology and Behaviour*, *56*, 54-73. https://doi.org/https://doi.org/10.1016/j.trf.2018.04.003

Curry, A. E., Peek-Asa, C., Hamann, C. J., & Mirman, J. H. (2015). Effectiveness of Parent-Focused Interventions to Increase Teen Driver Safety: A Critical Review. *Journal of Adolescent Health*, *57*(1, Supplement), S6-S14. https://doi.org/https://doi.org/10.1016/j.jadohealth.2015.01.003

Darwin, C. (2003). *On the origin of species* (D. Knight, Ed. Reprint ed.). Routledge.

Darwin, C., & Wallace, A. J. J. o. t. p. o. t. L. S. o. L. Z. (1858). On the tendency of species to form varieties; and on the perpetuation of varieties and species by natural means of selection. *Journal of the proceedings of the Linnean Society of London. Zoology*, *3*(9), 45-62.

Dunson, D. B. (2001). Commentary: practical advantages of Bayesian analysis of epidemiologic data. *American Journal of Epidemiology*, *153*(12), 1222-1226. https://doi.org/10.1093/aje/153.12.1222

Fan, J. (2022). *14th Five-Year Plan for National Road Traffic Safety Released*. Urban Planning Society of China. https://en.planning.org.cn/nua/view?id=740#:~:text=To%20reach%20these%20goals%2C%20the,vehicles%20and%20operational%20safety%3B%20enhance

Fei, X., Hamilton, G. G., & Zheng, W. (1992). *From the soil: The foundations of Chinese society*. University of California Press.

Geng, J., Yu, J., & Zhu, J. (2024). A comparative analysis of distracted driving behavior among drivers of different income levels: A case study in Huainan, China. *Heliyon*, *10*(7), e28668. https://doi.org/https://doi.org/10.1016/j.heliyon.2024.e28668

Gill, J. (2015). *Bayesian methods: A social and behavioral sciences approach* CRC Press.

Goffman, E. (1955). On face-work: An analysis of ritual elements in social interaction. *Psychiatry*, *18*(3), 213-231. https://doi.org/10.1080/00332747.1955.11023008

Granié, M.-A., Thévenet, C., Varet, F., Evennou, M., Oulid-Azouz, N., Lyon, C., . . . Van den Berghe, W. (2021). Effect of Culture on Gender Differences in Risky Driver Behavior through Comparative Analysis of 32 Countries. *Transportation Research Record*, *2675*(3), 274-287. https://doi.org/10.1177/0361198120970525

Guggenheim, N., Taubman-Ben-Ari, O., & Ben-Artzi, E. (2020). The contribution of driving with friends to young drivers' intention to take risks: An expansion of the theory of planned behavior. *Accid Anal Prev*, *139*, 105489. https://doi.org/10.1016/j.aap.2020.105489

Guggenheim, N., & Taubman–Ben-Ari, O. (2018). Safe driving climate among friends (SDCaF): A new scale. *Accident Analysis and Prevention*, *110*, 78-85. https://doi.org/10.1016/j.aap.2017.10.021

Guggenheim, N., & Taubman – Ben-Ari, O. (2015). Ultraorthodox young drivers in Israel – Driving through cultural lenses. *Transportation Research Part F: Traffic Psychology and Behaviour*, *33*, 87-96. https://doi.org/https://doi.org/10.1016/j.trf.2015.07.011

Halsey, L. G., Curran-Everett, D., Vowler, S. L., & Drummond, G. B. (2015). The fickle P value generates irreproducible results. *Nature Methods*, *12*(3), 179-185. https://doi.org/10.1038/nmeth.3288

Han, K. H. (2016). The Feeling of "Face" in Confucian Society: From a Perspective of Psychosocial Equilibrium. *Front Psychol*, *7*, 1055. https://doi.org/10.3389/fpsyg.2016.01055

Hertog, T. (2023). *On the origin of time: Stephen Hawking's final theory*. Random House. https://www.google.com/books/edition/On_the_Origin_of_Time/IlBTEAAAQBAJ

Houston, J. M., & Harris, P. (2003). The Aggressive Driving Behavior Scale: Developing a self-report measure of unsafe driving practices. *North American Journal of Psychology*, *5*, 193-202.

Hwang, K.-K., & Han, K.-H. (2010). Face and morality in Confucian society. In M. H. Bond (Ed.), *Oxford Handbook of Chinese psychology* (pp. 479–498). Oxford University Press.

La, V.-P., & Vuong, Q.-H. (2019). bayesvl: Visually learning the graphical structure of Bayesian networks and performing MCMC with 'Stan'. *The Comprehensive R Archive Network (CRAN)*. https://cran.r-project.org/web/packages/bayesvl/index.html

Lewis, H. M. (2006). Golden face: Cultural reciprocity in the articulation of mainland Chinese social structure. *Thunderbird International Business Review*, *48*(1), 9-23. https://doi.org/https://doi.org/10.1002/tie.20082

Lindstrom-Forneri, W., Tuokko, H. A., Garrett, D., & Molnar, F. (2010). Driving as an Everyday Competence: A Model of Driving Competence and Behavior. *Clinical Gerontologist*, *33*(4), 283-297. https://doi.org/10.1080/07317115.2010.502106

McCarty, D., & Kim, H. W. (2024). Risky behaviors and road safety: An exploration of age and gender influences on road accident rates. *PLOS ONE*, *19*(1), e0296663. https://doi.org/10.1371/journal.pone.0296663

McKenna, F. P., & Horswill, M. S. (2006). Risk taking from the participant's perspective: The case of driving and accident risk. *Health Psychology*, *25*(2), 163. https://doi.org/10.1037/0278-6133.25.2.163

Metzger, K. B., Sartin, E., Foss, R. D., Joyce, N., & Curry, A. E. (2020). Vehicle safety characteristics in vulnerable driver populations. *Traffic Injury Prevention*, *21*(sup1), S54-S59. https://doi.org/10.1080/15389588.2020.1805445

Nguyen, M.-H., La, V.-P., Le, T.-T., & Vuong, Q.-H. (2022). Introduction to Bayesian Mindsponge Framework analytics: An innovative method for social and

psychological research. *MethodsX*, *9*, 101808. https://doi.org/10.1016/j.mex.2022.101808
Nordfjærn, T., Şimşekoğlu, Ö., & Rundmo, T. (2014). Culture related to road traffic safety: a comparison of eight countries using two conceptualizations of culture. *Accid Anal Prev*, *62*, 319-328. https://doi.org/10.1016/j.aap.2013.10.018
Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716. https://doi.org/10.1126/science.aac4716
Padilla, J.-L., Sánchez, N., Doncel, P., Carmen Navarro-González, M., Taubman – Ben-Ari, O., & Castro, C. (2023). The young male driving problem: Relationship between Safe Driving Climate among Friends, Peer Pressure and Driving Styles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *98*, 141-156. https://doi.org/https://doi.org/10.1016/j.trf.2023.09.006
Padilla, J.-L., Sanchez, N., Doncel, P., Navarro-González, M. C., Taubman–Ben-Ari, O., & Castro, C. (2023). The young male driving problem: relationship between safe driving climate among friends, peer pressure and driving styles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *98*, 141-156. https://doi.org/10.1016/j.trf.2023.09.006
Pagomenos, A., Rodwell, D., & Larue, G. S. (2023). Predicting young drivers' safe behaviour of stopping in the dilemma zone. *Transportation Research Part F: Traffic Psychology and Behaviour*, *92*, 283-300. https://doi.org/https://doi.org/10.1016/j.trf.2022.11.017
Qi, X. (2011). Face: A Chinese concept in a global sociology. *Journal of Sociology*, *47*(3), 279-295. https://doi.org/10.1177/1440783311407692
Qi, X. (2017). Reconstructing the concept of face in cultural sociology: in Goffman's footsteps, following the Chinese case. *The Journal of Chinese Sociology*, *4*(1), 19. https://doi.org/10.1186/s40711-017-0069-y
Rose, D. M., Sieck, C. J., Kaur, A., Wheeler, K. K., Sullivan, L., & Yang, J. (2024). Factors Influencing Participation and Engagement in a Teen Safe Driving Intervention: A Qualitative Study. *Int J Environ Res Public Health*, *21*(7). https://doi.org/10.3390/ijerph21070928
Rovelli, C. (2018). *Reality is not what it seems: The journey to quantum gravity*. Penguin. https://www.google.com/books/edition/Reality_Is_Not_What_It_Seems/fsQiDAAAQBAJ
Sagberg, F., Selpi, Bianchi Piccinini, G. F., & Engström, J. (2015). A Review of Research on Driving Styles and Road Safety. *Human Factors*, *57*(7), 1248-1275. https://doi.org/10.1177/0018720815591313
Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379-423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x
Shen, B., Ge, Y., Qu, W., Sun, X., & Zhang, K. (2018). The different effects of personality on prosocial and aggressive driving behaviour in a Chinese sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, *56*, 268-279. https://doi.org/https://doi.org/10.1016/j.trf.2018.04.019
Simons-Morton, B. G., Ouimet, M. C., Chen, R., Klauer, S. G., Lee, S. E., Wang, J., & Dingus, T. A. (2012). Peer influence predicts speeding prevalence among teenage drivers. *Journal of Safety Research*, *43*(5), 397-403. https://doi.org/https://doi.org/10.1016/j.jsr.2012.10.002
Steinberg, L. (2007). Risk taking in adolescence: New perspectives from brain and behavioral science. *Current Directions in Psychological Science*, *16*(2), 55-59. https://doi.org/10.1111/j.1467-8721.2007.00475.x

Tan, H., Zhao, F., Hao, H., & Liu, Z. (2020). Cost analysis of road traffic crashes in China. *International Journal of Injury Control and Safety Promotion*, *27*(3), 385-391. https://doi.org/10.1080/17457300.2020.1785507

Taubman-Ben-Ari, O., & Katz-Ben-Ami, L. (2012). The contribution of family climate for road safety and social environment to the reported driving behavior of young drivers. *Accident Analysis and Prevention*, *47*, 1-10. https://doi.org/10.1016/j.aap.2012.01.003

Taubman-Ben-Ari, O., Musicant, O., Lotan, T., & Farah, H. (2014). The contribution of parents' driving behavior, family climate for road safety, and parent-targeted intervention to young male driving behavior. *Accident Analysis and Prevention*, *72*, 296-301. https://doi.org/10.1016/j.aap.2014.07.010

Tran, T. M. A. (2024). Conversations with Kingfisher: Wisdom from Vuong's Wild Wise Weird Stories. https://philpapers.org/rec/TRACWK

Trógolo, M. A., Ledesma, R., Medrano, L. A., & Dominguez-Lara, S. (2022). Peer pressure and risky driving: Development of a new scale. *Journal of Safety Research*, *82*, 48-56. https://doi.org/https://doi.org/10.1016/j.jsr.2022.04.005

Upahita, D. P., Wong, Y. D., & Lum, K. M. (2018). Effect of driving experience and driving inactivity on young driver's hazard mitigation skills. *Transportation Research Part F: Traffic Psychology and Behaviour*, *59*, 286-297. https://doi.org/10.1016/j.trf.2018.09.003

van Zyl, C. J. J. (2018). Frequentist and Bayesian inference: A conceptual primer. *New Ideas in Psychology*, *51*, 44-49. https://doi.org/10.1016/j.newideapsych.2018.06.004

Vuong, Q.-H. (2018). The (ir)rational consideration of the cost of science in transition economies. *Nature Human Behaviour*, *2*, 5. https://doi.org/10.1038/s41562-017-0281-4

Vuong, Q.-H. (2020). Reform retractions to make them more transparent. *Nature*, *582*(7811), 149. https://doi.org/10.1038/d41586-020-01694-x

Vuong, Q.-H. (2023). *Mindsponge theory*. Walter de Gruyter GmbH. https://www.amazon.com/dp/B0C3WHZ2B3/

Vuong, Q.-H., La, V.-P., & Nguyen, M.-H. (2025). Informational entropy-based value formation: A new paradigm for a deeper understanding of value. https://philarchive.org/rec/VUOIEV

Vuong, Q.-H., & Nguyen, M.-H. (2024a). *Better economics for the Earth: A lesson from quantum and information theories*. AISDL. https://www.amazon.com/dp/B0D98L5K44/

Vuong, Q.-H., & Nguyen, M.-H. (2024b). Exploring the role of rejection in scholarly knowledge production: Insights from granular interaction thinking and information theory. *Learned Publishing*, e1636. https://doi.org/10.1002/leap.1636

Vuong, Q.-H., & Nguyen, M.-H. (2024c). Further on informational quanta, interactions, and entropy under the granular view of value formation. *The VMOST Journal of Social Sciences and Humanities*. https://doi.org/10.2139/ssrn.4922461

Vuong, Q.-H., Nguyen, M.-H., & La, V.-P. (2022a). *The mindsponge and BMF analytics for innovative thinking in social sciences and humanities* (Vol. 9). De Gruyter.

Vuong, Q.-H., Nguyen, M.-H., & La, V.-P. (2022b). *The mindsponge and BMF analytics for innovative thinking in social sciences and humanities*. Walter de Gruyter GmbH. https://www.amazon.com/dp/B0C4ZK3M74/

Vuong, Q. H., & Napier, N. K. (2015). Acculturation and global mindsponge: an emerging market perspective. *International Journal of Intercultural Relations*, *49*, 354-367. https://doi.org/10.1016/j.ijintrel.2015.06.003

Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., . . . Epskamp, S. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin and Review*, *25*, 35-57. https://doi.org/10.3758/s13423-017-1343-3

Wang, H., Su, X., Fan, M., & Schwebel, D. C. (2024). The more peers are present, the more adventurous? How peer presence influences adolescent pedestrian safety. *Transportation Research Part F: Traffic Psychology and Behaviour*, *102*, 155-163. https://doi.org/https://doi.org/10.1016/j.trf.2024.03.001

Weston, L., & Hellier, E. (2018). Designing road safety interventions for young drivers – The power of peer influence. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 262-271. https://doi.org/https://doi.org/10.1016/j.trf.2018.03.003

WHO. (2022). *Preventing injuries and violence: an overview*. https://www.who.int/publications/i/item/9789240047136

WHO. (2023a). *Global status report on road safety 2023*. https://www.who.int/publications/i/item/9789240086517

WHO. (2023b). *Global status report on road safety 2023: Country and territory profiles*. https://cdn.who.int/media/docs/default-source/country-profiles/road-safety/road-safety-2023-chn.pdf

Wickens, C. M., Mann, R. E., Stoduto, G., Butters, J. E., Ialomiteanu, A., & Smart, R. G. (2012). Does gender moderate the relationship between driver aggression and its risk factors? *Accident Analysis & Prevention*, *45*, 10-18. https://doi.org/https://doi.org/10.1016/j.aap.2011.11.013

Xinhua. (2024). *China sees decline in major road accidents despite vehicle boom*. The State Council The People's Republic of China. https://english.www.gov.cn/news/202405/27/content_WS665447cbc6d0868f4e8e7877.html

Yang, Z., Sun, L., & Huo, Y. (2021). Adaptation of the safe driving climate among friends scale in Chinese drivers and its associations with risky driving behaviours. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 299-307. https://doi.org/https://doi.org/10.1016/j.trf.2021.02.019

Yousaf, A., & Wu, J. (2024). Cross-Cultural Behaviors: A Comparative Analysis of Driving Behaviors in Pakistan and China. *Sustainability*, *16*(12), 5225. https://www.mdpi.com/2071-1050/16/12/5225

Yutang, L. (1935). *My country and my people*. Reading Essentials.

Zeyin, Y., Long, S., & Gaoxiao, R. (2022). Effects of safe driving climate among friends on prosocial and aggressive driving behaviors of young drivers: The moderating role of traffic locus of control. *Journal of Safety Research*, *81*, 297-304. https://doi.org/https://doi.org/10.1016/j.jsr.2022.03.006

Zhang. (2024). *Number of fatalities in traffic accidents in China from 2010 to 2023*. National Bureau of Statistics of China. https://www.statista.com/statistics/276260/number-of-fatalities-in-traffic-accidents-in-china/

Zhang, F., Mehrotra, S., & Roberts, S. C. (2019). Driving distracted with friends: Effect of passengers and driver distraction on young drivers' behavior. *Accident Analysis and Prevention*, *132*, 105246. https://doi.org/10.1016/j.aap.2019.07.022

Zhang, M. (2023). A Review on Mianzi in Interpersonal, Familial, and Business Settings. *Communications in Humanities Research*, *16*(1), 54-58. https://doi.org/10.54254/2753-7064/16/20230100