Think more before you cheat: The influences of attitudes toward cheating and cognitive reflection on cheating behavior

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Abstract

Cheating is widely considered a condemnable behavior in society and a big problem in the educational system. In this study, we employ the information-processing-based Bayesian Mindsponge Framework to explore deeper the subjective cost-benefit evaluation involving the perceived value of cheating. Conducting Bayesian analysis on 493 university students from Germany, Vietnam, China, Taiwan, and Japan, we found that students who have more positive attitudes toward cheating are more likely to cheat. However, a higher capability of cognitive reflection acts as a moderator that negates the above effect. Re-evaluation of prior thoughts allows for more accurate assessments of the associated risks and possible costs, which help reduce the probability of carrying out cheating behavior. As rapid technological advancement may introduce new and efficient cheating methods, a better understanding of the psychology of cheating in students can help schools prepare better countermeasures.

Keywords: cheating behavior; attitude toward cheating; cognitive reflection; information processing; Bayesian Mindsponge Framework

"— Perch or carp, no matter what is up to the Heaven."

In "Joint Venture"; *The Kingfisher Story Collection* (2022)

1. Introduction

Humans naturally have an important ability that is often taken for granted: re-evaluating one's own thoughts. Its role becomes apparent when considering an extreme situation. When people approach dangerous areas without protective barriers, especially high places such as bridges and cliffs, many suddenly have an urge to jump off – which likely means death. This mysterious psychological phenomenon is commonly referred to as the "call of the void" (Le, 2023). Regardless of the possible causes of this strange urge, there is one thing for sure: without the ability to reflect on and re-evaluate the initial thought, a person would be more at risk of actually jumping off the edge into life-threatening danger. Overall, thanks to how information filtering in the mind happens through multiple processes in an updating manner as needed (Vuong et al., 2022), humans are able to reject a considerable number of thoughts about carrying out bad behaviors.

One of the common condemnable behaviors in human society is cheating. Cheating is commonly described as actions involving dishonesty, fraud, and violation of rules or norms to obtain unfair advantages or profit (McCabe et al., 2001; Whitley, 1998). Cheating can damage the trust and integrity of social institutions (McCabe et al., 2001; Shu et al., 2011; Tyler & Huo, 2002) as well as cause individuals emotional pain and distress (Shrout & Weigel, 2018). Individual factors (personality traits, moral values, etc.) and environmental factors (attractions, external pressures, etc.) can lead to cheating behavior (McCabe & Trevino, 1993; Welch et al., 2005). The issue of cheating is of special attention in the development of young generations. Cheating is a common problem in educational institutions globally

(McCabe et al., 2012). Plagiarism, duplicating others' work, utilizing prohibited resources during tests, fabricating data, and paying someone else to do one's own assignments are common examples of cheating behaviors in the educational system. Students may decide to cheat for a variety of reasons, including maintaining good grades, avoiding failure or punishment, complying with parental and cultural standards, insufficient preparation or understanding, etc. (Whitley, 1998). The culture of dishonesty can also contribute to the emergence and prevalence of academic cheating (Nonis & Swift, 2001). In such an infosphere, students may perceive that cheating is commonly carried out, has less negative ethical implications, and poses lower risks of consequential punishment. Thus, a deeper understanding of the psychology of cheating is needed to build a healthy educational system with better cheating-prevention methods and proper countermeasures for cheating (Cizek, 1999; Lang, 2013).

Psychosocial research has shown that the attitude toward a behavior can influence the actualization of that behavior. One of the most well-known theories on the attitude-behavior relationship is Icek Ajzen's Theory of Planned Behavior (Ajzen, 1991), which was further developed and improved upon his former Theory of Reasoned Action (Ajzen, 1985; Madden et al., 1992). In general, the theory posits that a person's attitude toward a behavior, subjective norms, and perceived behavioral control are the three main predictors of their intention to engage in that behavior, which in turn influences their actual behavior. Among the three main predictors, an attitude refers to a person's evaluation or judgment of a particular behavior. It is a combination of their beliefs about the behavior and their overall evaluation of it as positive or negative. Overall, if someone has a positive attitude towards a behavior, they are more likely to intend to engage in it and subsequently follow through with the behavior, and *vice versa*. Similarly, regarding collectively condemnable behaviors, negative attitudes may help negate them. This line of reasoning has been studied in various fields of social sciences, such as business ethics (Treviño et al., 2006) as well as substance abuse (Binswanger et al., 2013), digital piracy (Yoon, 2011), driving violations (Parker et al., 1992), etc. It is worth noting that the connection between attitude and behavior is not straightforward, and the psychological pathways often involve mediators and moderators (Armitage & Christian, 2003). The influence of social norms is one of the important factors within attitude-behavior pathways (Bergquist & Nilsson, 2019; Rivis & Sheeran, 2004). Furthermore, the information processing approach complements the notion of planned behavior with more detailed explanations of subjective cost-benefit judgments and the perceived value threshold of actualization (Nguyen et al., 2021; Vuong et al., 2022).

Because there are many mental processes on the pathway between attitude and behavior, the mind can reflect upon its own thoughts and corresponding reasoning. Cognitive reflection is the capacity to consider one's own thought processes as well as to solve problems systematically and logically. It entails preventing automatic reactions and coming up with substitutes that call for effort and focus (Frederick, 2005). From a developmental perspective, cognitive reflection is suggested to be a prerequisite for developing analytic thinking (Shtulman & Young, 2023). The tendency for being impulsive (lower accuracy) or reflective (higher accuracy) is related to time trade-offs (Jimenez et al., 2018). The Cognitive Reflection Test (CRT) was created by Shane Frederick as a tool for measuring cognitive reflection. It consists of questions that demand participants to suppress their default responses and think of more fitting solutions (Frederick, 2005). Since the original conceptualization, the CRT has been expanded based on further studies on psychological information processing (Thomson & Oppenheimer, 2016; Toplak et al., 2014). The concept of cognitive reflection and CRTs have been used to examine the link between low levels of cognitive reflection and a higher likelihood of engaging in unethical or dishonest behavior. For instance, research suggests that lower CRT scores may influence the psychological processes toward unethical behaviors such as bad work ethics (Corgnet et al., 2015).

To explore more about the psychological pathways from attitude to behavior, the information processing approach can be helpful. In this study, we employ Bayesian Mindsponge Framework (BMF) analytics – a research method based on information processing for constructing analytical models and conducting statistical analyses when studying psychosocial phenomena. More detailed reasonings for applying BMF and model construction rationale are presented in the methodology section. Based on the issues covered above, we have the following research questions (RQs).

RQ1: How do attitudes toward cheating influence the probability of cheating behavior?

RQ2: How does cognitive reflection moderate the above relationship?

2. Methodology

2.1. Theoretical foundation: Mindsponge theory and information filtering

The concept of mindsponge was coined by Vuong and Napier in a study on acculturation and globalization (Vuong & Napier, 2015). The concept was described as a dynamic process of assimilating new cultural values and discarding waning ones in response to changes in external environments. Mindsponge was further developed into a more expanded theory of information processing (Vuong, 2023). According to the mindsponge theory, the mind is an information collection-cum-processor, which is applicable to biological and social systems with various complexity levels. The extended mindsponge theory was developed using new evidence from natural sciences, especially neuroscience, taking into account fundamental human physiological structures and functions.

From a mindsponge standpoint, the mind possesses the following qualities. Some physical structures, such as the central nervous system, must serve as processing platforms. The system's memory serves as the repository for the mindset, which is made up of filtered and integrated information. On the basis of the mindset's current content, the filtering system decides what information is accepted or denied. Because of the activity of information filtering, both the mindset and the filtering system change throughout time (as mutual feedback loops). If necessary, the filtering process can be hastened by applying the trust mechanism (selective prioritization), thereby minimizing the amount of energy required to evaluate new information.

Through continual mindsponge processes, the mindset evolves continuously, affecting subsequent mental products (thoughts, attitudes, and behaviors) accordingly (Vuong et al., 2022; Vuong et al., 2023). The incorporation of new information regarded as favorable and the rejection of old information deemed no longer useful are the causes of mindset changes. To adapt to the constantly changing living environment, the set of trusted values that form a mindset is continuously changed. The operation of the filtering system is regulated by the mindset's content (serving as references for evaluation). New values are filtered differently as a result of the changes within the mindset. Mathematically, the updating mechanism of trusted values follows Bayes' Theorem (presented below), meaning that the posterior probability distribution is proportional to the prior probability distribution and the likelihood function.

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)}$$

Due to changes in memory content, responses to incoming stimuli are frequently updated (Procès et al., 2022). The functions of the human brain are dependent on the activity of neurons and their synapses and thus adhere to fundamental principles of biochemical activities. Different information-processing regions in the cerebral cortex are responsible for creating our social perceptions and behaviors (Maliske & Kanske, 2022). The activities and directions of adaptation of biological systems are reliant on consumable resources, particularly in terms of energy (Schrödinger, 1992). The adaptation happening in human minds is "live-wiring" – cognitive-based and dynamic – thanks to neuroplasticity (Eagleman, 2015). The natural evolutionary tendency of biosphere systems is reflected in the mechanisms of information filtering (Darwin, 2003; Vuong, 2023).

The main steps in a filtering process are summarized below:

1) The buffer zone temporarily keeps information received from the external environment or memory for the filtering system to evaluate the new information.

2) The value of information is assessed using subjective cost-benefit analyses. If the perceived benefits exceed the perceived costs, then the value of the information is considered positive, and vice versa. Existing trusted values in the mindset serve as references for the evaluation. After the filtering process, either of the following outcomes may happen, or further evaluation is needed.

• The information is accepted if the net perceived value is positive.

• The information is rejected if the net perceived value is negative.

3) After being accepted, the new information is integrated into the mindset as a new trusted value and can influence future evaluations of related information as well as the formation of mental products (thoughts, emotions, intentions, etc.).

2.2. Model construction

2.2.1. Materials and variable selection

For statistical analysis, in this study, we use secondary data from the data article "Cheating, Trust and Social Norms: Data from Germany, Vietnam, China, Taiwan, and Japan" (Huynh et al., 2022). The sample consists of 493 university students from these five nations/regions. The data collection was approved by the Institutional Review Board Committee #01112022 of the University of Economics Ho Chi Minh City (November 1st, 2020). Informed consent was obtained from all participants. All participants gave their informed consent. Participants had a mean age of 20.87. There were 44% males and 56% females in the sample. There were 21%, 34%, 17%, 13%, and 14% of students from Germany, Vietnam, China, Taiwan, and Japan, respectively.

Cheating behavior was measured using an experiment. Participants were asked to solve puzzles in a specified amount of time in the form of matrices containing twelve three-digit numbers. A participant could solve up to 20 matrices and receive a fixed amount of payment for each one. Participants received an answer sheet to independently evaluate their own correct responses after the period. A participant could cheat and overreport the total number of correctly solved matrices. The payment was made afterward. Before this experiment, participants were also asked to complete a questionnaire regarding socioeconomic characteristics, perceptions of social norms, and trust. In the questionnaire, there were also Cognitive Reflection Tests (CRT) (Frederick, 2005; Thomson & Oppenheimer, 2016), including six questions.

The variables used for analysis in this study are presented in Table 1. The variable selection follows the analytical model, which is presented in the next subsection "Model Formulation" together with the rationale.

Table 1. Variable description

Variable	Meaning	Type of variable	Value
Cheat	Whether the participant overreported the correct answers in the experiment	Binary	No is coded as 0; Yes is coded as 1

CheatAttitude	The participant's attitude about a student's behavior of cheating in an examination	Ordinal	From 1 (strongly negative) to 5 (strongly positive)
CRT	The number of correct answers on the Cognitive Reflection Tests	Ordinal	From 0 to 6

The variable *Cheat* represents cheating behavior, determined by whether a student overreported their own number of correct answers in the puzzle-solving experiment. The variable *CheatAttitude* represents participants' attitudes toward a hypothetical student who copied another student's answers in an examination. The attitude is measured using a 5-point scale from 1 (strongly negative) to 5 (strongly positive). The value of the variable CRT is the number of correct answers on six cognitive reflection questions. An example of the question is: "A farmer had 15 sheep, and all but 8 died. How many are left?"

2.2.2. Model formulation

A student will decide to carry out the act of cheating when such an act is perceived as beneficial. In other words, after the subjective cost-benefit evaluation of the value of the idea of cheating, its net perceived benefit is greater than its net perceived cost. For a behavior commonly deemed bad and unethical, such negative notions are what lowers the net value of the idea of committing that act. Simply speaking, people do not want to do bad actions because they perceive such actions to be bad. In the case of cheating in an examination, there can be various perceived costs, such as guilt, anxiety, difficulty in execution, possible punishment, reputation damage upon being caught, etc. Regardless of what costs are mentally simulated during the evaluation process, the behavioral outcome is binary (doing or not doing) based on whether the net perceived value passes a certain individual-specific threshold of actualization. Here, the belief that cheating is ethically and socially undesirable is a major input in subjective cost-benefit judgments. If a student does not believe that cheating is bad, then the total perceived cost of committing the act of cheating themselves will be less than someone who thinks that cheating is bad. Thus, students with positive attitudes toward cheating may have a higher probability of carrying out cheating behaviors themselves.

However, a trusted value can always be subjected to re-evaluation in face of new evidence or triggers. This mechanism is due to the fact that the mind's information filtering system is dynamic, which allows it to adapt to the ever-changing living environment (Nguyen et al., 2023; Vuong, 2023). An initial assessment of a bad action may be influenced by subconscious desires, the current state of emotion, or other untraceable subtle influences. This can sometimes be relatively quick, such as sudden ideation of intrusive thoughts. When an idea is potentially impactful, it can be prioritized to be filtered multiple times. When such a piece of information is re-evaluated to be more subjectively optimized, a rigorous process involving more rational considerations may be employed compared to the initial assessment. Thus, a student with a higher cognitive reflection capability may counter the influence of a positive attitude on cheating behavior.

Based on the reasoning above, we formulate the analytical models as follows.

$$Cheat \sim normal(\mu, \sigma) \quad (1)$$

$$\mu_i = \beta_0 + \beta_{CheatAttitude} * CheatAttitude_i + \beta_{CRT*CheatAttitude} * CRT_i * CheatAttitude_i \quad (2)$$

$$\beta \sim normal(M, S) \quad (3)$$

Regarding the outcome variable, the probability around μ is in the form of a normal distribution with standard deviation σ. Participant i's state of cheating behavior is indicated by μ_i. $CheatAttitude_i$ is participant i's attitude about cheating in an examination. CRT_i is participant i's CRT point. The model has an intercept β_0 and coefficients $\beta_{CheatAttitude}$ and $\beta_{CRT*CheatAttitude}$. Regarding the coefficients, the probability around M is in the form of a normal distribution with standard deviation S.

The logical network of the model is visualized in Figure 1.

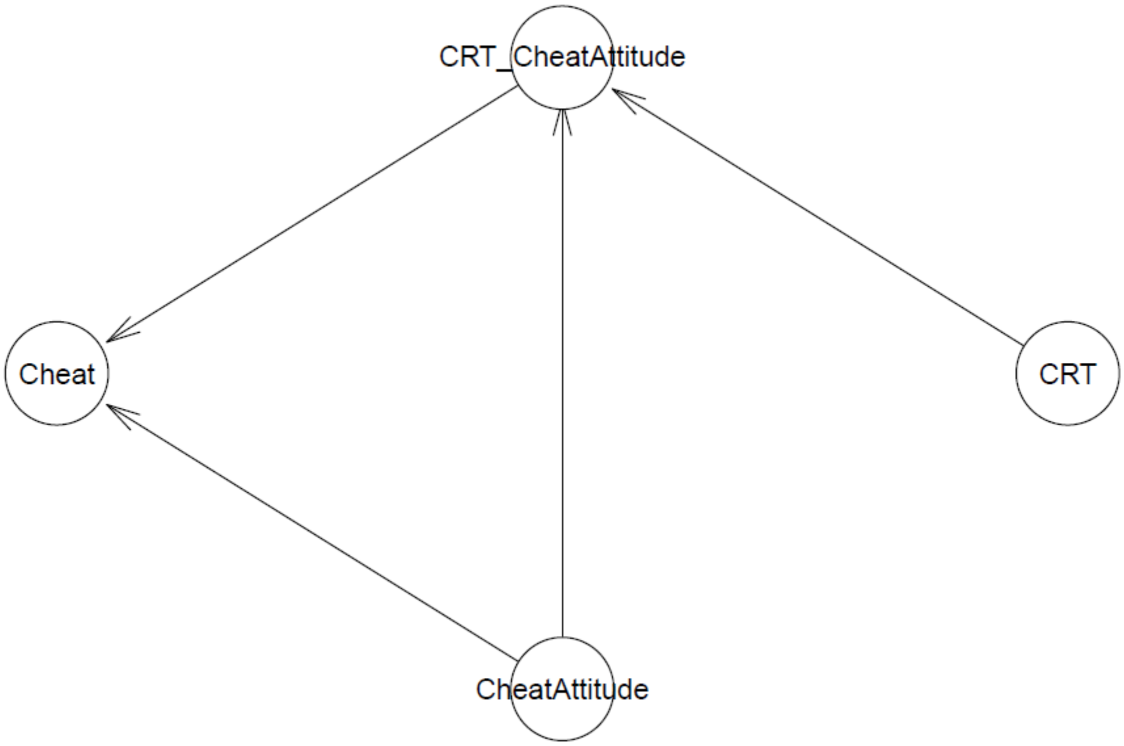

Figure 1. The model's logical network

2.3. Analysis and validation

In accordance with the BMF protocol, we employ Bayesian analysis assisted by Markov Chain Monte Carlo (MCMC) algorithms (Nguyen et al., 2022; Vuong et al., 2022). The mindsponge mechanism and Bayesian inference are philosophically and technically compatible. Bayesian inference treats all properties probabilistically, including unknown parameters. This allows for more accurate estimations when working with parsimonious models, which offer higher predictive power (Vuong et al., 2022). With the aid of MCMC algorithms (Nguyen & Vuong, 2007; Nguyen et al., 2005), Bayesian analysis has higher estimation accuracy and better computational flexibility. Furthermore, unlike the frequentist approach, the Bayesian approach uses credible intervals rather than the *p*-value for interpreting statistical reliability, which helps reduce the risks of overdependence on the *p*-value as well as rigidity in result interpretation.

The model's goodness-of-fit is diagnosed using the Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) method (Vehtari et al., 2017). LOO is computed using the following formula.

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

$p_{post(-i)}(\theta)$ is the posterior distribution based on the data minus data point i. When employing the PSIS method in R, *k*-Pareto values are used to compute leave-one-out cross-validation, which helps identify observations with a problematic influence on the PSIS estimate. If *k*-Pareto values are above 0.7, observations are considered highly influential and may negatively affect the estimation. if the *k* values are below 0.5, the model can be considered to have an appropriate degree of goodness-of-fit.

The Markov chains' convergence is statistically checked using the effective sample size (*n_eff*) and the Gelman-Rubin shrink factor (*Rhat*). The *n_eff* value represents the number of non-autocorrelated iterative samples during stochastic simulation. If the *n_eff* values are greater than 1000, the effective samples are deemed sufficient for reliable inference. The *Rhat* value (Gelman shrink factor) is another indicator of convergence. If the *Rhat* values are above 1.1, the chains may not converge. *Rhat* values equaling 1 are an indication of convergence. The Markov chains' convergence is also visually checked with trace plots, Gelman-Rubin-Brooks plots, and autocorrelation plots.

We use the **bayesvl** R package (La & Vuong, 2019) for conducting Bayesian analysis due to its open accessibility, high visualization quality, and transparent operation. The model's MCMC configuration is as follows: 5000 iterations including 2000 warm-up iterations and four chains. Considering the importance of transparency and the cost of science, especially regarding data sharing and the reproducibility crisis (Vuong, 2018, 2020), all data and code snippets of this study were deposited at an Open Science Framework server (https://osf.io/rjmx8/).

3. Results

The latest model fitting run was on March 29, 2023, R version 4.2.1, Windows 11, with a total elapsed time of 69.1 seconds.

Figure 2 shows the result of PSIS-LOO diagnostics, where all *k* values are below 0.5, indicating that the model has a healthy goodness-of-fit.

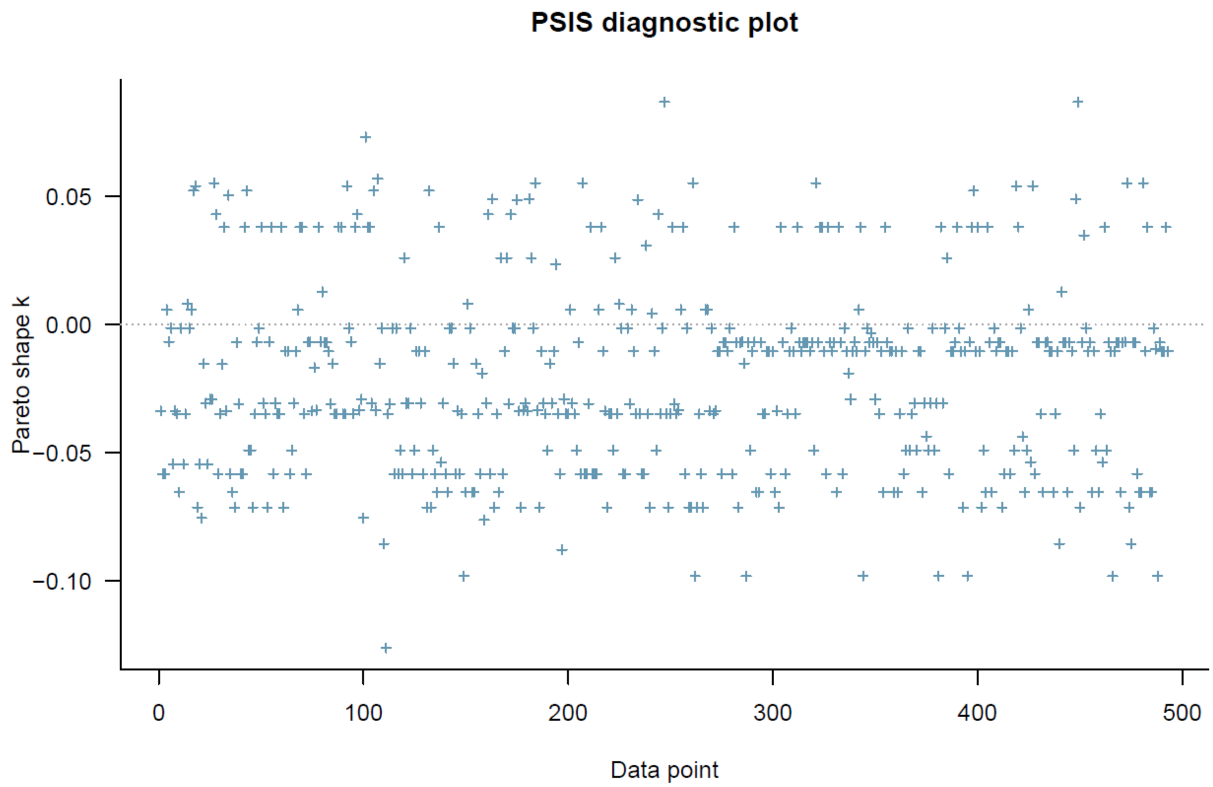

Figure 2. PSIS-LOO diagnostic plot for the model

The estimated posteriors for the parameters are presented in Table 2. The *n_eff* values are greater than 1000 and the *Rhat* values equal 1 for all parameters, which indicates good convergence of the Markov chains.

Table 2. Estimated posteriors

Parameters	Mean	SD	n_eff	Rhat
Constant	-2.31	0.36	5134	1
CheatAttitude	0.16	0.07	4256	1
*CRT*CheatAttitude*	-0.03	0.01	4536	1

The Markov chains' convergence is also validated visually through the trace plots, the Gelman-Rubin-Brooks plots, and the autocorrelation plots. In the trace plots (see Figure 3), it can be observed that the chains fluctuate around central equilibriums and do not deviate. In the Gelman-Rubin-Brooks plots (see Figure 4), the *Rhat* values are shown to rapidly drop to 1 within the warm-up period. In the autocorrelation plots (see Figure 5), the autocorrelation values within chains also quickly become zero.

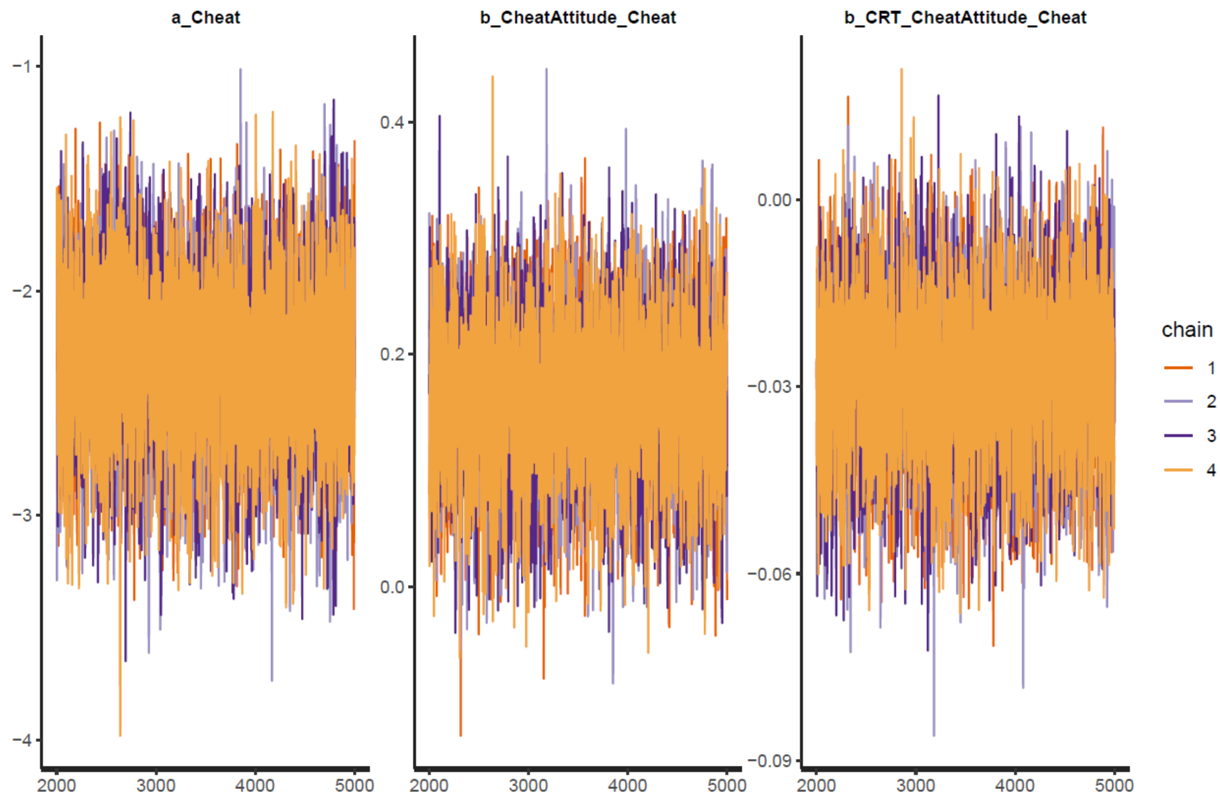

Figure 3. Trace plots for the model

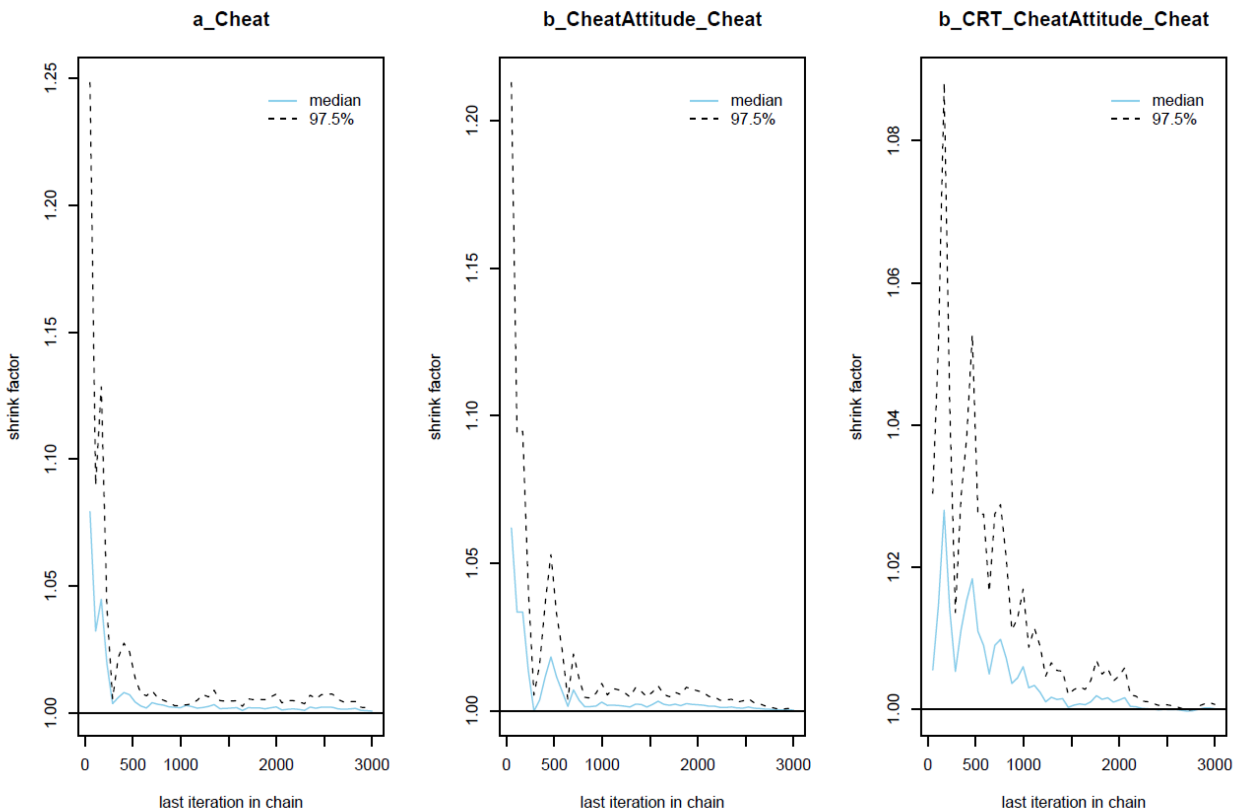

Figure 4. Gelman-Rubin-Brooks plots for the model

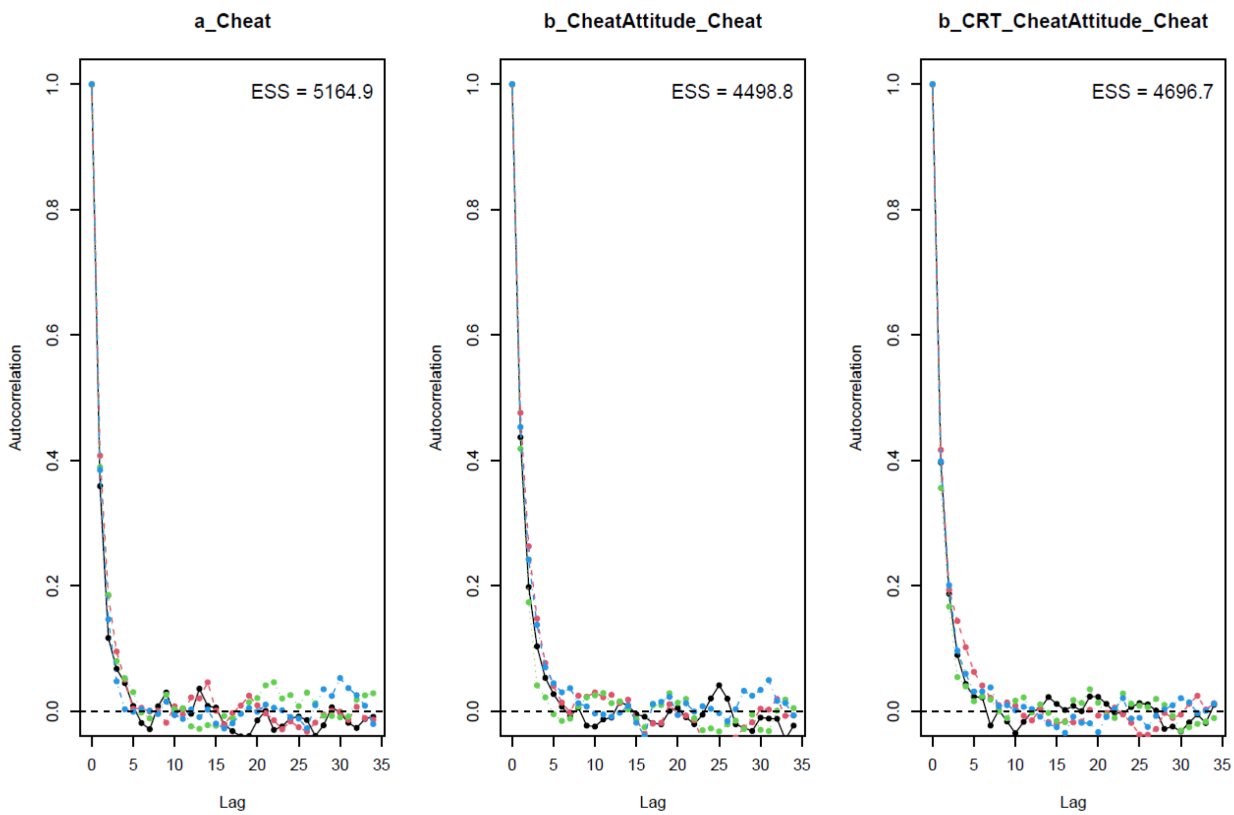

Figure 5. Autocorrelation plots for the model

The results of statistical analysis show that *CheatAttitude* is positively associated with *Cheat* ($M_{CheatAttitude} = 0.16$ and $SD_{CheatAttitude} = 0.07$). *CRT*CheatAttitude*, however, is positively associated with *Cheat* ($M_{CRT*CheatAttitude} = -0.03$ and $SD_{CRT*CheatAttitude} = 0.01$). This indicates that *CRT* moderates against the effect of *CheatAttitude* toward *Cheat*. On the two-dimensional density plot (see Figure 6), it can be observed that the distributions of *CheatAttitude* lie mostly on the positive side, and the distributions of *CRT*CheatAttitude* lie mostly on the negative side. This indicates that the effects seen in the statistical results are reliable.

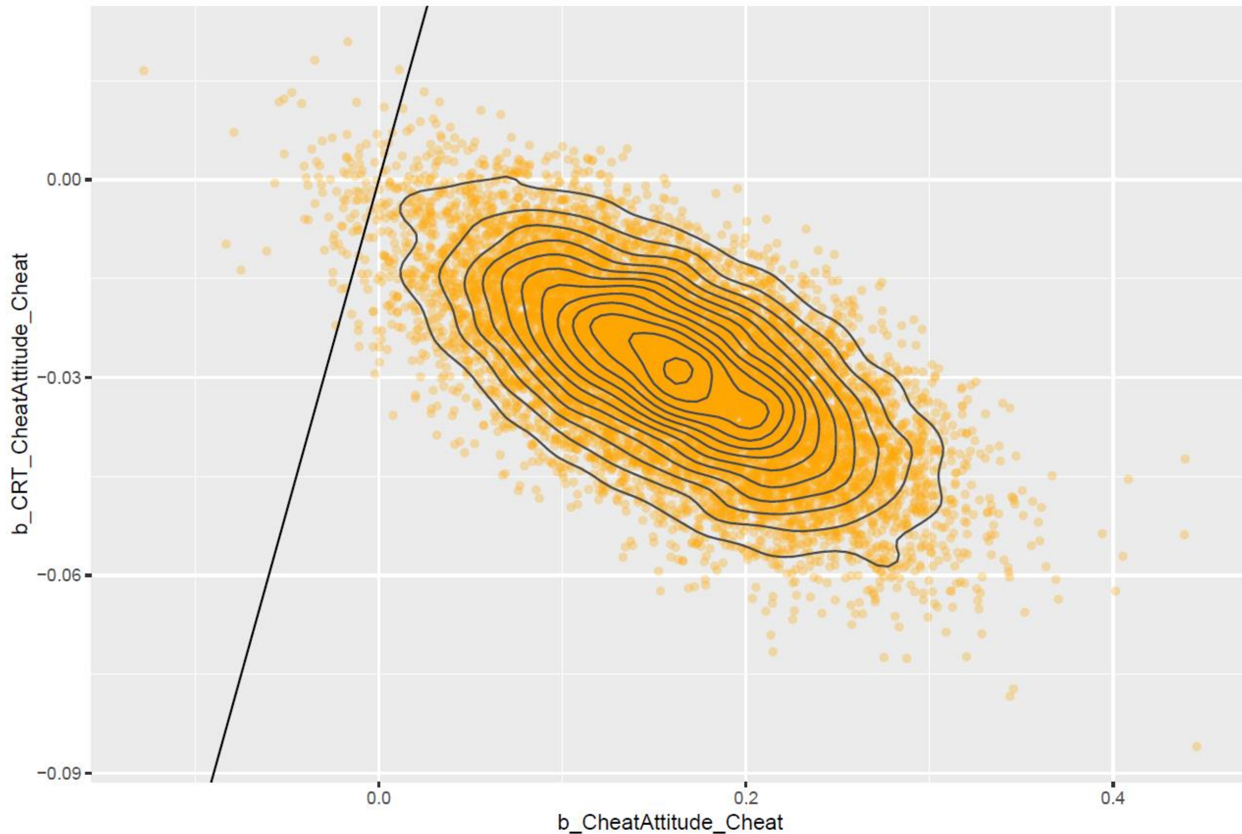

Figure 6. Pairwise posterior distributions of *CheatAttitude* and *CRT*CheatAttitude*

We also visualize the estimated probabilities of cheating behavior using the mean values of the posterior coefficients to aid result interpretation. The outcome probability is calculated using the following formula.

$$\ln \frac{\pi_{Cheating}}{\pi_{Not\ Cheating}} = -2.31 + 0.16 \times CheatAttitude - 0.03 \times CRT \times CheatAttitude$$

For example, the cheating probability of a student with a *CheatAttitude* value of 2 and a *CRT* score of 3 is calculated as follows.

$$\pi_{Cheating} = \frac{e^{-2.31+0.16\times 2-0.03\times 3\times 2}}{1+e^{-2.31+0.16\times 2-0.03\times 3\times 2}} = 0.1025 = 10.25\%$$

The visualized estimated probabilities are shown in Figure 7. The *y*-axis represents the probability of cheating behavior. The *x*-axis represents the CRT score. The color line represents the attitude toward cheating in an examination. Overall, the lines of more positive attitudes toward cheating are above, but they also have stronger downward trends as the CRT score becomes higher.

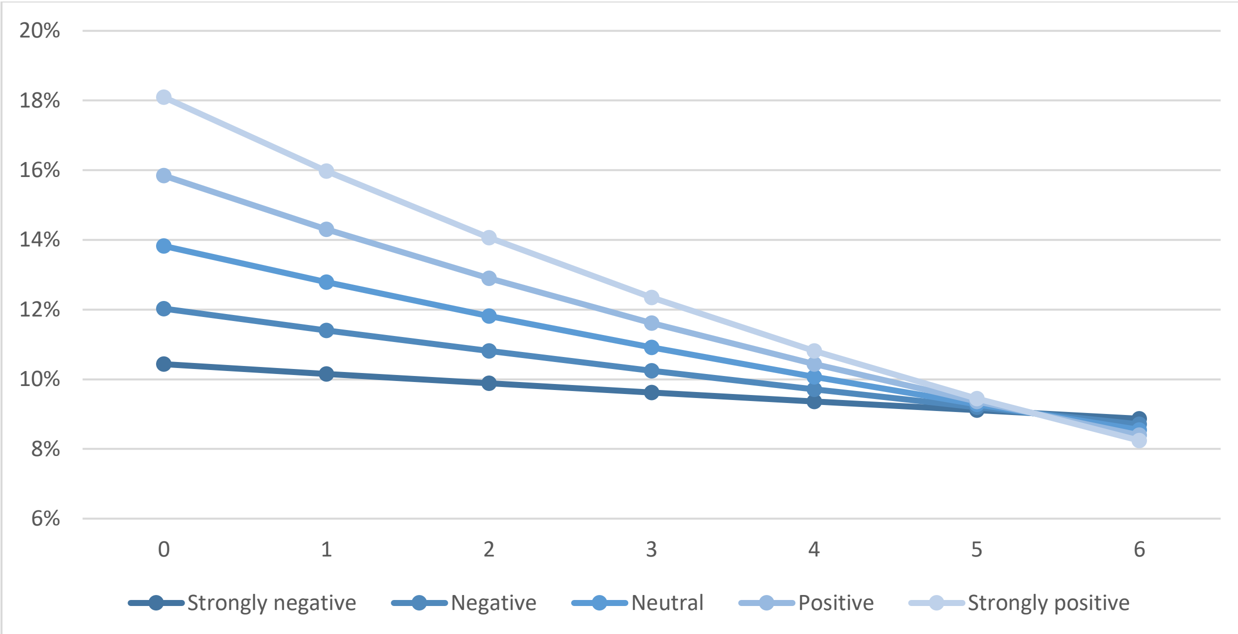

Figure 7. Estimated probabilities of cheating behavior based on attitude toward cheating and CRT score

4. Discussion

Our analysis results show that students who have more positive attitudes toward cheating are more likely to cheat. However, cognitive reflection lessens the above positive association. The inhibiting effect of cognitive reflection is stronger in those with more positive attitudes toward cheating. As a result, those with a high cognitive reflection capability have a relatively low probability of cheating regardless of attitudes toward cheating. The linear relationship between attitudes and cheating behaviors is in alignment with Ajzen's Theory of Planned Behavior (Ajzen, 1991). The findings of our study also support the notion that the psychological pathway from attitudes to behaviors is comprised of many processes and under the influences of other factors (Armitage & Christian, 2003). We also demonstrated that the information processing approach can be effective for investigating such processes following the filtering mechanism of subjective cost-benefit evaluation.

Deceptive behaviors are not rare in the natural world, but rather crucial survival strategies selected through the course of evolution (Mitchell & Thompson, 1986). Many species in the animal kingdom have been observed to deceive, such as male fiddler crabs faking their claw mass (Backwell et al., 2000), eastern grey squirrels covering empty sites to prevent cache pilferage (Steele et al., 2008), complex and subtle food-related deception among primate societies (Hall & Brosnan, 2017), etc. Even plants can deceive, such as food deception and sexual deception of many orchid species to attract pollinators (Schiestl, 2005). Overall, deceptive behaviors are carried out because an organism deems them beneficial for itself or its species. In the case of humans, however, our complex society today is built on thousands of years of optimization based on interpersonal interactions. Laws, regulations, and ethical principles are established to increase the effectiveness and efficiency of the collective. Socially undesirable behaviors such as cheating, thus, induce negative feedback to violators in the forms of direct punishment and reputation damage. University students know the negative consequences of cheating, both for themselves and the community (McCabe et al., 2012). Normally, these beliefs about the possible costs (reflected as negative attitudes) prevent a student from committing the act of cheating. However, other factors such as personal desires and external pressures are also evaluated in the subjective cost-benefit judgments (Whitley, 1998), which may increase the perceived value of the act of cheating. If a student believes that cheating is “okay” (reflected as positive attitudes), then the perceived benefits from other factors may push the net value pass a certain threshold and cause the act to be carried out. From the standpoint of the spheres of influence, such “impulsive” actions are because their values have not been well-optimized to better fit the working of reality (Nguyen et al., 2023).

Thanks to the ability to reflect upon one’s own thoughts to update – “fine-tune” them or find better alternatives – people can produce better solutions and decisions (Frederick, 2005; Vuong et al., 2022). While there may be trade-offs involving time and energy (Jimenez et al., 2018), a good mental product is often worth the effort, especially when it involves major risks or ethical issues. A piece of information can belong to a huge mental network of connected values. Intuitively, evaluating something takes time, depending on the complexity and intensity of the target. It is not possible to recall all related stored values spontaneously to perform a quick assessment. In the information processes of cognitive reflection, the mind retrieves more reference information from memory to re-evaluate prior beliefs. Here, existing beliefs about the risks of punishment and other negative feedback can be examined more clearly. Subsequent analytical processes will likely reduce the perceived benefit of the act of cheating, assuming they are conducted rather rationally from a relatively objective standpoint. After the reflection, the value of the initial thought is updated; when the updating result is considerably different compared to the prior value, it gives the appearance of a new correct response overriding the former incorrect one (Toplak et al., 2014). Thus, students with positive attitudes toward cheating may no longer think that cheating is beneficial over its costs after the reflecting process(es). Those with higher cognitive reflection capabilities are able to conduct these processes more effectively and efficiently, resulting in a stronger negating effect.

Modern technological development, especially recent advancements in the field of artificial intelligence (AI), is deeply changing the educational system. AI-assisted advanced tools enable students to cheat in new and efficient ways. In a sense, the perceived cost of execution difficulty for cheating behavior has been greatly reduced. The reality is that students have been starting to use cutting-edge technologies such as ChatGPT and other new digital applications to cheat in studying activities whether the institutions and teachers like it or not

(Klein, 2023). Even higher education is not an exception, as AI-generated content may even be able to deceive scientists (Else, 2023). While schools and teachers are trying to adapt to the management of new AI tools in education (Roose, 2023), this will take time and effort. During this rapid and difficult transitional period, the educational system should find ways to promote psychology-based internal anti-cheating. A healthy infosphere can serve as background knowledge and collective norms for building appropriate attitudes against cheating. Besides, cognitive reflection is a natural human ability for thinking, and it can influence a wide range of ethical considerations, which can be improved by supporting students in learning the information-processing mechanisms of thinking.

This study is not without limitations. Firstly, while the sample covers several different countries, it still does not sufficiently represent some other major cultures in the world. Secondly, the sample only consists of university students, who were relatively young and had less life experience compared to older groups, which might affect how they perceived unethical behaviors. Thirdly, this study did not go into detail about the different psychological pathways students may reflect upon their attitudes toward cheating in specific contexts. Further studies using qualitative approaches can provide more insights into this aspect.

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