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Construal level of traffic violation behavior: comparing the impacts of algorithmic monitoring and human monitoring on traffic compliance

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Abstract
Algorithmic monitoring, such as electronic police devices, and human policing are both commonly used to monitor traffic violations and increase compliance with traffic rules. To compare the influence of algorithmic monitoring with that of human monitoring on compliance, two studies involving scenario-based experiments and field observations were conducted. Our findings reveal that for traffic violation behaviors with low construal (e.g., speeding), individuals exhibited a greater degree of fit (i.e., feeling right) between the monitored behavior and algorithmic monitoring, thereby increasing their intention to comply with traffic rules. However, this effect was absent when errors occurred in algorithmic monitoring. Conversely, for traffic violation behaviors with high construal (e.g., failure to yield right-of-way), individuals demonstrated stronger intentions to comply with traffic rules, even when monitoring errors were highlighted. This relationship is mediated by the extent of fit between the monitoring agents and their monitored violations. Hence, the effectiveness of algorithmic monitoring over human monitoring in promoting compliance depends on the construal of traffic behavior, with algorithmic errors weakening its effectiveness for low-construal traffic behaviors. Therefore, when selecting a monitoring agent, traffic departments should consider the levels at which observed traffic violations at an intersection are construed rather than indiscriminately applying either algorithmic or human monitoring.

Keywords Algorithmic monitoring · Human monitoring · Traffic compliance · Construal level · Monitoring error

Introduction

With the rapid development of the economy, the number of motor vehicles has increased annually, and traffic safety remains a significant global concern. According to the WHO, approximately 1.19 million people die annually because of road traffic crashes (World Health Organization, 2023). Human factors, particularly traffic violation behaviors in which drivers fail to comply with traffic rules, are major contributors to these crashes. For example, speeding was a factor in 29% of all traffic fatalities in the U.S. in 2022 (National Highway Traffic Safety Administration, 2022). Enhancing traffic safety requires focused efforts to reduce violations and improve rule compliance.

Traffic monitoring has long been a cornerstone of transportation engineering and plays a crucial role in detecting and enforcing violations. Traditionally, traffic monitoring has relied heavily on human operators, with traffic police officers responsible for tracking violations on roads. Indeed, police presence can enhance traffic compliance (Dau et al., 2023; Nakano et al., 2019). However, human monitoring is challenging and time-consuming, as it is prone to inaccuracies and is affected by factors such as fatigue as well as by temporal and spatial limitations in road traffic management. With advancements in artificial intelligence (AI), algorithmic monitoring tools, such as electronic police devices, are increasingly used to monitor traffic violations and enhance compliance with traffic rules (Oleksy et al., 2023). Algorithmic monitoring not only overcomes many limitations of human monitoring but also offers additional advantages, including reduced labor costs and broader surveillance coverage. Despite the implementation of algorithmic

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monitoring to increase traffic compliance, human monitoring is still utilized, and it remains unclear whether algorithmic monitoring effectively improves compliance with traffic rules over human monitoring and its possible underlying psychological mechanisms. Investigating this issue could reveal the conditions under which algorithmic monitoring has a greater impact on individuals' compliance with traffic rules, thereby offering psychological insights into the implementation of both algorithmic and human monitoring systems on roads and how AI can be used to promote rule compliance.

How algorithms influence behaviors

Although direct comparisons of traffic compliance under human and algorithmic monitoring are limited, the intelligence and efficiency of algorithms often allow them to make decisions with accuracy comparable to or exceeding that of humans (Krügel et al., 2023; Longoni et al., 2019; Newman et al., 2020; You et al., 2022). This advantage leads to algorithm appreciation, where individuals prefer algorithmic advice in tasks such as numerical estimation, song popularity prediction, and academic performance forecasting (Logg et al., 2019; You et al., 2022). However, despite their advantages, algorithms are not universally preferred. In some cases, individuals exhibit algorithm aversion (Dietvorst & Bharti, 2020; Dietvorst et al., 2015; Sinha & Swearingen, 2001), favoring human recommendations for subjective choices such as books and movies. Hence, despite the many advantages of algorithm-driven intelligent systems, individuals hold both positive and negative attitudes toward them. These seemingly contradictory attitudes may shape their responses to algorithmic monitoring. Consequently, the impact of algorithmic monitoring on traffic compliance may not always surpass that of human monitoring and could instead depend on specific contextual factors. The present study explores these boundary conditions and provides a deeper understanding of the mechanisms influencing compliance under different monitoring agents.

Research conducted within the framework of construal level theory (CLT) indicates that individuals perceive human and algorithmic agents at different construal levels, which can lead to either algorithm appreciation or algorithm aversion depending on the task context (Kim & Duhachek, 2020; Ward et al., 2013). According to CLT, people perceive and interpret events and behaviors at different levels of abstraction: for high-level construal, individuals focus on the broader, more abstract aspects of a situation, i.e., the "why"; however, for low-level construal, they concentrate on the specific, concrete details, i.e., the "how" (Liberman et al., 2007; Trope & Liberman, 2003; 2010). Moreover, Ward et al. (2013) reported that because algorithmic entities lack autonomous goals and intentions, individuals characterize them with low-level construal, whereas they characterize humans with high-level construal because of their mental capacities (e.g., desires, feelings, self-control). Even when different actors engage in the same behavior, participants describe artificial entities at a low level of construal while perceiving human actors at a high level of construal (Kim & Duhachek, 2020). In addition to the agent, the behaviors performed by the agent are also construed at different levels. Research suggests that, owing to the differing construal levels associated with humans and algorithms, each is perceived as more effective when performing behaviors aligned with its respective construal (Cesario et al., 2004; Kim & Duhachek, 2020). This perception is measured by the extent of fit, which describes the degree to which participants feel that the combination of the human (or artificial) agent and the behavior conveyed by the agent is appropriate or "right". Thus, whether an algorithm is preferred or avoided largely depends on the construal level of the behaviors it performs or monitors. When the behavior's construal level aligns with that of the agent, individuals experience a greater sense of fit (i.e., "feeling right"), leading to a stronger influence on their cognition or behavior.

The above theoretical framework helps us understand whether and how the effectiveness of algorithmic vs. human monitoring varies across different types of traffic violations. Certain traffic behaviors, such as failing to yield right-of-way, can be considered high-construal behaviors because they involve goal-directed components and are often described in terms of "why" the behavior occurs (e.g., believing they will not hit the pedestrian). In contrast, other traffic behaviors, such as speeding, can be considered low-construal behaviors, as they are typically seen as specific, technical violations of traffic rules and relate more to "how" the behavior is conducted (e.g., driving while exceeding the speed limit). Hence, we hypothesize that the effect of the monitoring agent on compliance intentions depends on the construal level of the traffic behavior, with the extent of fit serving as a mediator. This hypothesis reflects the perceived alignment ("feeling right") between the monitoring agent and the specific traffic violation, similar to previous research (Kim & Duhachek, 2020). Specifically:

> H1: (a) For traffic behaviors construed at a high level, individuals have greater compliance intentions with traffic rules under human monitoring than under algorithmic monitoring; (b) For traffic behaviors construed at a low level, individuals show greater compliance intentions under algorithmic monitoring than under human monitoring; (c) These effects are mediated by the extent of fit.

How algorithms influence behaviors under errors

Both human and algorithmic monitoring systems encounter challenges in fully detecting all traffic violations, making monitoring errors common. In this study, an "error" refers to a monitoring failure—an instance where the monitoring agent (human or algorithm) fails to detect traffic violations—without differentiating between specific types of errors (Dietvorst et al., 2015; Mahmud et al., 2022). For example, in a district of Zhengzhou city (a provincial capital city in China) in 2020, more than 6,000 appeals were recorded by drivers through the Traffic Management platform (an online platform used by the Chinese Ministry of Transport for handling traffic violations) due to errors in both human and algorithmic monitoring (Zhang, 2021). Given the awareness of monitoring errors, how do monitoring agents (algorithms vs. humans) influence compliance with traffic rules for traffic behaviors construed at different levels? Algorithm-based application has been found to be hindered by inaccurate advice, with participants more strongly disregarding inaccurate advice labeled as algorithmic than equally inaccurate advice labeled as coming from a crowd of peers (Bogert et al., 2021). Moreover, after monitoring errors are observed, the effect of algorithmic monitoring on compliance with traffic rules is weakened, whereas no such change or a smaller change is observed for human monitoring (Dietvorst et al., 2015; Mahmud et al., 2022). As this effect depends on the fit between the construal levels of the agent and the traffic behavior, we hypothesize that this influence remains mediated by the extent of fit. Specifically:

> H2: (a) After monitoring errors occur, for traffic behaviors construed at a low level, the enhancement of compliance intentions with traffic rules under algorithmic monitoring is reduced or absent; (b) for traffic behaviors construed at a high level, the enhancement of compliance intentions with traffic rules under human monitoring remains similar; (c) these effect are mediated by the extent of fit between the monitoring agent and the specific behavior being monitored.

The present research

To investigate the impact of algorithmic monitoring on compliance with traffic rules and to test the hypotheses outlined above, two studies involving situational tests and field observations were conducted. In Study 1, scenario-based experiments were employed to investigate whether algorithmic monitoring influences the intention to comply with traffic rules for behaviors construed at different levels and to examine the mediating role of the extent of fit in this relationship. The participants were presented with everyday scenarios, including potential traffic violations identified in a pilot investigation (such as speeding), and were then asked to report their thoughts under human or algorithmic monitoring, such as their intention to comply with traffic rules and the perceived extent of fit between the monitoring agent and the violation. Study 2 explored the effect of algorithmic monitoring under conditions of monitoring errors on the intention to comply with traffic rules for behaviors construed at different levels, as well as the mediating role of the extent of fit. Like Study 1, Study 2 used comparable traffic behavior scenarios but introduced descriptions of monitoring errors indicating that some traffic rule violations were not detected by the monitoring agent.

Study 1: The influence of algorithmic monitoring on the intention to comply with traffic rules

Study 1 aims to investigate the influence of algorithmic monitoring versus human monitoring on the intention to comply with traffic rules across different construal levels of traffic behavior. Traffic behaviors representing various construal levels were identified based on common traffic violations and were then described using everyday scenarios to assess participants' intention to comply with the traffic rules in those situations.

Methods

Transparency and openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and we follow JARS (Kazak, 2018). All data and analysis codes for each condition have been made publicly available at the OSF and can be accessed at https://osf.io/62kcn/?view_only=f80de7dc566c41619d3d9ba05e3e763c. The research materials can be found in the Supplementary Material. The data were analyzed using R, version 4.1.2, with the library bruceR, version 0.8.9, and the package ggplot2, version 3.4.2. No study designs were preregistered.

Participants

The sample size for this study was determined by using G*Power 3.1 with an alpha level of 0.05 and a power of 0.80. For a between-subjects design to compare the influence of the construal level of traffic behavior on the intention to comply with traffic rules between two groups of participants (human monitoring vs. algorithmic monitoring), a suggested sample size of at least 100 individuals in each between-subjects condition was determined as necessary to obtain a small-to-medium effect size (Cohen's d= 0.40). This effect size is consistent with previous studies by Bonezzi et al. (2022) and Wu et al. (2020). Thus, we aimed to recruit a minimum of 100 participants per condition, totaling at least 200 participants. Participants were recruited through online advertising, targeting individuals with a driver's license, who were then invited to complete paper questionnaires. The recruitment process ensured a balanced gender distribution, with an approximately equal number of male and female participants across different experimental conditions. Ultimately, 217 participants were enrolled, each receiving a $1 gift. After 7 participants who did not complete the questionnaires were excluded, a total of 210 valid participants were included in the analysis. Among these, 107 participants were in the human monitoring condition (46 males, 61 females), and 103 participants were in the algorithmic monitoring condition (46 males, 57 females). The age of the participants ranged from 18 to 42 years (M= 23.08, SD= 3.69), and their driving experience ranged from 0 to 13 years (M= 2.45, SD= 2.34).

All the participants received information sheets detailing the experimental procedure and agreed to complete the questionnaires after being informed of the purpose and procedures of the experiment. The research titled "Algorithmic Monitoring and Traffic Violations" was approved by the Research Ethics Board of the Department of Psychology at the authors' university and was conducted in compliance with the relevant guidelines and regulations.

Materials

The experiment adopted a mixed design of 2 (monitoring agent: human, algorithm; between-subjects) × 2 (construal of traffic behavior: low construal, high construal; within-subjects). The participants were randomly assigned to either the human monitoring condition or the algorithm monitoring condition. Each monitoring agent condition included two levels of construal for traffic behaviors, and each construal level was represented by two traffic behaviors selected in the pilot investigations.

To obtain traffic behaviors with different construal levels, we conducted a pilot investigation with 132 valid participants who were asked to rate the construal level and perceived commonality of ten traffic violations (see the Supplementary Material). These violations were sourced from publicly available data from the Ministry of Public Security of the People's Republic of China. The item measuring the construal level was adapted from the Behavioral Identification Form (BIF) developed by Vallacher & Wegner (1989), following a methodology similar to that used in a previous study (Kim & Duhachek, 2020). Finally, based on the evaluated construal level and high perceived commonality, we selected two high-construal traffic behaviors (i.e., using a handheld phone while driving and failure to yield right-of-way) and two low-level construal traffic behaviors (i.e., speeding and improper lighting). These two types of traffic behaviors were matched with the perceived commonality.

The scenarios used to describe the collected violation behaviors were framed to make them familiar and relatable to participants, i.e., using everyday situations. For example, one scenario was as follows: "*Imagine you are an employee of a company. Today, you are driving to work. Due to heavy traffic on the previous stretch of road, you lost a significant amount of time. Finally getting through the congested area, you are driving anxiously at about 60 km/h, trying to make up for lost time. At this moment, you notice a speed limit sign indicating 40 km/h, and there is a traffic policeman on duty at the roadside."* In the algorithmic monitoring condition, this figure was described as "*an electronic police monitoring device installed by the roadside*", whereas in the human monitoring condition, it was described as "*a traffic policeman on duty at the roadside*". The corresponding traffic behavior was adjusted for each condition. Detailed scenarios for each condition are provided in Supplementary Table S2.

To better evaluate whether the presence of monitoring (by either algorithmic or human means) enhances compliance with traffic rules, we included a baseline control condition without monitoring. In this no monitoring condition, we exclusively measured compliance with traffic rules. The findings from this baseline condition, detailed in the pilot investigation of the Supplementary Material, indicate that the presence of monitoring—whether human or algorithmic—significantly increases compliance with traffic rules.

Procedure

The participants first provided information on their years of driving, driving distance, driving experience, and familiarity with traffic rules. The survey included the following items: "*Driving __ years, driving distance __ kilometers*"; "*Please rate your driving experience from 0 (almost no experience) to 100 (highly experienced)* ___"; "*Rate your familiarity with traffic rules from 0 (almost unfamiliar) to 100 (very familiar)* ___." These items were set to rule out that participants'driving experience and familiarity with traffic rules may impact their compliance with these rules.

Next, the participants read the scenarios described above and then completed a series of items concerning their intention to comply with traffic rules, the extent of fit between the construal characteristics of the monitoring agent and the traffic behavior, and the perceived monitoring accuracy.

For the intention to comply with traffic rules, referring to the study by Kim and Duhachek (2020), the query was structured as follows: "*To what extent do you think, in the aforementioned scenario, that you would [adjust the statement based on the presented traffic behavior, e.g., failure to yield right-of-way]?*" The item used a 7-point scale (1 = almost impossible, 7 = completely possible).

Following Kim & Duhachek (2020) and Wu et al. (2020), the extent of fit comprised three items: "*In the described scenario, do you agree that the algorithmic monitoring by electronic police (human monitoring by traffic police) is appropriate/effective/right for monitoring [adjust the statement based on the presented traffic behavior, e.g., failure to yield right-of-way]*?" The items were measured on a 7-point scale (1 = strongly disagree, 7 = strongly agree).

To capture the perceived monitoring accuracy, inspired by Kim & Duhachek's (2020) approach to measuring algorithm/human recommendation proficiency, the question was phrased as follows: "*To what extent do you believe, in the aforementioned scenario, that the algorithmic monitoring by electronic police (human monitoring by traffic police) can accurately monitor [adjust the statement based on the presented traffic behavior, e.g., failing to yield as required]*?" The items used a 10-point rating (0 = not accurate at all (0%), 10 = extremely accurate (100%)).

Data analysis

The three items measuring the extent of fit demonstrated satisfactory consistency ($0.81 \leq \alpha \leq 0.90$) and were averaged for subsequent analysis. The correlation between the two scenarios at each construal level of traffic behavior was high for each measurement (rs ≥ 0.18, ps ≤ 0.008). Accordingly, the mean scores of the corresponding items in the two scenarios, considering different construal levels of traffic behavior, were computed as data for subsequent statistical analysis. A 2 (monitoring agent: human, algorithm; between-subjects) × 2 (construal of traffic behavior: low construal, high construal; within-subjects) mixed-design analysis of variance (ANOVA) was conducted for each measurement, and a 95% confidence interval (CI) for effect size was reported. The Bayes factor (BF_{10}), which represents the ratio of the alternative hypothesis to the null hypothesis, was also calculated for critical comparisons. A BF_{10} value below 0.33 indicates substantial evidence against differences between conditions, whereas a BF_{10} value exceeding 3.00 indicates strong evidence in favor of such differences. Values ranging from 0.33 to 3.00 are interpreted as inconclusive (Dienes, 2014).

Results

Figure 1 illustrates participants' intention to comply with traffic rules and the extent of fit across different conditions. The ANOVA revealed no significant main effect for the monitoring agent ($F(1, 208) = 0.03$, $p = 0.875$, $\eta_p^2 < 0.01$, 95% CI = [0.00, 0.01], $BF_{10} = 0.12$). However, the main effect of the construal of traffic behavior was significant ($F(1, 208) = 76.75$, $p < 0.001$, $\eta_p^2 = 0.27$, 95% CI = [0.19, 0.35], $BF_{10} = 1.75 \times 10^{13}$), indicating that participants exhibited higher intention to comply with traffic rules under the low-construal traffic behavior ($M = 6.16$, $SE = 0.07$) compared to the high-construal traffic behavior ($M = 5.25$, $SE = 0.08$). Importantly, a significant interaction effect was found ($F(1, 208) = 19.78$, $p < 0.001$, $\eta_p^2 = 0.09$, 95% CI = [0.04, 0.15], $BF_{10} = 2.08 \times 10^3$). The simple effects analysis revealed that for high-construal behavior, human monitoring led to higher compliance ($M = 5.49$, $SE = 0.12$) than did algorithmic monitoring ($M = 5.00$, $SE = 0.12$; $t(208)$

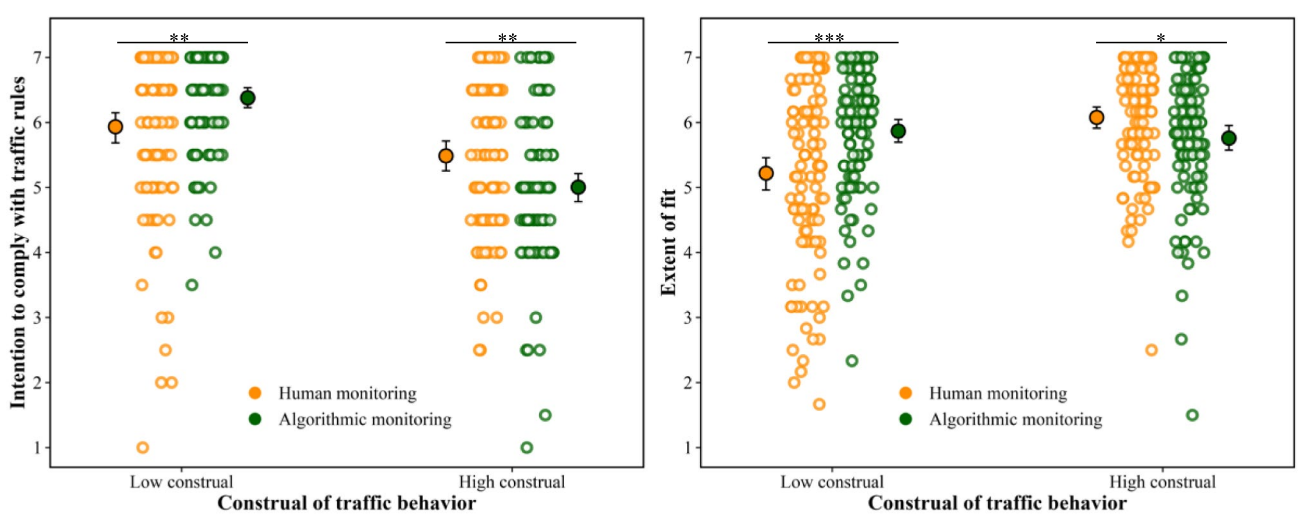

Fig. 1 The intention to comply with traffic rules and the extent of fit under different conditions in Study 1

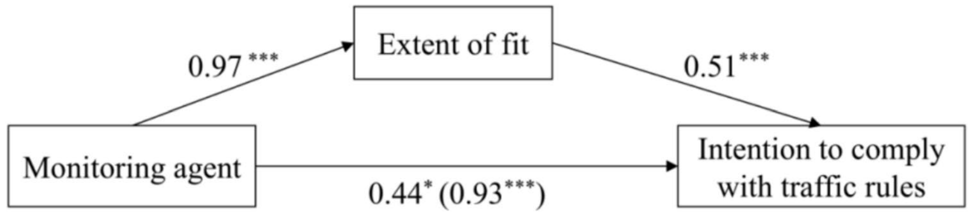

Fig. 2 The mediation analysis revealed that the extent of fit mediates the effect of the monitoring agent on the intention to comply with traffic rules in Study 1

$=2.89$, $p=0.004$, Cohen's $d=0.32$, 95% CI $=[0.10, 0.54]$, $BF_{10}=7.26$). For low-construal behavior, compliance was lower under human monitoring ($M=5.93$, $SE=0.13$) than under algorithmic monitoring ($M=6.38$, $SE=0.08$; $t(208)=-3.00$, $p=0.003$, Cohen's $d=-0.30$, 95% CI $=[-0.49, -0.10]$, $BF_{10}=9.75$).

The ANOVA on the extent of fit revealed a similar pattern. No significant main effect was found for the monitoring agent ($F(1, 208)=1.70$, $p=0.194$, $\eta_p^2<0.01$, 95% CI $=[0.00, 0.04]$, $BF_{10}=0.34$), while the main effect of the construal of traffic behavior was significant ($F(1, 208)=23.64$, $p<0.001$, $\eta_p^2=0.10$, 95% CI $=[0.05, 0.17]$, $BF_{10}=6.93\times10^6$). The interaction effect between two factors was found to be significant ($F(1, 208)=39.29$, $p<0.001$, $\eta_p^2=0.16$, 95% CI $=[0.09, 0.23]$, $BF_{10}=2.08\times10^3$). Under high-construal behavior, human monitoring led to a higher extent of fit ($M=6.08$, $SE=0.09$) than did algorithmic monitoring ($M=5.76$, $SE=0.09$; $t(208)=2.47$, $p=0.014$, Cohen's $d=0.29$, 95% CI $=[0.06, 0.52]$, $BF_{10}=2.56$). Conversely, under low-construal behavior, the extent of fit was lower under human monitoring ($M=5.22$, $SE=0.12$) than under algorithmic monitoring ($M=5.87$, $SE=0.12$; $t(208)=3.94$, $p<0.001$, Cohen's $d=0.58$, 95% CI $=[0.29, 0.87]$, $BF_{10}=1.83\times10^2$).

Considering the construal of traffic behavior as a within-subjects variable, following previous research (Bonezzi et al., 2022), the extent of fit and intention to comply with traffic rules scores under low-construal traffic behavior were subtracted from those under high-construal traffic behavior. The resulting difference in the extent of fit was taken as the mediating variable, and the difference in the intention to comply with traffic rules was taken as the dependent variable (for brevity, the extent of fit and the intention to comply with traffic rules were still used as variable terms below). The monitoring agent was taken as the independent variable (human monitoring $=0$, algorithmic monitoring $=1$) for the analysis of the mediating effect. As shown in Fig. 2, consistent with H1c, the results indicated that the effect of the monitoring agent on the intention to comply with traffic rules was mediated by an indirect effect of the extent of fit (indirect effect: $0.97\times0.51=0.49$; 95% CI from 5000 sample bootstraps $=[0.24, 0.85]$).

The experimental results remained consistent across all the aforementioned analyses after controlling for covariates such as years of driving, driving experience, driving distance, and familiarity with traffic rules. Additionally, differences in the perceived monitoring accuracy did not explain the results. Specifically, the ANOVA revealed a nonsignificant main effect of the construal of traffic behavior ($F(1, 208)=0.83$, $p=0.364$, $\eta_p^2<0.01$, 95% CI $=[0.00, 0.03]$, $BF_{10}=0.17$) but a significant interaction ($F(1, 208)=5.99$, $p=0.015$, $\eta_p^2=0.03$, 95% CI $=[0.003, 0.08]$, $BF_{10}=3.30$). Further simple effect analysis revealed that, for both low-construal ($t(208)=5.39$, $p<0.001$, Cohen's $d=0.60$, 95% CI $=[0.38, 0.81]$, $BF_{10}=6.42\times10^4$) and high-construal ($t(208)=2.68$, $p=0.008$, Cohen's $d=0.26$, 95% CI $=[0.07, 0.45]$, $BF_{10}=4.23$) traffic behavior conditions, participants perceived algorithmic monitoring accuracy to be higher than human monitoring accuracy (descriptive statistics are provided in Table 1).

Table 1 The perceived monitoring accuracy under different conditions in Study 1

Construal of traffic behavior	Monitoring agent	*M*	*SE*
Low construal	Human	6.30	0.20
	Algorithm	7.71	0.16
High construal	Human	6.85	0.16
	Algorithm	7.46	0.16

Discussion

The impact of the monitoring agent on the intention to comply with traffic rules depends on the construal level of the traffic behavior. Specifically, for low-construal traffic behaviors, algorithmic monitoring increases compliance intentions. However, for high-construal traffic behaviors, human monitoring increases compliance intentions, which was also observed in real-world traffic scenarios using a field observation approach (see Study S2 in the Supplementary Material). Importantly, the effect of the monitoring agent on compliance intentions is mediated by the extent of fit. These findings are robust, as they were replicated in Study S1 with a sample of older adults who had more driving experience while controlling for demographic factors such as job occupation and place of residence (e.g., urban or rural).

Study 2: How algorithmic monitoring with errors influences the intention to comply with traffic rules

Study 2 employed traffic behaviors similar to those in Study 1 but explicitly highlighted monitoring errors in detecting traffic violations. It aimed to investigate whether and how algorithmic monitoring with errors influences the intention to comply with traffic rules by assessing the extent of fit between the construal levels of agents and traffic behaviors.

Methods

The sample size determination and participant recruitment process for Study 2 were identical to those for Study 1, resulting in a total of 223 recruited participants. After 9 participants who did not complete the questionnaires were excluded, a total of 214 valid participants were included in the analysis. Among these, 107 participants were assigned to the human monitoring condition (68 males, 39 females), and 107 were assigned to the algorithmic monitoring condition (76 males, 31 females). The age of the participants ranged from 18 to 35 years (M= 22.11, SD= 2.67), and their driving experience ranged from 0 to 11 years (M= 2.26, SD= 1.70).

The materials, design and procedure of this study were similar to those of Study 1, with minor adjustments to the traffic behavior scenarios. Specifically, descriptions of monitoring errors were added, indicating instances where past drivers did not comply with traffic rules but were not detected by the monitoring agent. For example, in the scenario of the failure to yield right-of-way, the following sentence was added at the end of the traffic behavior scenarios used in Study 1: "*It is understood that although some drivers did not yield to pedestrians as required, a few of them were still not detected by this traffic policemen/electronic police monitoring device*." After reading the scenarios, the participants completed a series of items measuring their intention to comply with traffic rules, the extent of fit between the construal characteristics of the monitoring agent and the traffic behavior, and the perceived monitoring accuracy.

Results

Figure 3 depicts participants' scores on the intention to comply with traffic rules and the extent of fit across different conditions. The ANOVA revealed a significant main effect of the monitoring agent (F(1, 212) = 11.58, p < 0.001, η_p^2 = 0.05, 95% CI = [0.01, 0.11], BF_{10} = 13.37). The main effect of the construal of traffic behavior was also significant (F(1, 212) = 4.78, p = 0.030, η_p^2 = 0.02, 95% CI = [0.001, 0.07], BF_{10} = 1.32). The interaction effect between the two variables was significant (F(1, 212) = 8.62, p = 0.004, η_p^2 = 0.04, 95% CI = [0.008, 0.09], BF_{10} = 13.12). The simple effects analysis revealed that under low-construal traffic behavior, no significant difference in participants' intentions to comply with traffic rules between human monitoring (M = 4.95, SE = 0.14) and algorithmic monitoring (M = 4.89, SE = 0.14; t(212) = 0.32, p = 0.751, Cohen's d = 0.04, 95% CI = [−0.18, 0.25], BF_{10} = 0.16) was found. However, under high-construal traffic behavior, participants showed a significantly higher intention to comply with traffic rules under human monitoring (M = 5.04, SE = 0.10) than under algorithmic monitoring (M = 4.28, SE = 0.10; t(212) = 5.31, p < 0.001, Cohen's d = 0.44, 95% CI = [0.28, 0.60], BF_{10} = 4.46 × 10^4).

The ANOVA on the extent of fit revealed that neither the main effect for monitoring agent (F(1, 212) = 0.78, p = 0.379, η_p^2 < 0.01, BF_{10} = 0.17) nor the main effect of

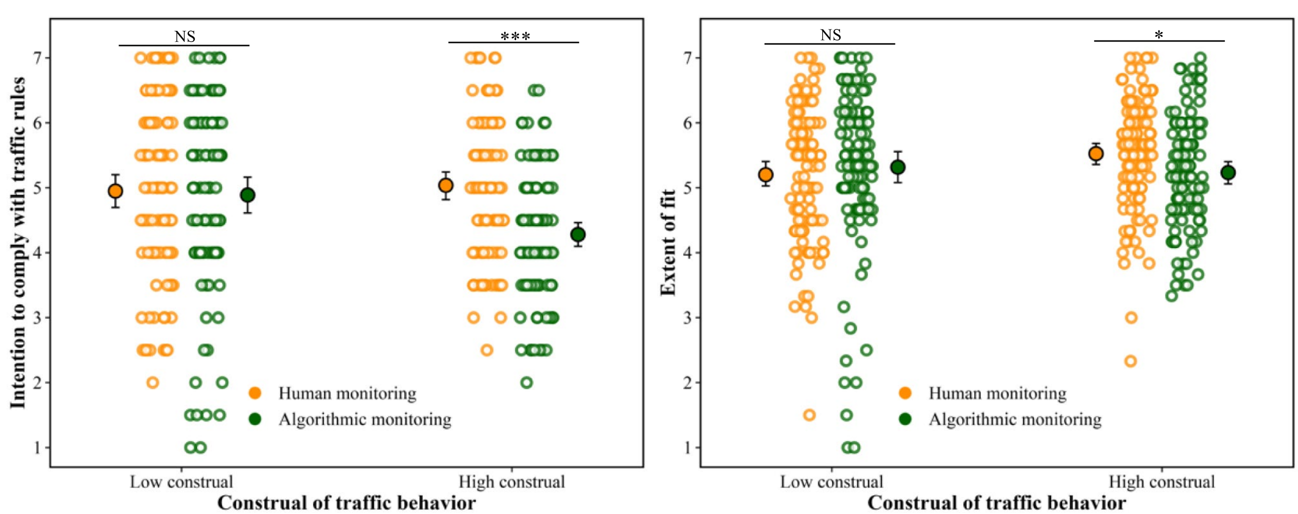

Fig. 3 The intention to comply with traffic rules and the extent of fit under different conditions in Study 2

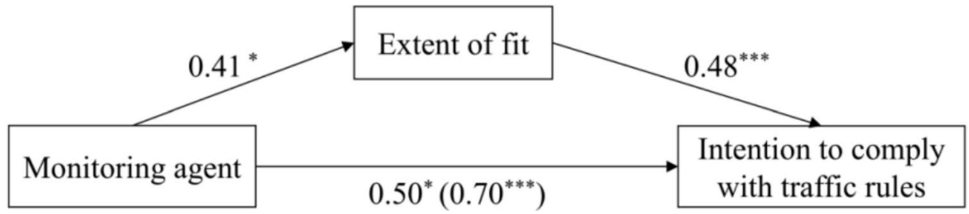

Fig. 4 The mediation analysis revealed that the extent of fit mediates the effect of the monitoring agent on the intention to comply with traffic rules in Study 2

Table 2 The perceived monitoring accuracy under different conditions in Study 2

Construal of traffic behavior	Monitoring agent	*M*	*SE*
Low construal	Human	7.00	0.16
	Algorithm	7.49	0.16
High construal	Human	6.34	0.14
	Algorithm	7.20	0.14

the construal of traffic behavior was significant (F(1, 212) = 1.50, p = 0.223, $\eta_p{}^2 < 0.01$, 95% CI = [0.00, 0.04], BF_{10} = 0.23). However, the interaction between the two factors was significant (F(1, 212) = 4.26, p = 0.040, $\eta_p{}^2 = 0.02$, 95% CI = [0.00, 0.03], BF_{10} = 1.38). The simple effects analysis revealed that under the low-construal traffic behavior condition, there was no significant difference in the extent of fit between human monitoring (M = 5.20, SE = 0.11) and algorithmic monitoring (M = 5.32, SE = 0.11; t(212) = −0.73, p = 0.468, Cohen's d = 0.08, 95% CI = [−0.30, 0.14], BF_{10} = 0.19). However, under the high-construal traffic behavior condition, the participants reported a significantly higher extent of fit under human monitoring (M = 5.53, SE = 0.09) than under algorithmic monitoring (M = 5.23, SE = 0.09; t(212) = 2.43, p = 0.016, Cohen's d = 0.20, 95% CI = [0.04, 0.37], BF_{10} = 2.33).

The mediation analysis method was similar to that used in Study 1. As shown in Fig. 4, despite monitoring errors, the effect of the monitoring agent on the intention to comply with traffic rules was still mediated by the variable of the extent of fit (indirect effect: 0.41 × 0.48 = 0.19; 95% CI from 5000 sample bootstraps = [0.02, 0.40]).

The experimental results remained consistent across all the aforementioned analyses after controlling for covariates such as years of driving, driving experience, driving distance, and familiarity with traffic rules. Moreover, differences in the perceived monitoring accuracy did not explain the results. Specifically, although the ANOVA revealed a nonsignificant interaction effect (F(1, 212) = 2.78, p = 0.097, $\eta_p{}^2 = 0.01$, 95% CI = [0.00, 0.05], BF_{10} = 0.52), the participants' perceived monitoring accuracy was higher for algorithmic monitoring than for human monitoring, regardless of whether the traffic behavior was low construal (t(212) = 2.16, p = 0.032, Cohen's d = 0.29, 95% CI = [0.03, 0.56], BF_{10} = 1.31) or high construal (t(212) = 4.25, p < 0.001, Cohen's d = 0.52, 95% CI = [0.28, 0.77], $BF_{10} = 5.64 \times 10^2$) (the descriptive statistics are provided in Table 2).

Between-study comparison

To further explore whether the presence of monitoring errors influences the intention to comply with traffic rules between Study 1 and Study 2, a between-study comparison of the results was conducted. A 2 (error information: none in Study 1, present in Study 2) × 2 (monitoring agent: human, algorithm) fully between-subjects ANOVA was conducted to assess the intention to comply with traffic rules for each construal level of traffic behavior, with a focus on the interaction effect.

For low-construal traffic behavior, the interaction effect was significant (F(1, 420) = 4.33, p = 0.038, $\eta_p{}^2 = 0.01$, 95% CI = [0.00, 0.03], BF_{10} = 1.16). Specifically, in the absence of error information, the compliance intention was lower under human monitoring than under algorithmic monitoring. However, when errors were disclosed, the difference between human monitoring and algorithmic monitoring was no longer significant, as reported above. For high-construal traffic behavior, the interaction effect was not significant (F(1, 420) = 1.59, p = 0.208, $\eta_p{}^2 < 0.01$, 95% CI = [0.00, 0.02], BF_{10} = 0.30), suggesting that human monitoring consistently enhances compliance intention regardless of whether error information is presented.

Discussion

This study suggests that when individuals are aware of error information about the monitoring agent, human monitoring of high-construal traffic behavior still increases their intention to comply with traffic rules compared with that under algorithmic monitoring. However, for low-construal traffic behavior, in contrast to the findings of Study 1, this increase in intention disappears when comparing algorithmic monitoring to human monitoring. These findings were replicated in Study S3 without measuring the extent of fit. Furthermore, it was found that even in the presence of monitoring errors, the monitoring agent can still influence the intention to comply with traffic rules through the extent of fit.

General discussion

In exploring the impact of algorithmic monitoring on compliance with traffic rules, this study posited that the intention to comply with rules is strengthened when both monitoring agents and traffic behaviors align at the construal level. Consistent with our hypothesis (H1), Study 1 revealed that for low-construal traffic behaviors, individuals demonstrated a higher degree of fit under algorithmic monitoring than under human monitoring, consequently increasing their compliance intention with traffic rules. Conversely, for high-construal traffic behaviors, individuals exhibited a higher degree of fit under human monitoring than under algorithmic monitoring, resulting in a stronger compliance intention with traffic rules. Further investigation supported H2, demonstrating that the monitoring agent with errors still influences the intention to comply with traffic rules at different construal levels, albeit with different patterns than those observed in Study 1. Specifically, for high-construal traffic behaviors, human monitoring continues to increase compliance intention with traffic rules, whereas for low-construal traffic behaviors, compliance intention is similar between algorithmic monitoring and human monitoring. These relationships are still mediated by the extent of fit between the monitoring agents and their monitored violations. In summary, the influence of the monitoring agent (algorithm versus human) on the intention to comply with traffic rules depends on the construal level of traffic behavior, with the extent of fit playing a mediating role. Furthermore, monitoring errors have a greater impact on algorithmic monitoring than on human monitoring.

The algorithm demonstrates both superior (i.e., higher compliance intention under algorithmic monitoring for low-construal traffic behaviors) and inferior (i.e., lower compliance intention under algorithmic monitoring for high-construal traffic behaviors) effectiveness relative to human monitoring in the traffic domain. This pattern aligns with the seemingly contradictory attitudes toward algorithms, suggesting that whether individuals show algorithm appreciation or aversion may depend on the construal level of the task at hand. This finding is consistent with that of Kim & Duhachek (2020) in the field of algorithmic persuasion. Specifically, when artificial intelligence uses a low-construal message to recommend products (e.g., how to use sunscreen), it is more persuasive than when using a high-construal message (e.g., why to use sunscreen). However, when artificial intelligence is described as possessing human-like features (e.g., human traits of consciousness), the aforementioned results are reversed. Therefore, the construal level of the behaviors performed or regulated by algorithms is a crucial variable in determining aversion or appreciation. Consistent with CLT, which suggests that individuals process information at different levels of abstraction (Kim & Duhachek, 2020; Ward et al., 2013), this effect is linked to how people construe algorithmic and human agents and perceive their fit with a given behavior. While humans are conscious and can learn autonomously, algorithms are programs designed by humans and lack consciousness and active learning capabilities. People have certain expectations about which behaviors algorithms are suited to perform, and when these expectations align with the actual behaviors, individuals perceive a higher extent of fit, leading to greater efficacy and demonstrating algorithm appreciation. Conversely, when there is a mismatch, algorithmic aversion is observed. The present study also confirmed the mediating role of the extent of fit in the influence of algorithmic monitoring on traffic behaviors. Numerous studies have provided evidence for the impact of the extent of fit on behaviors. For example, Lee & Aaker (2004) found that when message framing (gain vs. loss) aligns with individuals' regulatory focus (promotion vs. prevention), people experience higher fluency, leading to greater fit and enhancing the persuasive effect of the message. In conclusion, the effect of algorithms on individuals' behavior (algorithm appreciation versus algorithm aversion) is shaped by the construal level of the behavior being regulated, with the extent of fit serving as a key mediating factor in this process.

Monitoring errors not only weaken the overall intention to comply with traffic rules but also, in the case of low-construal traffic behaviors, change the effectiveness of algorithmic monitoring more than that of human monitoring. Specifically, the enhancing effect of algorithmic monitoring on the intention to comply with traffic rules was absent. This finding is consistent with previous research on algorithmic errors, which indicates that such errors are often systematic and difficult to rectify. Unlike humans, algorithms have difficulty learning from and correcting their mistakes, leading to lower tolerance for algorithmic errors and ultimately weakening the effectiveness of algorithms on individual behaviors (Dietvorst et al., 2015; Mahmud et al., 2022). With respect to the results of our research on the extent of fit, algorithmic errors also diminished the extent of fit between algorithmic monitoring and low-construal traffic behaviors. This result suggests that people's available representations or expectations about algorithmic monitoring are more susceptible to errors, and accordingly, people rely more on the actual performance of algorithms to form their understanding of them. Regarding human monitoring, people's interpretations and representations not only are based on actual observed performance but also rely significantly on prior knowledge. This prior knowledge, such as the economy and flexibility of human behavior (Ionescu, 2017), is relatively stable and difficult to change in a short period (Carruthers et al., 2008). Therefore, even when aware of human errors, people still rely on their prior knowledge to determine the perceived extent of fit between a human agent and monitoring behavior, leading to results that are similar to those when no error information is provided.

This research revealed that the perceived accuracy of different monitoring agents alone cannot fully explain the differences in traffic compliance between them. The results revealed that perceived accuracy showed different patterns than rule compliance did, and the variable “extent of fit” partially mediated the effects of the monitoring agent on compliance with traffic rules. Notably, in high-construal traffic behavior, even though algorithmic monitoring is perceived as more accurate than human monitoring is, the latter still enhances the intention to comply with traffic rules. Therefore, when confronted with different types of monitoring, people’s choice of compliance may depend not only on the accuracy or utility of monitoring but also on the evaluation of certain unique human characteristics. Morewedge (2022) proposed that the degree of algorithmic influence depends on two dimensions of tasks or decision contexts: the ambiguity of the evaluative criteria and the relevance to human identity. Algorithm aversion increases with these two dimensions. With respect to traffic violations, there are both clear instances, such as speeding, and ambiguous situations, such as the failure to yield right-of-way. In terms of the relevance to human identity, concerning the two high-construal traffic behaviors examined in this study (failure to yield right-of-way and using a handheld phone while driving), because of the involvement of intention recognition, the ambiguity of the evaluative criteria regarding whether traffic rules are violated far surpasses those of the two low-construal traffic behaviors (speeding and improper use of lights). Dietvorst & Bharti (2020) proposed that the key to this uniqueness lies in the flexibility of human decision-making, which results in higher variance in performance than that under algorithms. Since people have diminishing sensitivity to forecasting error, the higher variance in performance expected from human forecasters is more likely to sway choosers. Therefore, traffic behaviors influenced by the element of human uniqueness led participants to consider factors beyond monitoring accuracy. This finding does not diminish the importance of monitoring accuracy for algorithmic monitoring. Indeed, some studies have confirmed that increasing algorithm accuracy can improve compliance with traffic rules (Revadala et al., 2024). However, our findings suggest that going beyond improving monitoring accuracy from a technical standpoint to incorporate human features (e.g., anthropomorphism) into algorithmic systems during the monitoring of high-construal violations, such as failing to yield right-of-way, could further enhance their effectiveness. This suggestion implies a nuanced approach to designing monitoring systems that considers more than technical precision.

The conclusions drawn from this study can offer valuable insights into the utilization of artificial intelligence algorithms to increase compliance with traffic regulations. The differential effects observed between monitoring agents concerning compliance with traffic rules across varying construal levels suggest that transportation authorities should adopt a targeted approach when deploying algorithmic or human monitoring. Rather than employing a one-size-fits-all strategy, the prevalent types of traffic violations should be carefully considered when improving road safety. For example, intersections prone to common infractions such as the failure to yield right-of-way may benefit from the presence of traffic policemen, whereas algorithmic monitoring might be more effective for locations susceptible to speeding violations. Moreover, given the diminished effectiveness of algorithmic monitoring in the presence of errors, it is advisable for transportation departments to maintain flexibility in their deployment strategies. This approach could involve deploying traffic policemen at intersections where electronic police devices sometimes make errors and overlook violations, thereby helping mitigate the adverse effects of algorithmic errors.

This study has some limitations regarding the generalizability of its findings. First, although our selection process followed strict standards to ensure the representativeness of traffic violations for each construal level, other violations could also be classified as low or high construal. Testing these findings in different scenarios would strengthen the conclusions. Second, the presentation of algorithmic errors in this study highlights primarily general monitoring failures. As this study served as an initial exploration, we did not manipulate the error type or frequency. Future studies could examine how these variations influence compliance with the monitoring system. Finally, with the rapid advancement of autonomous driving technologies (e.g., adaptive cruise control and automatic emergency braking), drivers’ compliance with traffic regulations may shift. As reliance on AI-assisted driving increases, the balance between human control and automation could influence compliance behaviors. This integration of human- and AI-supported driving may alter the effectiveness of monitoring systems. Future research should explore whether autonomous driving technology mitigates or amplifies the influence of monitoring agents on traffic compliance.

Conclusion

From the perspective of the construal of traffic behavior, we investigated the influence of algorithmic monitoring on compliance with traffic rules. Our findings indicate that the effectiveness of algorithmic monitoring over human monitoring varies depending on the construal level of traffic behavior. Specifically, for traffic behaviors characterized by a low construal level (e.g., improper lighting), individuals exhibit a higher degree of fit under algorithmic monitoring than under human monitoring, thereby enhancing their compliance intention with traffic rules. However, when errors are present in algorithmic monitoring, this enhancing effect is absent. Conversely, for high-construal traffic behaviors (e.g., failure to yield right-of-way), individuals demonstrate a higher degree of fit under human monitoring than under algorithmic monitoring, leading to a stronger compliance intention with traffic rules. Importantly, this effect persists even when errors are known. These results contribute to a broader understanding of algorithmic applications and provide valuable insights for transportation authorities aiming to deploy algorithmic or human monitoring at intersections based on prevalent types of traffic violations.

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Data availability All data and analysis code have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/62kcn/?view_only=f80de7dc566c41619d3d9ba05e3e763c. None of the studies was preregistered.

Declarations

Ethics statement The study was approved by the Research Ethics Board of the Department of Psychology at Ningbo University and was performed in accordance with the relevant guidelines and regulations.

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author note All data and analysis code have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/62kcn/?view_only=f80de7dc566c41619d3d9ba05e3e763c. None of studies were preregistered.

During the preparation of this work, we used ChatGPT 3.5 in order to improve readability and language. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Bogert, E., Schecter, A., & Watson, R. T. (2021). Humans rely more on algorithms than social influence as a task becomes more difficult. *Scientific Reports, 11*(1), 8028.

Bonezzi, A., Ostinelli, M., & Melzner, J. (2022). The human black-box: The illusion of understanding human better than algorithmic decision-making. *Journal of Experimental Psychology: General, 151*(9), 2250–2258.

Carruthers, P., Laurence, S., & Stich, S. (2008). The innate mind: Volume 3: Foundations and the future. *Oxford University Press.*

Cesario, J., Grant, H., & Higgins, E. T. (2004). Regulatory fit and persuasion: Transfer from "feeling right." *Journal of Personality and Social Psychology, 86*(3), 388–404.

Dau, P. M., Vandeviver, C., Dewinter, M., Witlox, F., & Vander Beken, T. (2023). Policing directions: A systematic review on the effectiveness of police presence. *European Journal on Criminal Policy and Research, 29*(2), 191–225.

Dienes, Z. (2014). Using Bayes to get the most out of non-significant results. *Frontiers in Psychology, 5*, 781.

Dietvorst, B. J., & Bharti, S. (2020). People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. *Psychological Science, 31*(10), 1302–1314.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126.

Ionescu, T. (2017). The variability-stability-flexibility pattern: A possible key to understanding the flexibility of the human mind. *Review of General Psychology, 21*(2), 123–131.

Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist, 73*(1), 1–2.

Kim, T. W., & Duhachek, A. (2020). Artificial intelligence and persuasion: A construal-level account. *Psychological Science, 31*(4), 363–380.

Krügel, S., Ostermaier, A., & Uhl, M. (2023). Algorithms as partners in crime: A lesson in ethics by design. *Computers in Human Behavior, 138*, 107483.

Lee, A. Y., & Aaker, J. L. (2004). Bringing the frame into focus: The influence of regulatory fit on processing fluency and persuasion. *Journal of Personality and Social Psychology, 86*(2), 205–218.

Liberman, N., Trope, Y., McCrea, S. M., & Sherman, S. J. (2007). The effect of level of construal on the temporal distance of activity enactment. *Journal of Experimental Social Psychology, 43*(1), 143–149.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650.

Mahmud, H., Islam, A. K. M. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change, 175*, 121390.

Morewedge, C. K. (2022). Preference for human, not algorithm aversion. *Trends in Cognitive Sciences, 26*(10), 824–826.

Nakano, Y., Okamura, K., Kosuge, R., Kihira, M., & Fujita, G. (2019). Effect of visible presence of policing activities on drivers' vigilance and intention to refrain from non–driving activities: A

scenario-based survey of general Japanese drivers. *Accident Analysis & Prevention, 133*, 105293.
National Highway Traffic Safety Administration. (2022). *Speeding*. NHTSA https://www.nhtsa.gov/risky-driving/speeding
Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes, 160*, 149–167.
Oleksy, T., Wnuk, A., Domaradzka, A., & Maison, D. (2023). What shapes our attitudes towards algorithms in urban governance? The role of perceived friendliness and controllability of the city, and human-algorithm cooperation. *Computers in Human Behavior, 142*, 107653.
Revadala, A., Reddy, S. R. C., & Kumar, M. (2024). Efficient intelligent based compliance, detection, tracking, and proximity model for traffic system. In *2024 International Conference on Intelligent Systems for Cybersecurity* (ISCS) (pp. 1-6). IEEE.
Sinha, R. R., & Swearingen, K. (2001). Comparing recommendations made by online systems and friends. *DELOS, 106*.
Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review, 117*(2), 440–463.
Vallacher, R. R., & Wegner, D. M. (1989). Levels of personal agency: Individual variation in action identification. *Journal of Personality and Social Psychology, 57*(4), 660–671.
Ward, A. F., Olsen, A. S., & Wegner, D. M. (2013). The harm-made mind: Observing victimization augments attribution of minds to vegetative patients, robots, and the dead. *Psychological Science, 24*(8), 1437–1445.
World Health Organization. (2023). *Road traffic injuries*. WHO. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries
Wu, J. F., Yu, H. Y., Zhu, Y. M., & Zhang, X. Y. (2020). Impact of artificial intelligence recommendation on consumers' willingness to adopt. *Journal of Management Science, 33*(5), 29–43.
You, S., Yang, C. L., & Li, X. (2022). Algorithmic versus human advice: Does presenting prediction performance matter for algorithm appreciation? *Journal of Management Information Systems, 39*(2), 336–365.
Zhang, X. Y. (2021). Research on legal issues of road traffic electronic law enforcement. *Henan University.*

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