PACIS 2023 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

7-8-2023

Promoting Driving Safety with Self-Evaluation Maintenance: Human-Human and Human-Artificial Intelligence Performance Comparisons

Zhiyin Li
Nanyang Technological University, zhiyin001@e.ntu.edu.sg

Ben Choi
Nanyang Technological University, benchoi@ntu.edu.sg

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Completed Research Paper

Zhiyin LI
City University of Hong Kong
83 Tat Chee Ave, Hong Kong
zhiyinli1234@gmail.com

Ben CHOI
Nanyang Technological University
52 Nanyang Ave, Singapore
benchoi@ntu.edu.sg

Abstract

In this study, we develop and test a model that explains individuals' behavioral changes in driving safety after viewing the visualizations, which depict their driving performance against that of artificial intelligence (AI). This study draws on the self-evaluation literature to understand performance comparisons and extends the self-evaluation perspective to the context of human-AI comparisons. Furthermore, this study illustrates that individuals can be incited emotionally by performance comparisons, and these emotional responses influence their driving behaviors subsequently. The results of this study generally support our model. Overall, this study sheds light on how competition between humans and computers can be utilized to promote desirable behaviors.

Keywords: Self-evaluation, human-artificial intelligence comparisons, visualizations, driving safety

Introduction

Artificial intelligence (AI) has become one of the most-discussed technologies in research and practice. In a joint report issued by the national science and technology council and the U.S. Department of Transportation, it is predicted that vehicles driven by artificial agents (i.e., autonomous vehicles) will provide improved quality of life, access, and mobility for all citizens (Chao 2022). More importantly, artificial agents can be a game-changer by removing the possibility of human error for safer transportation. Despite the promising benefits, a survey of 10,260 individuals in the U.S. has revealed that about 54% believe AI would be a bad idea for society or remained highly skeptical (Lee 2022). As many tasks and activities are being delegated to artificial agents, individuals could become the involuntary subjects of comparison, be it formal work performance or informal leisure activities, against artificial agents. The possibility of being outperformed by artificial agents aggravates the problem by challenging individuals' identities and self-esteem. In traditional human-human comparison, individuals typically rely on interpersonal similarities and psychological closeness in identifying relevant comparative referents; however, with artificial agents, interpersonal similarity and psychological closeness are not entirely appropriate.

Yet it has been observed that individuals might still feel threatened by artificial agents despite the apparent lack of humanness. According to the Boston Consulting Group, it is estimated that about one-quarter of the miles Americans travel by 2030 will be in driverless vehicles, causing a significant disruption to the automotive industry (Eisenstein 2017). More importantly, professional drivers face unprecedented competition in maintaining their legitimacy in the transportation industry. Hence, it would be essential to understand why individuals compare their performance against artificial agents.

Past research has made some progress in understanding individuals' affective and behavioral responses toward AI. For instance, AI that is perceived as helpful and reliable by individuals can elicit positive emotional responses such as trust, enjoyment, and satisfaction (Glikson and Woolley 2020). Conversely, negative emotional responses toward AI, such as frustration and annoyance, may arise from AI being perceived as competent and unresponsive. Additionally, Teodorescu et al. (2021) opined that humans and artificial intelligence could complement each other to increase productivity by relying on their strengths and overcoming weaknesses. More importantly, the authors suggest it is essential to consider fairness in human-artificial intelligence interactions by ensuring human oversight and supervision. Notwithstanding these findings, our understanding of the determinants of behavioral responses to artificial agents beyond the usage contexts remains fragmented. Hence, our first motivation is to investigate what influences individuals' performance-specific responses to artificial agents in the context of driving safety.

Our second motivation is to unpack individuals' emotional responses to performance evaluation against artificial agents. Given the apparent differences between human-human and human-AI comparisons, our theoretical development would need to embrace the unique aspects of artificial agents. For example, in comparison with artificial agents, individuals might expect the referent to be error-free and completely reliable. In contrast, in comparison with human agents, individuals might focus on identifying interpersonal differences to avoid being outperformed by human referents. Furthermore, while the self-evaluation literature has demonstrated the importance of emotional responses in performance comparison, past research has relied on surveys to capture individuals' emotions. Given the retrospective nature of survey studies, past research might not have accurately captured individuals' emotional responses specific to self-evaluation.

Third, although task performance is considered a typical outcome of self-evaluation, past research has often focused on transactional and straightforward tasks. Our study utilizes a driving simulator to enable a fine-grained observation of individuals' safe driving practices. It is worth noting that although we employed a laboratory experiment, our unique driving simulation environment presents subjects with a continuous driving situation, which is fundamentally different from typical cross-sectional studies.

Related Literature

Artificial Agents and Self-Evaluation in Driving Safety

Artificial agents are computer programs that can accomplish complex goals and perform practical actions within an environment, such as artificial intelligence and robotic process automation (Dellermann et al. 2019). A fundamental difference between artificial agents and traditional information systems is that artificial agents can adapt to different contextual situations through learning performance outcomes (Maedche et al. 2019). Significant advancements in artificial intelligence approaches, such as deep learning and neural networks, have strengthened artificial agents' capability in rapid diagnoses and object-identifying tasks. Artificial agents are widely expected to improve workplace efficiencies and augment humans' work. For instance, artificial agents can take over repetitive or dangerous work, enabling the human workforce to focus on other tasks, such as creative and social work. Given the capabilities of artificial agents, companies and organizations are increasingly evaluating the ability of intelligent agents to existing staff to improve productivity.

In vehicular operations, artificial agents hold substantial promise in improving efficiency, passage comfort, and safety (Zhao et al. 2021). Despite the promises, artificial intelligence has instigated anxiety among those who evaluate the performance of artificial agents against human performance. Indeed, evidence suggests that artificial agents can be considerably more proficient than humans in performing some tasks. For example, in the game of Go, the artificial intelligence computer program developed by Google has beaten the best human Go player, winning 4 out of 5 games (Granter et al. 2017). Furthermore, artificial agents can be frowned upon for increasingly replacing human jobs, if not eliminating some occupations (Li and Huang 2020). Considering the intricate relationships between humans and artificial agents, it is necessary to devise a systematic account of the impact of performance evaluation between humans and artificial agents on individuals' psychological and behavioral responses.

The Self-Evaluation Maintenance Model

We draw upon the social comparison literature to understand the effect of self-evaluation in influencing individuals' behaviors. Self-evaluation is about determining an actor's progress or weighing up personal worth relative to a referent's progress or worth. It can naturally occur when actors are exposed to referents' performance information without prompting actors explicitly with a comparative setting. The motivation literature has broadly demonstrated the importance of self-evaluation in promoting behavior changes. For instance, Fanapanel et al. (2019) found that social feedback on comparing drivers' eco-driving performance could powerfully enhance the subsequent driving economy. Past motivation research suggests that self-evaluation is critical to actors' understanding of the performance gap, i.e., whether actors are superior or inferior to referents. Depending on the assessment, psychological needs can be met with compensatory and restorative behavioral responses. Although different views of self-evaluation have emerged, theorists generally agree on three parameters of self-evaluation, Tesser (1988), in his seminal work on the self-evaluation maintenance (SEM) model, posits three critical parameters that influence self-evaluation: (1) a referent's performance relative to one's own, (2) degree of closeness with the referent, (3) and relevance of the comparison dimension. In the following sections, these three parameters are discussed.

Referent's Relative Performance and Comparative Referents

Referent performance is about *how* one stands in self-evaluation. The self-evaluation literature has advanced that a referent can influence an individual's performance in an activity because the referent's performance provides comparative information for evaluating the individual's performance. Indeed, the social comparison perspective robustly illustrates that a referent's performance is a standard against which individuals understand their ability and competence (e.g., Bandura 1986). Understanding how the referent has performed is essential to satisfying self-enhancement motive, increasing self-esteem, and regulating emotions and well-being (Vogel et al. 2014). Recent IS research has consistently illustrated the importance of referent performance in the digital environment. For instance, Li et al. (2021) found that referent performance could motivate student competition, reducing procrastination and improving academic performance.

Considering the importance of referent performance in self-evaluation, this study considers two comparative referent types: better-off referent and worse-off referent. A better-off referent represents a comparer with superior performance about an individual., whereas a worse-off referent indicates relatively inferior performance by the comparer. A better-off referent facilitates upward comparison, generally recognized for its inspirational effect on driving safety (Festinger 1954). Indeed, upward referent comparison is often essential to motivate actors to exert additional efforts for performance improvement. For instance, Diel et al. (2021b) found that comparison against a superior referent would activate a motivational boost, driving to push for self-improvement. Individuals might also seek upward comparative information for basking-in-reflected glory (Cialdini et al. 1976). In a study examining contribution behavior in virtual communities, Tsai and Bagozzi (2014) showed that active participation could be encouraged when users were proud of the achievement and reputation of others in the online community.

While referents' success can be inspiring, better-off referents can be threatening. Comparative information regarding one's relative inferiority has been associated with feelings of envy and anger, as well as intrusive thoughts (Moran and Schweitzer 2008). Accordingly, upward referent comparison threatens relative evaluation and consumes actors' attention to the evaluated activity, leading to deteriorated performance (Normand and Croizet 2013). Ample research has demonstrated the threatening effect of upward referent comparison. For example, Krasnova et al. (2015) examined online social information consumption. They found that exposure to others' boastful posts was associated with undesirable consequences, such as the unpleasant and painful state of envy, frustration, and cognitive evaluations of life.

By contrast, a worse-off referent facilitates a downward comparison that emphasizes the actor's relative superiority over the referent. Consequently, a worse-off referent often bolsters self-esteem and increases life satisfaction (Van der Zee et al. 1998). Some researchers have recognized downward referent comparison as a motivation to promote behavior changes (e.g., Gibbons et al. 2002). Their crucial rationale is that downward referent comparison provides actors a preview of the undesired future outcomes if changes are not enacted. Accordingly, actors can be sparked to improve their performance or change their behaviors to avoid undesired consequences. Corroborating this logic, Lane and Gibbons (2007) showed that by comparing students' exam performance to those who performed worse than they did, these students achieved substantially improved academic performance in the following semester.

Referent Closeness and Agent Types

Referent closeness is about *who* is being compared with an individual in self-evaluation. Tesser (1988) offered that referent closeness "increases with similarity, physical proximity, family ties, similarity in place of origin, and the like" (p. 438). This broad definition has inspired a variety of operationalizations, such as co-presence, professional acquaintanceship, and interpersonal relationships (Obloj and Zenger 2017). Scholars have predominately agreed that referent closeness indicates whether the referent is appropriate for meaningful and diagnostic evaluation. Low referent closeness indicates a referent who shares limited similarities with an act and is unlikely to constitute meaningful relative evaluation. However, high referent closeness implies evaluation with others of similar characteristics or attributes related to the performance outcome (Stapel and Koomen 1998).

Despite the importance of interpersonal similarity, rarely has past research unraveled a detailed explanation of the impact of referent closeness on individuals' self-evaluation. This study draws on the self-congruity theory to offer a systematic account. The theory posits that self-congruity subsumes the outcome of comparing individuals' self-concept against their understanding of a comparison target, such as an activity, a social role, or another individual (Sirgy et al. 1997). The comparison either leads to a low or high self-congruence outcome. A low self-congruence outcome denotes a mismatch between individuals' self-concept and the target. Since individuals are motivated to maintain self-concept, they would likely avoid associations with a largely incongruent target. By contrast, a high self-congruence outcome represents a match between individuals' self-concept and the target. Accordingly, individuals tend to identify with the target to expand and elevate their self-concept. Consistent with the self-congruity theory, with low referent closeness, individuals are likely to focus on the lack of congruity between their self-concept and the referent, hence deemphasizing the importance of referent performance. High referent closeness, however, underscores the high congruity between self-concept and the referent and is likely to elevate individuals' attention to referent performance.

Emerging work on self-evaluation has begun to examine performance comparisons between human and artificial agents, such as robots, avatars, and artificial intelligence. However, the impact of artificial agents in performance comparison still needs to be more conclusive. Some scholars opine that artificial agents can hardly be relevant to individuals' self-evaluation. A key rationale is that artificial agents are fundamentally different from humans, which inhibits individuals from identifying common social reference points for self-evaluation. Furthermore, although artificial agents might be designed to assume a humanoid appearance and demonstrate human-like behaviors, they are rarely considered equal members of human societies, whereby individuals cooperate, compete, and compare. Consequently, artificial agents are deemed inappropriate referents in self-evaluations. By contrast, recent human-robot interaction research reveals that artificial agents can be seen as social actors, constituting meaningful referents. Since artificial agents no longer require direct human intervention and often function autonomously, people increasingly consider intelligent agents to possess their agency (Gambino et al. 2020). The notion of Computers-Are-Social-Actors (CASA) offers a theoretical explanation for people's extension of self-evaluation against a human agent to that about an intelligent agent (Nass et al. 1994). According to CASA, the unconscious awareness state of individuals depends on the context of interactions. Furthermore, individuals can mindlessly apply social heuristics for human interactions to non-human interactions (Nass and Moon 2000), attributing performance comparison with artificial agents similar to human agents.

While traditional self-evaluation research predominately focuses on performance comparisons with human referents, the increasing prevalence of artificial, non-human agents presents fundamental challenges to understanding self-evaluation. This study examines two types of agents, namely human agents and artificial agents. Whereas the former represents a referent of high similarity, the latter denotes a referent with limited, if not virtually non-existent, similarity. A human agent resembles a traditional self-evaluation context in which people compare performance against another individual engaging in the same task or activity. In performance evaluation, an artificial agent is considered when individuals are matched against a non-human, intelligent agent.

Comparison of Relevance and Relevance to the Self

Comparison relevance is about *what* is being compared in self-evaluation. According to Tesser (1988), while individuals can recognize and value others' performance on various dimensions, only a small subset of performance dimensions are relevant to one's self-definition. A specific performance dimension becomes appropriate when an individual is concerned about their competence in the dimension, describes themselves in terms of the dimension, or freely chooses to engage in an activity related to the dimension. For example, while some students might consider being top of the class essential to their self-definition, they might deem physical fitness entirely trivial. It is worth noting that some past research might have misconstrued comparison relevance with referent relevance. Comparison relevance focuses on the importance of a comparison dimension to individuals' self-concept, whereas referent relevance is about the comparability between individuals and referents. Scholars explained that performance comparison is often viewed as drawing an analogy between the self and the other (Wood 1989). The formulation of such analogy facilitates self-expansion, in which individuals might extend their self-concept onto that of another, facilitating the spillover of referent relevance to performance relevance (Gardner et al. 2002).

Considering the importance of comparison relevance, this study focuses on two types of relevance: low self-relevance and high self-relevance. Low self-relevance subsumes self-evaluation on dimensions irrelevant to individuals' self-concept. When self-evaluation involves dimensions irrelevant to self-concept, individuals are indifferent to their relative performance. High self-relevance constitutes self-evaluation on dimensions central to individuals' self-concept. Since the domain, in comparison, is highly relevant to the self, individuals are particularly sensitized toward their relative performance.

Research Model and Hypothesis Development

Grounded in the self-evaluation perspective, we present the research model (Figure 1) that explains the determinants and consequences of relative evaluations between humans and human and artificial agents.

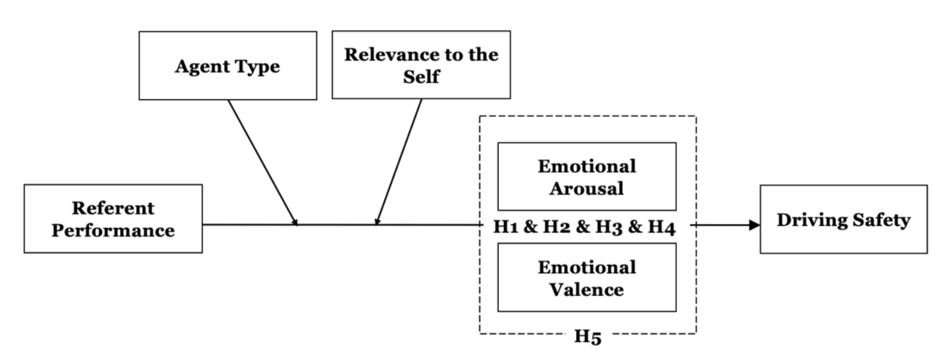


Figure 1. Research Model

Referent Performance and Driving Safety

Individuals have a fundamental desire to know where they stand relative to others in the domains of abilities (Tesser 1988). The performance of a referent provides a comparison standard through which individuals can assess their relative standing. A superior referent underscores individuals' inability to reach the comparison standard, which could induce ruminative thoughts that intrude on individuals' conscious thinking and focus on the evaluative activity (Koole et al. 1999). Ruminative thoughts would consume attentional resources and could be equated with distractions. More importantly, ruminative thoughts associated with one's relative inferiority have been shown to trigger an attentional focusing phenomenon, galvanizing individuals' focus on the evaluative activity and facilitating performance improvement (Muller and Butera 2007). Additionally, the performance discrepancy associated with a superior referent can motivate individuals to exercise proactive regulation to elevate their performance towards the referent (Vohs and Baumeister 2004).

Similarly, their inability to match the comparison standard will be emphasized when individuals are evaluated against a superior referent in driving safety performance. Individuals' poor relative standing in driving safety can induce ruminative thoughts, elevating their focus on maintaining driving safety. Furthermore, a superior referent can incite individuals to take on proactive regulation in disregarding suboptimal approaches to driving and adopting the referent's way of driving. Therefore, we propose the following hypothesis:

H1: Compared with a worse-off referent, a better-off referent will improve driving safety.

Interaction between Referent Performance and Agent Type

The SEM literature suggests that referent closeness fundamentally shapes how individuals interpret referent performance in self-evaluation (Tesser 1988). Individuals with high referent closeness would assume substantial interpersonal similarity, deducing that the referent is appropriate for self-evaluation. By contrast, individuals would likely focus on inherent differences with low referent closeness, assuming that the referent performance is unsuitable for self-evaluation. More importantly, according to the self-evaluation maintenance model, individuals would typically emphasize their performance evaluation about referents of high closeness, which can intensify their motivation for performance improvement.

In evaluating driving safety performance against a superior referent, individuals' relatively poor standing would be emphasized, elevating their attentional focus and proactive regulation to improve subsequent driving safety. Individuals are unlikely to identify common social reference points with an artificial agent so interpersonal similarity will become irrelevant. Accordingly, individuals are likely to deduce weak self-congruity, if not complete incongruity, with the artificial agent, thus deemphasizing referent driving safety performance. However, a human agent facilitates relatively feasible identification of common social reference between the individual and referent, enhancing interpersonal similarity in self-evaluation. As such, individuals are likely to experience strong self-congruity with the human agent, which compels individuals to emphasize their driving safety performance gap against the agent. A superior human agent highlights individuals' inability to match a self-congruent driving safety standard, which can substantially elevate their attentional focus and proactive regulation in subsequent driving behaviors. Thus, we predict the following effects:

H2: The motivating effect of a better-off referent on driving safety is more robust with a human agent than with an artificial agent.

Interaction between Referent Performance and Relevance to the Self

The SEM model provides an informative perspective explaining individuals' responses to driving safety evaluation. Whereas individuals' relative standing in driving safety is central to their self-concept, their relative standing in driving safety can be less critical when their standing is irrelevant. Accordingly, with high self-relevance, compared with an inferior referent, a superior referent would underscore individuals' inability to maintain a high driving safety standard, which is likely incongruent with their expectations. Individuals would probably be motivated to improve their subsequent driving safety performance to reduce the incongruence. By contrast, with low self-relevance, a superior referent is less relevant to individuals' self-concept. Consequently, the effect of referent driving safety performance on individuals' subsequent driving behaviors will not be as marked. Therefore, we posit:

H3: The motivating effect of a better-off referent on driving safety is stronger with high self-relevance than with low self-relevance.

The Joint Effect of Referent Performance, Agent Type, and Relevance to the Self

The self-evaluation maintenance model holds that the effects of referent performance and referent closeness on performance improvement are moderated by comparison relevance. According to the model, the relevance of a referent's performance to one's self-definition determines the occurrence of one of the two antagonistic processes, namely the reflection and comparison processes.

The reflection process, also termed basking-in-reflected-glory, occurs when an individual is outperformed by a close referent on a dimension irrelevant to the individual's self-definition. When reflection occurs, the individual's self-definition will not be damaged but can be enhanced despite inferior performance. Drawing on the image management perspective, Cialdini et al. (1976) explained that individuals function simultaneously as actors and observers in performance evaluations. Consequently, individuals are aware of the strong associations that observers might assume in evaluating irrelevant performance comparisons between individuals of high closeness. Therefore, with high referent closeness, observers are expected to extend the positive evaluation of the referent to that of the individual, thereby contributing to a positive evaluation from not only the observers but also oneself. Similarly, when driving safety is irrelevant to one's self-definition, individuals are unlikely to be highly sensitized to being outperformed by a referent in driving safety performance.

The comparison process occurs when self-evaluation is conducted on a dimension highly relevant to individuals' self-definition (Suls and Wills 1991). With high comparison relevance, a better-off referent of high closeness would put individuals under unfavorable comparison, damaging their self-definition. The potentially detrimental effect of the comparison process has been revealed in past research. For instance, Reh et al. (2018) found that when competitive employees compared their career development with other faster-rising coworkers, they would find their status threatened and might strive to undermine the coworkers' raise. Similarly, when driving safety is highly self-relevance to individuals' self-definition, they are likely to pay high attention to their relative standing in driving safety performance. Furthermore, when human agent outperforms individuals in driving safety, they are likely motivated to improve subsequent driving safety performance.

H4: With high self-relevance, compared with a better-off artificial agent, a better-off human agent will lead to better-driving safety; the three-way interaction effect on driving safety is not as marked with low self-relevance.

Mediating Role of Emotional Arousal and Emotional Valence

Past social comparison literature has broadly examined social comparison-based emotions and suggested that comparing the self with a superior other may result in positive emotions, such as inspiration or optimism, or negative emotions, such as depression or envy. Furthermore, comparing the self with an inferior other may also lead to pleasant emotions, such as pride or schadenfreude, or unpleasant emotions, like worry or sympathy (Smith 2000). More importantly, the literature has generally suggested that these emotions, triggered in the social comparison process, can powerfully alter individuals' subsequent performance (Brown et al. 2001). In particular, scholars have consistently underscored the importance of emotional valence and arousal in understanding the effects of self-evaluation on subsequent performance. For example, Liu et al. (2019) examined experience sharing on social media. They found that social networking site users would be undermined by others sharing luxury travel experiences and experiencing various magnitudes of envy emotions.

Following the self-evaluation maintenance literature, we propose that referent performance, referent type, and task type would jointly influence individuals' emotional responses, affecting their subsequent driving safety performance. Past research examining emotions has predominately focused on two aspects of emotional responses, namely emotional valence, and emotional arousal. Emotional valence is about the positive or negative emotional state activated through self-evaluation (Mousas et al. 2018). Emotional arousal refers to the intensity of an activated emotional state (Safryghin et al. 2019). Regarding the relationship between the three parameters of self-evaluation and emotional responses, we argue that a human agent who is better off in driving safety performance would increase positive emotions and emotional arousal when self-relevance is low. A close referent performing superiorly in a largely irrelevant dimension would encourage reflection, enabling individuals to galvanize their self-esteem through basking-in-reflected glory. By contrast, a better-off human agent in driving safety would increase negative emotions and emotional arousal when self-relevance is high.

Regarding the relationship between emotional responses and subsequent driving safety performance, we argue that emotional valence and arousal affect individuals' following driving behaviors. Past research examining emotions has demonstrated emotional arousal and valence's impact on performance improvement. For instance, in a study examining the emotional effects of social comparison in sports, Diel et al. (2021a) found that upward comparison between athletes could arouse strong negative emotions, which boosted their motivation and subsequent sports performance. By contrast, when the downward comparison is performed, positive and strong emotions could be produced, which hindered athletes' motivation to improve subsequent performance. Collectively, we postulate the following:

H5A: The effects of referent performance, referent type, and relevance to the self on driving safety are mediated by emotional arousal.

H5B: The effects of referent performance, referent type, and relevance to the self on driving safety are mediated by emotional valence.

Research Method

Experimental Design

An experiment with a 2 (referent performance, worse-off referent versus better-off referent) × 2 (agent type, human agent versus artificial agent) × 2 (relevance to the self, low self-relevance versus high self-relevance) between-subjects factorial design was conducted. Referent performance in the experiment was manipulated through the relative performance of the comparer. In the worse-off referent condition, subjects were presented with a referent whose task performance was about 10% worse than their performance. In the better-off referent condition, the referent performance was about 10% better than the subject (Figure 2). Agent type was manipulated by varying between human and artificial referents (Figure 2). With a human referent, subjects were informed that another participant would perform the assigned task concurrently in another room. With an artificial referent, subjects were told that a new form of experimental artificial intelligence program would perform the assigned task concurrently. Following past research examining comparison relevance (O'Mahen et al. 2000), we considered subjects' perceived expertise in driving. To facilitate the manipulation of significance to the self, we applied a median split on perceived driving expertise to categorize subjects into low or high self-relevance groups.

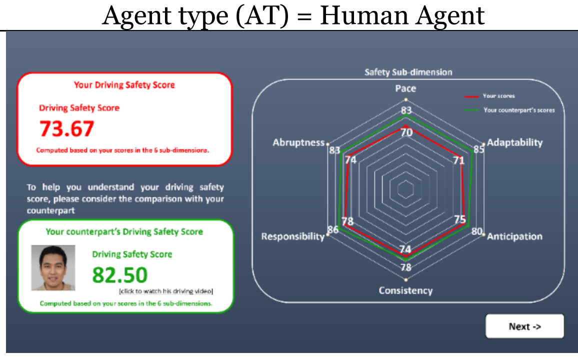
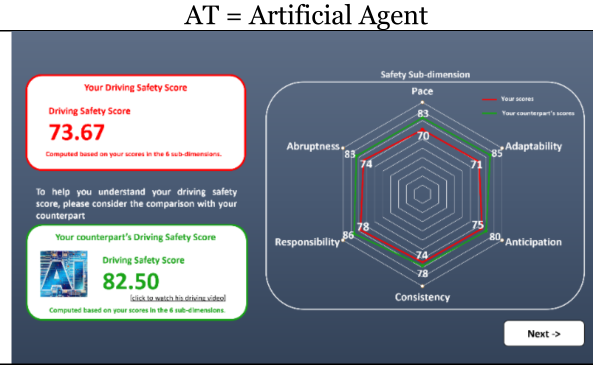
Comparison referent (CR) = Better-off Referent, Agent type (AT) = Human Agent	CR = Better-off Referent, AT = Artificial Agent
	

Figure 2. Manipulations

Note: To enhance subjects' perception of similarity with the human agent, the purported photo of the human agent was generated based on each subject's actual appearance (i.e., subjects' facial images are captured during GSR collaboration) using a photo anonymizer (https://generated.photos/anonymizer).

Sample and Experimental Procedures

Subjects in this experiment were customers of a major car rental company. Recruitment was facilitated by broadcasting a message to its members that contained a study registration link. One week before the experiment, they were instructed to complete a pre-study survey that captured their demographic information, driving experience, and perceived driving expertise. Additionally, customers' driving license age, weekly driving frequency, weekly driving time duration, and weekly driving distance were obtained from the company.

One hundred and eighty-three participants who did not participate in the pilot studies were recruited to participate in the experiment. They were randomly assigned to one of the eight experimental conditions

(Table 1). After arriving at the laboratory, a research assistant helped the subjects put on the galvanic skin response (GSR) sensor. Afterward, subjects were instructed to complete a filler task (i.e., ten simple arithmetic problems) to accommodate them with the sensor. After completing the filler task, they were asked to remain seated and relax for three minutes. Subjects were instructed to complete three rounds of the driving simulation (i.e., a familiarization drive, the first scenario drive, and the second scenario drive). The key objective of the familiarization drive was to get subjects accustomed to the driving simulation environment. In the two scenario drives, subjects were told to imagine a situation where they had to reach a destination for an essential appointment during the morning peak hour. After completing the first round of the driving simulation, subjects were informed that a counterpart (i.e., another human driver or an autonomous driving program) had concurrently completed the driving simulation. Subjects were then presented with visualizations depicting their driving safety performance and their counterparts. They were then asked to complete a survey that contained manipulation checks. Afterward, subjects were asked to complete the second driving simulation.

	Worse-off Referent	Better-off Referent
Human Agent		
Low Self-relevance	24	22
High Self-relevance	22	24
Artificial Agent		
Low Self-relevance	23	22
High Self-relevance	22	24

Table 1. Experimental Conditions

We utilized GSR to measure subjects' emotional arousal during performance evaluation. GSR measures emotional arousal by capturing levels of perspiration on the surface of the skin, indicating the intensity of emotional response to stimuli. To facilitate objective measures of subjects' emotional valence during performance evaluation, we employed automatic facial expression analysis (FEA) using computer vision. Following the general FEA practices, our analysis consists of three steps, namely (i) face detection, (ii) facial feature detection, and (iii) facial expression and emotion classification. Face detection is the process in which an algorithm is applied to detect a subject's face in a video frame. Facial feature detection is performed by detecting facial landmarks such as eyes, brows, mouth, and other facial features. Facial expression and emotion classification focus on matching the detected facial features with pre-established facial appearance databases.

Data Analysis

Subject Demographics

Among the 183 subjects, 95 were female, and the age of the subjects ranged from 31 to 55. No significant differences were found among subjects randomly assigned to the eight experimental conditions concerning age, gender, driving experience, driving license age, and trait self-esteem.

Measurement

Driving safety was computed based on the subjects' driving patterns in the simulation. We utilized the Symbolic Aggregate Approximation (SAX) method to translate a subject's simulation driving data (i.e., the recorded speed at every 0.1 seconds) into a single score (Chen et al. 2019). A higher score indicates better driving safety. Emotional arousal was operationalized through galvanic skin response data. Following the standard practice, we down-sampled the GSR time series data using the epoching pre-processing method. The processed data is used to compute electrodermal activity (EDA) peaks per minute and average peak amplitude. A higher EDA peak per minute indicates more frequent emotional arousal. Emotional valence was operationalized through facial expression analysis. Following past research examining facial expression (Kulke et al. 2020), we utilized the Affectiva Affdex algorithm to obtain real-time data for the seven basic emotion likelihoods (i.e., joy, anger, surprise, contempt, fear, sadness, and disgust) at 30 Hz. The basic emotion likelihoods were then used to compute the percentage of negative emotions.

The Direct Effect

The Main Effect of Referent Performance

Results of *t*-test results suggest that individuals in the better-off referent group (mean = 0.55, standard deviation = 0.13) showed a higher level of driving safety ($t = 3.16$, $p < 0.01$) than those in the worse-off referent group (mean = 0.42, standard deviation = 0.19). Therefore, H1 is supported.

The Two-Way Interaction Effect

ANOVA with driving safety as the dependent variable reveals the significant effects of referent performance ($F(1,183) = 8.06$, $p < 0.01$), agent type ($F(1,183) = 116.54$, $p < 0.01$), and relevance to the self ($F(1,183) = 12.63$, $p < 0.01$) (see Table 2). Results of the simple mean effect analyses suggest that (1) a better-off referent is associated with significantly greater driving safety (F(1,91 = 11.57, $p < 0.01$) than a worse-off referent under the artificial agent condition, and (2) a better-off referent is associated with significantly lower driving safety (F(1,92 = 98.12, $p < 0.01$) than a worse-off referent under the human agent condition (see Tables 2 and 3, Figure 3). Therefore, H2 is not supported.

Source	Type III sum of squares	df	Mean square	F	Sig.
RP	0.19	1	0.19	8.06	0.01
AT	2.72	1	2.72	116.54	0.00
RtS	0.30	1	0.30	12.63	0.00
RP × AT	1.58	1	1.58	67.72	0.00
RP × RtS	0.38	1	0.38	16.25	0.00
AT × RtS	0.27	1	0.27	11.40	0.00
RP × AT × RtS	0.75	1	0.75	31.95	0.00
Error	4.09	175	0.02		
Total	52.91	183			
AT = Human Agent					
RP	1.50	1	1.50	98.12	0.00
Error	1.38	90	0.02		
Total	10.89	92			
AT = Artificial Agent					
RP	0.43	1	0.43	11.57	0.00
Error	3.30	89	0.04		
Total	31.02	91			
RtS = Low					
RP	0.02	1	0.02	0.26	0.62
Error	5.74	89	0.06		
Total	23.53	91			
RtS = High					
RP	0.58	1	0.58	14.88	0.00
Error	3.52	90	0.04		
Total	29.38	92			

Table 2. ANOVA Results and Analysis of Simple Mean Effects

Notes. The dependent variable driving safety; RP, referent performance; AT, agent type; RtS, relevance to the self.

	Human Agent	Artificial Agent	Mean
Worse-off	0.42	0.48	0.45
Better-off	0.30	0.73	0.52
Mean	0.36	0.60	

Table 3. Mean Values of Driving Safety

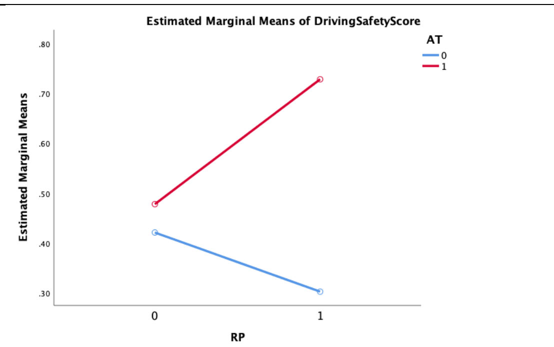


Figure 3. Mean Plot of Driving Safety

The interaction between referent performance and relevance to the self on driving safety is also significant (F(1,183) = 16.25, $p < 0.01$). Results of the simple mean effect analyses suggest that (1) a better-off referent is associated with significantly greater driving safety (F(1,92) = 14.88, $p < 0.01$) than a worse-off referent under the high self-relevance condition, and (2) a better-off referent and a worse-off referent are not different from each other in affecting driving safety (F(1,91) = 0.26, $p = 0.62$) under the low self-relevance condition (see Tables 2 and 4, Figure 4). Therefore, H3 is supported.

	Low Self-Relevance	High Self-Relevance	Mean
Worse-off	0.46	0.44	0.45
Better-off	0.43	0.60	0.52
Mean	0.44	0.52	

Table 4. Mean Values of Driving Safety

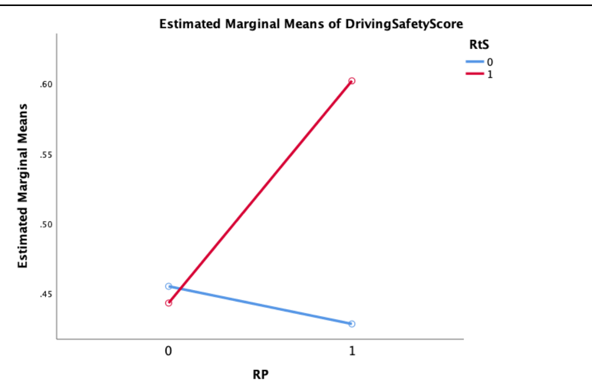


Figure 4. Mean Plot of Driving Safety

The Three-Way Interaction Effect

A significant three-way interaction of referent performance, agent type, and relevance to the self-influences driving safety (F(1,183) = 31.95, $p < 0.01$) (see Table 2). Using simple effect tests, we explore the nature of this interaction and find, in particular, that the two-way interaction between referent performance and agent type has a significant effect on driving safety under the low self-relevance condition (F(1,91) = 148.77, $p < 0.01$) and a significant impact under the high self-relevance condition (F(1,92) = 3.47, $p < 0.05$) (see Table 5). Mean comparisons (see Table 6, Figures 5 and 6) show that with low relevance to the self, a better-off human agent leads to less driving safety than a worse-off human agent. However, a better-off artificial agent leads to higher driving safety than a worse-off artificial agent. With high relevance to the self, a better-off agent improves driving safety regardless of a human or artificial agent. However, the improvement is more pronounced with an artificial than a human agent. These findings partially support the interaction effect hypothesized in H4.

Source	Type III sum of squares	df	Mean square	F	Sig.
RtS = Low					
RP	0.02	1	0.02	1.10	0.30
AT	2.33	1	2.33	155.05	0.00
RP × AT	2.24	1	2.24	148.77	0.00
Error	1.31	87	0.02		
Total	23.53	91			
RtS = High					
RP	0.56	1	0.56	17.56	0.00
AT	0.65	1	0.65	20.47	0.00
RP × AT	0.08	1	0.08	3.47	0.04
Error	2.78	88	0.03		
Total	29.38	92			

Table 5. Simple Effect Tests

Notes. The dependent variable driving safety; RP, referent performance; AT, agent type; RtS, relevance to the self.

RtS = Low			
	Human Agent	Artificial Agent	Mean
Worse-off	0.45	0.46	0.46
Better-off	0.11	0.75	0.43
Mean	0.28	0.61	
RtS = High			
	Human Agent	Artificial Agent	Mean
Worse-off	0.39	0.50	0.45
Better-off	0.49	0.71	0.60
Mean	0.44	0.61	

Table 6. Mean Values of Driving Safety

Notes. RtS, relevance to the self

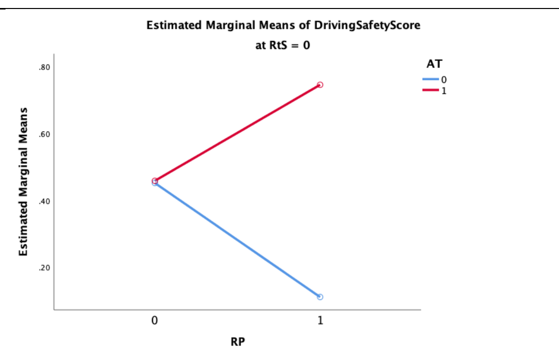


Figure 5. Mean Plot of Driving Safety

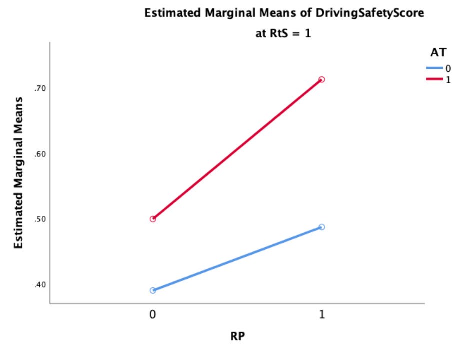


Figure 6. Mean Plot of Driving Safety

The Mediated Effect

We posit that the effects of self-evaluation on driving safety are mediated by emotional arousal and valence. We utilized the procedure proposed by Preacher and Hayes (2004) to test the hypothesized mediation effects. Results suggest that the impact of the independent variables (i.e., referent performance, agent type, and relevance to the self) on the mediators are significant. Furthermore, emotional arousal and emotional valence significantly mediate the direct effects. Therefore, H5a and H5b are supported.

Driving Efficiency Score					
The indirect effect of CR at conditions of AT and RtS via EA					
AT	RtS	β	BootSE	LL	UL
= human	= low	0.01	0.01	-0.01	0.12
	= high	0.11	0.05	0.02	0.22
AT	RtS	β	BootSE	LL	UL
= artificial	= low	0.12	0.07	0.03	0.21
	= high	0.25	0.09	0.12	0.35
Indirect effect of CR at conditions of AT and RtS via EV					
AT	RtS	β	BootSE	LL	UL
= human	= low	0.08	0.05	0.06	0.14
	= high	0.21	0.10	0.11	0.30
AT	RtS	β	BootSE	LL	UL
= artificial	= low	0.05	0.02	0.01	0.05
	= high	0.34	0.09	0.15	0.48

Table 7. Mediated Results

Discussion of Results

Our results largely supported our hypotheses. First, consistent with our expectation, a better-off referent led to better driving safety than a worse-off referent. We also argued that the effects of comparative referent interacted with agent types in influencing safe driving behaviors. Additionally, we posited that the impact of comparative referent interacted with relevance to the self in affecting driving safety performance. Our results illustrated that the better-off referent promoted driving safety more than, the worse-off referent with high self-relevance. The effects of better-off referent on driving safety were less pronounced with low self-relevance. Additionally, we observed that emotional arousal and valence mediated the impact of self-evaluation on driving safety performance. As hypothesized, referent performance, agent type, and relevance to the self jointly affect individuals' emotional arousal and valence in performance comparison, influencing their subsequent driving safety practices.

We postulate that the motivating effect of a better-off referent on driving safety is more robust with a human agent than with an artificial agent. Contrary to our expectations, our results show that a better-off artificial agent leads to better driving safety scores than a worse-off artificial agent. In comparison, a better-off human agent leads to worse driving safety than a worse-off human agent. Our interpretation is that while artificial agents are expected to have limited interpersonal similarity with individuals compared with human agents, individuals' relative inferiority against non-human comparers might be especially powerful in activating their competitive mindset. Consequently, individuals become enormously motivated to improve their driving safety performance. The unexpected impact of a better-off human agent on reducing driving safety performance is potentially caused by a lack of concrete relationships between individuals and the purported human referent. Consequently, in responding to being outperformed by the human agent, individuals might be able to dissociate themselves from the stranger and assume basketing-in-reflected-glory.

We hypothesized that a better-off human agent would lead to greater driving safety when self-relevance is high. However, the effect on driving safety is not as prominent with low self-relevance. Our results show that, as expected, with low self-relevance, there is no difference between a human referent and an artificial referent in influencing driving safety. Contrary to our expectations, our results show that with high self-relevance, when a human agent outperforms, they would obtain less driving safety than being outperformed by an artificial agent. A plausible explanation is that being outperformed by a non-human referent might trigger individuals' perception of a threat to their self-concept and incite anxiety toward artificial intelligence. Past IS research has considered individuals' resistance to information technology (IT) as an IT identity threat, about individuals' anticipation of harm to their self-beliefs caused by using IT (Craig et al. 2019). Similarly, individuals who take pride in their driving abilities can become especially safety antagonized for being outperformed by an artificial agent in driving.

Limitations and Future Directions

There are several limitations that readers should take note of. This study examines driving safety using a driving simulator. While the simulation environment facilitates fine-grained monitoring of emotional responses and capturing of driving performance, the driver simulator might need to be able to provide a driving experience fully equivalent to that in the actual environment. In addition, despite our best efforts to familiarize subjects with the driving simulator, some people might typically drive on a specific route and find the novel way in the driving simulation somewhat challenging. Furthermore, this study focuses on understanding the driving behaviors of typical drivers. Vocational drivers may have vastly different driving experiences and possess additional skills in operating vehicles and responding to impromptu traffic conditions.

Theoretical and Practical Implications

This paper contributes to the IS literature by illustrating the effects of human-human and human-computer interactions on behaviors. Past human-computer interaction research has focused on the collaborative aspect of human-machine interaction. While individuals are predominately experienced with utilizing computers to automate routine tasks and augment their performance of complex tasks, they might need to gain more experience interacting with intelligent machines. This study thus makes an essential contribution to the IS literature by revealing how competition between computers and humans can be utilized to promote desirable behaviors. Specifically, being outperformed by an artificial agent can powerfully motivate individuals to improve subsequent driving safety, especially when they deem driving competence an essential dimension of their self-concept. We believe self-evaluation against artificial agents can apply beyond the driving safety context, especially when performance evaluation can be central to individuals' self-esteem.

Additionally, while the self-evaluation literature suggests that emotional responses can be critical to underlying the effects of self-evaluation on subsequent behaviors, this study presents a novel empirical strategy to verify the proposed lo. Specifically, we utilize physiological measures to capture both emotional valence and arousal during self-evaluation. Our findings complement past self-evaluation research examining emotional responses. More importantly, it contributes to the behavior change literature by illustrating a fine-grained perspective on the underlying psychology of self-evaluation.

We also provide fresh insights into the importance of referent closeness in self-evaluation. While past research has focused on the interpersonal comparison, self-evaluation about a non-human comparer has yet to be examined. The apparent dissimilarity between humans and computers is expected to inhibit the formulation of psychological closeness between individuals and computers in performance comparison. Our findings show that being outperformed by an artificial agent could powerfully arouse strong negative emotions among individuals, above and beyond the negative arousal incited by a superior human referent. To this end, we illustrate a boundary condition of the theory in which the extant conceptualization of referent closeness might need reinterpretation.

This study uncovers a new way to understand human-machine interactions through the self-evaluation of artificial agents. Specifically, we found that superior performance by an artificial agent promotes subsequent driving safety among individuals who perceived high driving competence. Hence, we recommend that driving safety training consider artificial co-actors in designing training materials. Furthermore, the effect of artificial agents on promoting performance improvement can be applied in contexts beyond driving safety, such as compliance training and self-regulation interventions. For instance, AI systems can be used as "artificial co-workers" to support and, more importantly, augment human performance. Companies need to provide training and support to help employees understand how the AI systems work and how they will impact their jobs, triggering employees' competitive mindset. Furthermore, companies should regularly evaluate the impact of the AI system's performance on employees' performance to ensure that it delivers the desired results.

Conclusion

This study examines the effects of human-human and human-computer comparison on promoting driving safety. Our results show that better-off referent increases driving safety. We also offer the interaction between referent performance and agent type and between referent performance and relevance to the self on driving safety. Additionally, we reveal the three-way interaction between referent performance, agent type, and relevance to the self on driving safety. This study also provides the underlying mechanics of the impact of self-evaluation on performance improvement.

Acknowledgements

This research is supported by the Social Science & Humanities Research (SSHR) 2025 Seed Grant (award no: 022536-00001).

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