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Original Articles

Effects of Using Artificial Intelligence on Interpersonal Perceptions of Job Applicants

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Abstract

Text-based artificial intelligence (AI) systems are increasingly integrated into a host of interpersonal domains. Although decision-making and person perception in hiring and employment opportunities have been an area of psychological interest for many years, only recently have scholars begun to investigate the role that AI plays in this context. To better understand the impact of AI in employment-related contexts, we conducted two experiments investigating how the use of AI by applicants influences their job opportunities. In our preregistered Study 1, we examined how a prospective job applicants' use of AI, as well as their language status (native English speaker or non-native English speaker), influenced participants' impressions of their warmth, competence, social attractiveness, and hiring desirability. In Study 2, we examined how receiving assistance impacted interpersonal perceptions, and how perceptions might change whether the help was provided by AI or by another human. The results from both experiments suggest that the use of AI technologies can negatively influence perceptions of jobseekers. This negative impact may be grounded in the perception of receiving *any* type of help, whether it be from a machine or a person. These studies provide additional evidence for the Computers as Social Actors framework and advance our understanding of AI-Mediated Communication. The results also raise questions about transparency and deception related to AI use in interpersonal contexts.

Keywords: AI-mediated communication, interpersonal perception, hiring, language status

Introduction

With the advance of artificial intelligence (AI) and its use in human-to-human interaction, technology is shifting from a passive mediator of human communication to a more agentic role. The phenomenon in which AI augments or even generates content to achieve interpersonal goals has been referred to as AI-mediated communication (AI-MC).[1] For example, AI systems provide suggestions for our messages and online profiles, make calls on our behalf, and create believable fake videos.[2] Text-based AI systems in particular are already increasingly integrated into a host of interpersonal domains.

A recent report suggests that 12 percent of Gmail users incorporate AI-generated language into their own messages,[3] meaning over 36 billion messages may contain AI-generated language on a daily basis. As algorithms for natural language generation improve,[4] AI technologies will be able to create online profiles without the individual's input, or even generate messages in synchronous communications.[5] How will AI's role in human communication influence interpersonal relationships?

AI in employment contexts

Although decision-making and person perception in hiring have been an area of psychological interest for decades (e.g. Bertrand and Mullainathan[6] and Branscombe and Smith[7]), the role that AI plays in this context is not well understood. Most of the attention has been focused on how algorithmic biases impact job candidates' prospects,[8] so to better understand the impact of AI in employment-related contexts, it is also necessary to examine the other side of the relationship: how the use of AI by the applicants influences their job opportunities.

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In addition, technical improvements in machine translation mean that opportunities that were once inaccessible to non-native English speakers are now more widely available. However, non-native English speakers have faced xenophobia in hiring because of their nationality, accent, or English fluency levels in writing or speaking (e.g. Timming[9]), possibly due to the formation of negative impressions.[10]

Warmth and competence are typically regarded as two of the most important and predictive dimensions for decision-making and impression formation. Judgments about a person's warmth and competence are made extremely quickly (often within 100 milliseconds).[11] Impressions of warmth help determine if the person is a friend or a foe (e.g., whether they would be a compassionate coworker or not), whereas impressions of competence help people make judgments about whether or not a person can act on their intentions (e.g., whether they could complete their job duties).[12] Some employers may also be interested in social attractiveness—or how personable an applicant may be.[13] Recruiters and employers often rely on minimal cues to make decisions about applicants, so first impressions may have an outsized influence on employment choices.

Study 1

In our preregistered Study 1, we examined how a prospective job applicant's use of AI, as well as their language status, influenced a participants' impressions of the job applicant's warmth, competence, social attractiveness, and hiring desirability. Past work on perceptions of non-native English speakers suggest they will face discriminatory attitudes from employers,[9,14] and thus we predict:

H1: Candidates who speak English as a second language (non-native) will be rated as less competent, less socially desirable, and will be less likely to be hired than L1 (native) English speakers.

Furthermore, we anticipated that candidates who were perceived to have used AI technologies would be viewed more negatively and show a preference toward content generated by humans.[15,16]

H2: Candidates who use AI technology to revise their applications will be rated as less competent, less socially desirable, and less likely to be hired than those who do not use AI technology.

However, we predicted that native English speakers would be viewed more favorably regardless of their AI use due to discriminatory attitudes toward non-native English speakers.

H3: There will be an interaction effect between technology use and language status so that L1 English speakers (native) will receive more favorable ratings across technology-use conditions.

Methods

Full details of the protocol can be found at this link: https://bit.ly/2V4d7mW. These studies received IRB approval on October 2019 (IRB #: 51574).

Participants

After conducting an *a priori* power analysis (expected effect size = 0.25, $\alpha = 0.05$, power = 0.80) indicating a required sample size of 196, we recruited participants within the United States who spoke English from Amazon Mechanical Turk for our 10-minute study. Participants were compensated with $1.25. We had 244 participants in our final sample (36.1 percent female; 80.3 percent white, $M_{\mathrm{age}} = 40.93$, standard deviation $(SD)_{\mathrm{age}} = 12.84$).

Procedure

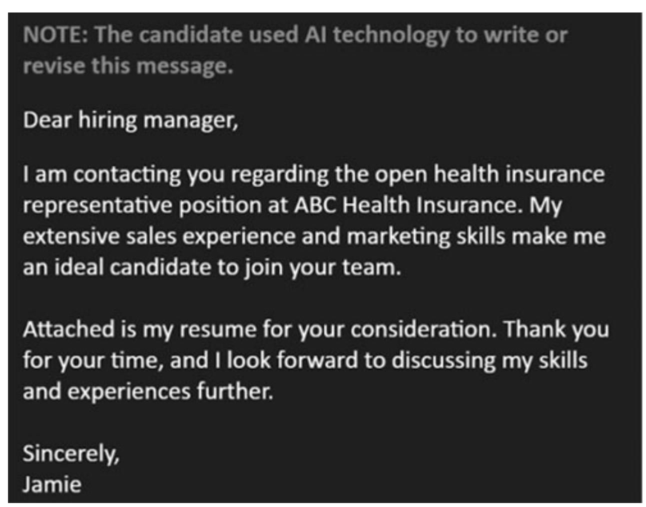
If participants indicated their agreement with our consent form, they proceeded to the rest of the questionnaire. In our 2 (AI use) × 2 (language status) between-subjects design, participants were randomly assigned to read a fictional candidate profile and application e-mail from one of four conditions: non-native English speaker who used AI, non-native English speaker who did not use AI, native English speaker who used AI, and native English speaker who did not use AI. In the AI conditions, a note at the top of the e-mail read ''Note: This candidate used AI technology to write or revise this message'' in bold orange font (Fig. 1).

The candidate profiles of native English speakers included ''Language: English (native), [other language],'' whereas the candidate profiles of non-native English speakers included ''Language: [other language] (native), English.'' The ''other language'' was randomly selected from Chinese, French, Spanish, Russian, or German so that all participants read applications from bilingual candidates. All candidates were named ''Jamie,'' which is typically perceived to be both a male and female name[17] to avoid gender-based bias in responses.

Measures

Warmth and competence. We asked participants to rate how warm or competent[18] their partner was on a 5-point scale anchored by 1 (not at all) to 5 (extremely). Overall, participants perceived applicants to be moderately warm ($\alpha = 0.89$, $M = 3.34$, $SD = 0.73$) and competent ($\alpha = 0.90$, $M = 3.58$, $SD = 0.80$).

Social attraction. Participants completed the social attraction scale.[13] Response options were anchored by 1 (not at


NOTE: The candidate used AI technology to write or revise this message.

Dear hiring manager,

I am contacting you regarding the open health insurance representative position at ABC Health Insurance. My extensive sales experience and marketing skills make me an ideal candidate to join your team.

Attached is my resume for your consideration. Thank you for your time, and I look forward to discussing my skills and experiences further.

Sincerely,
Jamie

FIG. 1. E-mail screenshot shown to participants in the ''With AI'' conditions in Study 1. AI, artificial intelligence.

all) and 5 (extremely). Overall, participants felt the social attraction statements represented their attitudes toward their partner moderately well ($\alpha = 0.90$, $M = 3.15$, $SD = 0.86$).

Hiring intention. We asked participants ''How likely would you be to take the following actions, after reading Jamie's application?'' with three actions: invite Jamie for an interview, recommending Jamie for the job, and hiring Jamie. Overall, participants expressed a moderate intention to hire them ($\alpha = 0.90$, $M = 3.32$, $SD = 0.93$).

Results

We conducted a two-way multivariate analysis of variance (MANOVA) with perceived warmth, perceived competence, hiring intention, and social attraction as the dependent variables (Figs. 2–5).We did not find support for H1, as the effects of language status [Wilk's $\Lambda = 0.99$, $F(4, 240) = 1.27$, *n.s.*, $\eta^2 p = 0.02$] was not significant for all dependent variables. However, the results suggested that there was a significant effect of AI, supporting H2 [Wilk's $\Lambda = 0.93$, $F(4, 240) = 4.56$, $p < 0.1$, $\eta^2 p = 0.07$]. When candidates used an AI tool, participants rated these candidates significantly less warm [$F(1, 243) = 10.34$, $p < 0.01$, $\eta^2 p = 0.04$], less competent [$F(1, 243) = 5.47$, $p < 0.05$, $\eta^2 p = 0.02$], less socially attractive [$F(1, 243) = 6.26$, $p < 0.05$, $\eta^2 p = 0.03$] with a lesser intention to hire them [$F(1, 243) = 14.92$, $p < 0.001$, $\eta^2 p = 0.06$], compared with the candidates who did not use an AI tool.

Furthermore, interactions between language status and AI [Wilk's $\Lambda = 0.99$, $F(4, 240) = 0.90$, *n.s.*, $\eta^2 p = 0.02$] were not significant for all dependent variables that did not support H3. Finally, there were no significant differences between Chinese, French, Spanish, Russian, or German-speaking candidate profiles.

Discussion

The results of Study 1 suggest that, in line with H2 and conclusions from past work,[15,16] jobseekers who used AI in their application e-mail receive less favorable impressions and behavioral intentions. However, we did not find evidence for H1 or H3, regarding less favorable impressions of nonnative English speakers. As such, past work on discriminatory hiring attitudes based on language status[9,14] was not corroborated. Overall, Study 1 indicates that receiving application assistance from AI may negatively affect perceptions of job applicants, regardless of their native language.

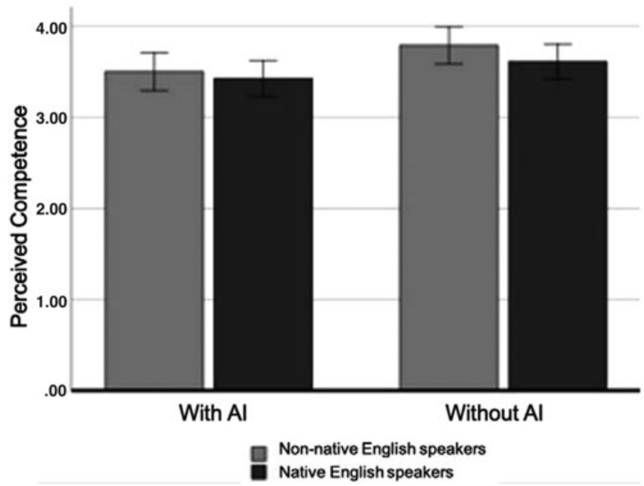


FIG. 3. Effect of AI and language status on mean perceived competence (SE) in Study 1.

Study 2

It is still unclear whether application assistance from AI would be viewed differently than assistance received from another human. During the job application process, many prospective employees enlist human proofreading services to improve their resumes, cover letters, as well as other job materials. Similarly, there are a number of AI systems that could provide language suggestions or modifications for job applicants.

In Study 2, we are interested in how interpersonal perceptions might change depending on whether the help was provided by AI or by another human. The Computers as Social Agents (CASA) framework argues that people automatically respond to social cues from machines.[19] For example, people attribute personality traits to computers and believe that gender stereotypes apply to computers.[20] Furthermore,

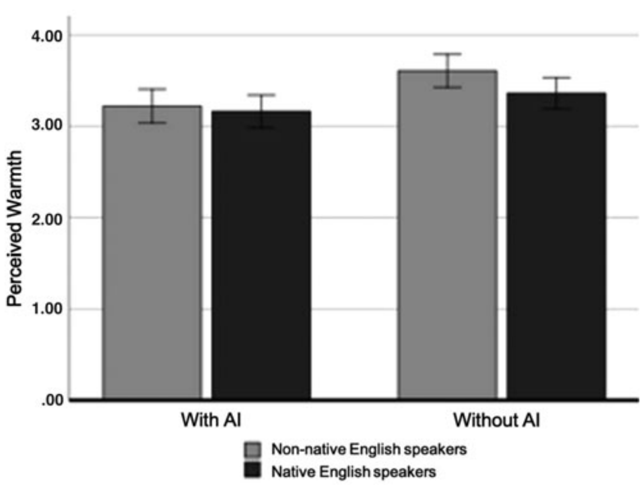


FIG. 2. Effect of AI and language status on mean perceived warmth (SE) in Study 1. SE, standard error.

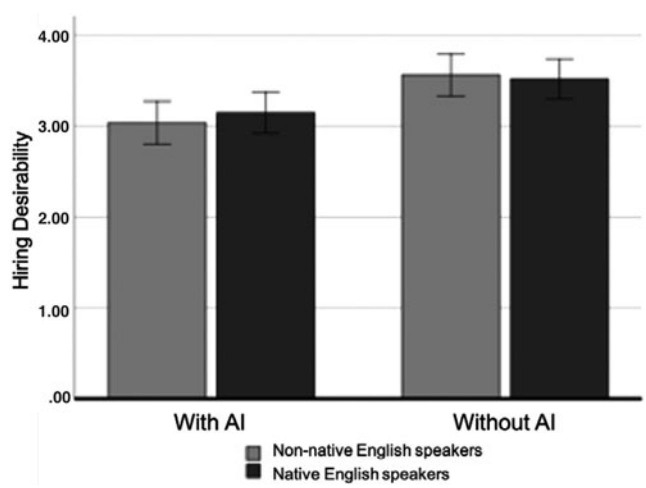


FIG. 4. Effect of AI and language status on mean hiring desirability (SE) in Study 1.

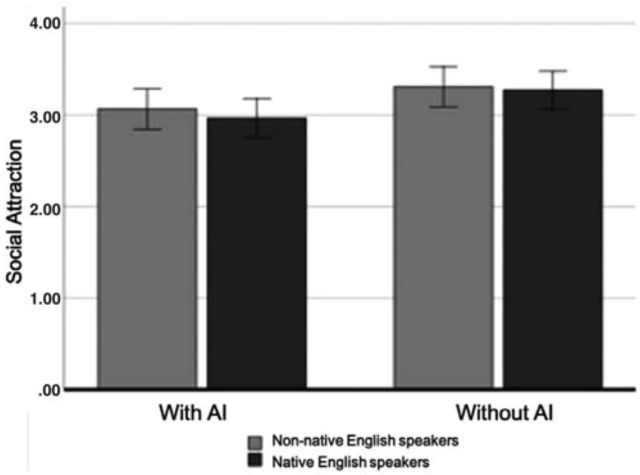


FIG. 5. Effect of AI and language status on mean social attractiveness (SE) in Study 1.

Nass and Moon[21] state that ''the more computers present characteristics… associated with humans, the more likely they are to elicit social behavior.'' For example, people communicate reciprocally to computers when they disclose information.[22]

In the context of this framework, *any* assistance in a job application, by AI or by humans, would be perceived negatively because the applicant could not complete the task by themselves. Thus, participants would rate applicants receiving AI *or* human assistance as less warmth, competent, and socially attractive, with a lesser desire to hire them, as compared with an applicant who received no assistance.

Yet another study suggests that AI tends to be viewed as more ''objective'' than humans.[23] This area of research suggests that perceptions of objectivity tend to be correlated with perceptions of other characteristics, such as accuracy. These ideas about AI may lead to more positive ratings for applicants using it. Thus, participants would rate applicants receiving AI assistance as more warm, competent, and socially attractive, with a greater desire to hire them, as compared with an applicant who received human assistance.

To better understand the mechanisms underlying our findings in Study 1, in Study 2 we asked:

RQ1: How will application assistance from AI, as compared with a human, influence perceptions of warmth, competence, social attraction, and hiring intentions?

Methods

Participants

After conducting an *a priori* power analysis (expected effect size = 0.25, $\alpha = 0.05$, power = 0.80) indicating a required sample size of 246, we recruited participants within the United States that spoke English from Amazon Mechanical Turk for our 4-minute study. Participants were compensated for \$0.50. In total, we had 261 participants in our final sample (46.6 percent female; 81.8 percent white, $M_{age} = 41.49$, $SD_{age} = 11.92$).


Note: The candidate received help from a friend to write or revise this email.

Dear hiring manager,

I am contacting you regarding the open health insurance representative position at ABC Health Insurance. My extensive sales experience and marketing skills make me an ideal candidate to join your team.

Attached is my resume for your consideration. Thank you for your time, and I look forward to discussing my skills and experiences further.

Sincerely,
Jamie

FIG. 6. E-mail screenshot shown to participants in the human application assistance condition in Study 2.

Procedure

The instructions, consent, and debriefing protocol were the same as Study 1. In our between-subjects design, participants were randomly assigned to read a fictional application from one of three conditions: no application assistance (control), AI application assistance, and human application assistance. In the condition in which the job applicant received AI assistance, a note at the top of the e-mail read ''Note: This candidate used AI technology to write or revise this message'' in bold colored font (Fig. 1). When the applicant received human assistance, the note read ''NOTE. The candidate received help from a friend to write or revise this email'' (Fig. 6). In the control condition, there were no additional notes. As in Study 1, the applicant was named Jamie.

Measures

We used the same measures described in Study 1. On average, participants perceived applicants to be moderately warm ($\alpha = 0.90$, $M = 3.29$, $SD = 0.76$) and competent ($\alpha = 0.91$, $M = 3.39$, $SD = 0.85$), somewhat socially attractive ($\alpha = 0.94$, $M = 2.94$, $SD = 0.91$) and had a moderate intention to hire them ($\alpha = 0.91$, $M = 3.05$, $SD = 0.97$).

TABLE 1. MEANS AND STANDARD DEVIATIONS OF VARIABLES IN STUDY 2

	Condition	*Mean*	*SD*
Perceived warmth	AI	3.09	0.72
	Human	3.32	0.68
	Control	3.47	0.82
Perceived competence	AI	3.34	0.77
	Human	3.15	0.83
	Control	3.67	0.87
Hiring desirability	AI	2.85	0.99
	Human	2.92	0.95
	Control	3.38	0.90
Social attraction	AI	2.64	0.90
	Human	2.96	0.91
	Control	3.19	0.85

Note: For each condition, $n = 87$ participants.
AI, artificial intelligence; SD, standard deviation.

Results

We conducted a one-way MANOVA with perceived warmth, perceived competence, hiring intention, and social attraction as the dependent variables (Table 1). The results indicated that there were significant effects for all four dependent variables: perceived warmth [$F(2, 261) = 5.59$, $p < 0.01$], perceived competence [$F(2, 261) = 7.80$, $p < 0.01$], hiring intention [$F(2, 261) = 7.93$, $p < 0.001$], and social attraction [$F(2, 261) = 8.31$, $p < 0.001$]. To answer RQ1, we conducted *post hoc* tests.

When candidates used an AI tool (mean $M = 3.09$, standard error $SE = 0.08$), they were rated significantly less warm than the candidates in the human condition [$M = 3.32$, $SE = 0.07$, $t(174) = -2.26$, $p < 0.05$] and the candidates in the control condition [$M = 3.47$, $SE = 0.09$, $t(174) = -3.19$, $p < 0.01$]. The difference between the candidates in the human condition and the candidates in the control condition was not significant. For perceived competence, compared with the candidates in the control condition ($M = 3.67$, $SE = 0.09$), candidates who used an AI tool [$M = 3.34$, $SE = 0.08$, $t(174) = -2.60$, $p < 0.01$] and candidates who asked a friend to help [$M = 3.15$, $SE = 0.09$, $t(174) = -3.76$, $p < 0.001$] both were rated significantly less competent than in the control condition, whereas the difference between the AI condition and the human condition was not significant.

For social attraction, candidates who used an AI tool ($M = 2.64$, $SE = 0.10$) were rated significantly less socially attractive than the candidates who asked a friend to help [$M = 2.96$, $SE = 0.10$, $t(174) = -2.44$, $p < 0.05$] and the candidates in the control condition [$M = 3.19$, $SE = 0.10$, $t(174) = -4.12$, $p < 0.001$], whereas there was no difference between the human condition and the control condition. Finally, compared with the candidates in the control condition ($M = 3.38$, $SE = 0.10$), candidates who used an AI tool [$M = 2.85$, $SE = 0.10$, $t(174) = -3.73$, $p < 0.001$] and candidates who asked a friend to help [$M = 2.92$, $SE = 0.10$, $t(174) = -3.17$, $p < 0.01$] received lower ratings on hiring intentions. The difference between the AI condition and the human condition was not significant.

General Discussion

We examined how language status and use of AI technologies in communication between people, or AI-MC, influenced perceptions of key dimensions of impression formation, warmth and competence, as well as social attraction and hiring intentions in our first study. Although there was no evidence to suggest an effect of language status, we found that applicants who used AI in their application e-mail were viewed as less warm, competent, socially attractive, and received lower ratings on hiring intentions. Our findings from Study 1 corroborate past work where participants indicate a preference for human-generated content as opposed to AI-generated content,[15] and expand the effect to the realm of job seeking.

To understand the mechanism underlying this apparent preference for human-generated content, in Study 2 we examined how perceptions of assistance depended on whether the help was AI or human. Our findings present additional support for the CASA framework, or that people think and act toward AI much like they do to people.[19] Compared with a control condition where the applicant received no assistance, applicants in both the AI assistance and human assistance conditions received less favorable impressions of competence, social attraction, and hiring intentions, but not warmth.

Together, our research suggests that integrating AI into interpersonal communication has the potential to negatively influence perceptions of job seekers. This negative impact is likely grounded in receiving *any* type of help, whether it be from a machine or a person. In Study 1, we did not find evidence of negative attitudes toward non-native English speakers, underscoring the relatively powerful influence of AI on impression formation in a job application context. Furthermore, in Study 2, although AI assistance and human assistance lead to lower ratings of competence, social attraction, and hiring intentions, the same pattern did not hold for perceptions of warmth.

Only applicants in the AI assistance condition received less favorable warmth ratings, suggesting that the participants might have viewed AI as colder or more ''objective''[23] than humans providing assistance. The ''uncanny valley,'' or entities ''that appear or behave not quite human''[24] receiving lower impressions of warmth, may explain this effect. Understanding the boundaries of this effect in text-based AI is a relevant area for future study.

Our findings also raise important questions about transparency and deception related to AI use in interpersonal contexts. For instance, if an employer's decision hinges on whether or not an applicant received assistance, then the applicant may choose not to be forthcoming about their use of AI due to the potential for unfavorable outcomes. As such, it is important that we understand its effects of AI-MC on social cognition and associated ethical implications.

Limitations

Our studies have several important limitations. First, we chose a fictional job applicant name that was not primarily associated with any gender. However, we did not measure perceptions of the applicant's masculinity or femininity. Since there has been a great deal of research on sexism in employment contexts, applying this study to an AI-MC context in the future could provide novel insights into the role of AI in gender biases.

Second, there are a number of AI systems that purport to write resumes for job applicants (e.g., Skillroads.com or Rezi.io) and there is increasing evidence that the integration of AI systems into media can increase uncertainty and decrease trust.[25] However, employers are not notified of AI use on behalf of the sender, although this may change under new legislation (e.g., California Senate Bill 1001). As such, our results from these two laboratory experiments require further replication in contexts with increased ecological validity.

Finally, these samples of participants from Amazon Mechanical Turk may not sufficiently represent diverse experiences with AI, particularly in the case of nonwhite participants. To fully understand perceptions and downstream effects of AI-MC, our future research will emphasize findings from a variety of demographic backgrounds.

Conclusion

The results of two experiments suggest that using AI in a job application may increase negative perspectives of the applicant, but not more than if they received assistance from a human. In addition to providing additional evidence for CASA and expanding the effects of AI-MC into an employment context, our study raises key questions for the future of AI in interpersonal communication and its effects on trustworthiness, deception, and ethical considerations.

Authors' Contributions

D.W. helped with theoretical framing, experimental design, preregistration, and writing. S.X.L. helped with theoretical framing, experimental design, preregistration, data analysis, and writing. H.M. helped with theoretical framing, experimental design, and writing. J.T.H. helped with theoretical framing, experimental design, and writing.

Author Disclosure Statement

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