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No Person Is an Island: Unpacking the Work and After-Work Consequences of Interacting With Artificial Intelligence

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The artificial intelligence (AI) revolution has arrived, as AI systems are increasingly being integrated across organizational functions into the work lives of employees. This coupling of employees and machines fundamentally alters the work-related interactions to which employees are accustomed, as employees find themselves increasingly interacting with, and relying on, AI systems instead of human coworkers. This increased coupling of employees and AI portends a shift toward more of an "asocial system," wherein people may feel socially disconnected at work. Drawing upon the social affiliation model, we develop a model delineating both adaptive and maladaptive consequences of this situation. Specifically, we theorize that the more employees interact with AI in the pursuit of work goals, the more they experience a need for social affiliation (adaptive)—which may contribute to more helping behavior toward coworkers at work—as well as a feeling of loneliness (maladaptive), which then further impair employee well-being after work (i.e., more insomnia and alcohol consumption). In addition, we submit that these effects should be especially pronounced among employees with higher levels of attachment anxiety. Results across *four* studies ($N = 794$) with mixed methodologies (i.e., survey study, field experiment, and simulation study; Studies 1–4) with employees from four different regions (i.e., Taiwan, Indonesia, United States, and Malaysia) generally support our hypotheses.

Keywords: artificial intelligence, need for affiliation, loneliness, attachment anxiety, social affiliation model

In the 2009 movie Surrogates, a revolution in artificial intelligence (AI) has transformed work. In this future, people accomplish their daily work tasks by interacting with AI systems that have largely eliminated direct interpersonal contact with people. Yet, the protagonist, Bruce Willis, finds these interactions empty and unfulfilling. The movie's climax occurs when he abandons his AI system to seek out a direct social connection with others. This movie depicts a sensationalized example of which is becoming a commonplace workplace phenomenon—that many work interactions are not with human coworkers but rather with AI systems that give advice, make decisions, and increasingly are employees' primary collaborators in the pursuit of work goals (e.g., Kellogg et al., 2020; Meister, 2019; Wilson & Daugherty, 2018)—indeed, Oracle estimates half of the employees already utilize AI in some form on a daily basis (Oracle, 2019), and McKinsey Global Institute expects that the augmentation of organizational functions such as marketing, sales, and manufacturing may generate $2 trillion in value over 20 years (The Economist, 2018).

This coupling creates a phenomenon captured poignantly by Bruce Willis' character, as the incorporation of AI systems alters the work interactions to which employees are accustomed (Chitty, 2018; Miller, 2019; Raisch & Krakowski, 2021). For example, where employees may once have consulted with a coworker to get a second opinion on a decision or obtain additional information, AI can (much more efficiently) perform these tasks (Davenport & Kirby, 2016). Yet, AI systems, in contrast to those coworkers, are deficient in terms of providing an engaging and socially rich user-experience (Mühlhoff, 2020; Tizhoosh & Pantanowitz, 2018). We posit that this may be problematic because interacting with AI may (similarly as interacting with human coworkers) activate primitive processes within people that have evolved to monitor the nature and quality of social interactions with others (Leary & Baumeister, 2000; Sussman et al., 2005).

We draw in particular from O'Connor and Rosenblood (1996), who describe these processes as an evolutionary imperative (a "social drive" in their words; p. 531) that motivates people to action when deprived of social affiliation. This drive is viewed as operating via a regulatory mechanism (e.g., Johnson et al., 2006) that is sensitive to deviations from a desired level of affiliation and is "satisfied by social interaction." Drawing from their work, interactions with coworkers are expected to trigger and satiate the

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aforementioned processes. Yet, interactions with AI complicate the picture. Importantly, both scholarly work across multiple disciplines (D'Haussy, 2018; Kolbjørnsrud et al., 2016; Nyholm & Smids, 2020; Tang, Koopman, McClean, et al., 2022), as well as practitioner-focused publications (Mittal et al., 2019; Wilson & Daugherty, 2018) argue that AI is also seen by employees as a "coworker." This is because these systems are designed to function as an autonomous work partner (De Cremer, 2020; Guzman & Lewis, 2020). Interactions with AI may thus also trigger those regulatory processes. Yet, unlike with a human coworker, interactions with AI likely cannot provide the type of social feedback our primitive "social drive" is designed to detect (O'Connor & Rosenblood, 1996). We thus expect employees may instead feel socially deprived after interacting with AI (Dwivedi et al., 2019; S. G. Lee & Sathikh, 2013).

Unpacking the above is important because not only does it permit us the opportunity to shine a light on a phenomenon that may have important implications for employee behavior, but also it permits us the opportunity to integrate what is currently a somewhat fragmented literature on social affiliation processes and their impact on human functioning (Lazarus, 1999; Leary, 2010; O'Connor & Rosenblood, 1996; Powell, 2022). In line with theorizing from O'Connor and Rosenblood (1996), along with a recent extension (e.g., Hall, 2017), this body of work has focused on the more *active* (what we term adaptive) consequences of social deprivation—the subsequent motivation to cope by socially reconnecting with others. In summarizing that work, however, Reissmann et al. (2021) noted that social deprivation may also drive *passive* (what we term maladaptive) coping responses as well—a subsequent motivation to instead withdraw.

Applying this to the context of our model, socially depriving situations (i.e., interactions with AI) may, on the one hand, trigger an *adaptive* coping response to reconnect with others (as we see with Bruce Willis' character—reflected in a heightened need for affiliation; O'Connor & Rosenblood, 1996) that prompts individuals to seek social contact with other via more active and social behavior (i.e., helping; Van Dyne & LePine, 1998). Yet, on the other hand, such situations may trigger a *maladaptive* coping response. Specifically, recent affiliation-based work has identified the potential for heightened feelings of loneliness (Reissmann et al., 2021), which may not only have negative implications for well-being by triggering insomnia (Barnes et al., 2015; K. Graham & Schmidt, 1999; Moss, 2018), but also may prompt individuals to engage in more avoidant types of behavior such as after-work drinking. If true, this can be problematic for organizations as it may affect the mental fitness of the workforce and may have long-term implications for employees' behaviors at work (e.g., Edwards, 1992; Sonnentag et al., 2022).

Importantly, the adaptive and maladaptive mechanisms discussed above that transmit the effects of socially depriving situations have largely been discussed in isolation in the affiliation literature. Thus, beyond bringing them together in a single model, there remains a critical (as yet unanswered) question—*for whom* will our hypothesized effects be more pronounced. A consistent point of emphasis among affiliation scholars is that people should differ on the above mechanisms based on their sensitivity to the absence of social connection in daily interactions (Hall, 2017; O'Connor & Rosenblood, 1996). Notably, attachment theory speaks directly to this point in that individuals with stronger attachment anxiety should be particularly sensitive to the absence of social connections (Bowlby, 1969, 1973). Thus, we extend research on social affiliation model by integrating theory on attachment styles (Simpson, 1990; Simpson & Rholes, 2015; Simpson et al., 1992).[1] Taken together, we submit that attachment-anxious employees (i.e., those with a tendency to want close relationships who worry about being socially isolated or abandoned; Liu et al., 2013; Mikulincer & Shaver, 2007) should experience stronger social deficit upon interacting with AI at work. This should amplify *both* the adaptive and maladaptive responses (i.e., heightened need for affiliation and loneliness) among these employees.

To test our model (see Figure 1), we adopt a "full-cycle research approach" (Chatman & Flynn, 2005, p. 434) by designing and conducting three studies that (a) employ different research methodologies (i.e., field and experimental designs), (b) recruit participants from different industries (i.e., biomedical and real-estate for Studies 1 and 2, as well as a wide range of industries and business functions in Studies 3 and 4), and (c) recruit participants from different regions (i.e., Taiwan, Indonesia, United States, and Malaysia). By doing so, we make three important contributions to scholarship on AI, social affiliation model, and attachment theory, respectively.

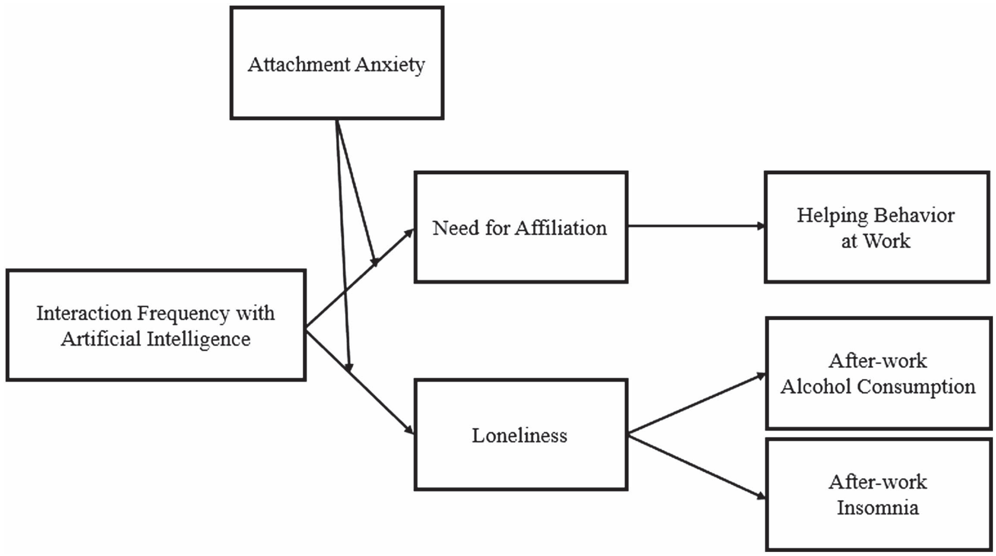
First, we widen the scope of ongoing conversations on the integration of AI into the workplace, which have tended to be more one-sided in terms of whether incorporating AI has *either* beneficial (Murray et al., 2021; Wilson & Daugherty, 2018) *or* aversive (e.g., Efendić et al., 2020; Newman et al., 2020) outcomes. We instead highlight that such integration may be a double-edged sword (i.e., while interactions from this integration may have positive outcomes in terms of affiliative behaviors, there may be negative outcomes as well in the form of impairing employees' well-being; Barnes et al., 2017; K. Graham & Schmidt, 1999). Thus, our research paints a more complete picture about how work interactions with AI impact employees.

Our second contribution lies in our incorporation of (the somewhat scattered) research on social affiliation across different disciplines—thus extending this body of work. That is, the social affiliation model (O'Connor & Rosenblood, 1996) is one part of the broad spectrum of theory and research on social affiliation (Leary, 2010; Powell, 2022). By holistically integrating knowledge in this stream of research, not only do we show that it meaningfully explains the consequences of this emerging phenomenon at work, but we also contribute back to this research by simultaneously unpacking the (active) adaptive and (passive) maladaptive consequences of social deprivation (along with further examining outcomes in multiple domains). In so doing, our research sheds new light on the application of social affiliation research to understand the consequences of human–machine interactions both at work and at home.

Finally, we extend social affiliation research by integrating it with attachment theory (Simpson, 1990; Simpson & Rholes, 2015;

[1] Attachment theorists also note another style termed attachment avoidance (e.g., Simpson, 1990). Although we focus on the moderating effect of attachment anxiety, based on the arguments noted above, an anonymous reviewer emphasized that opposing arguments could potentially be made for attachment avoidance (i.e., while attachment-anxious employees may be sensitive to the absence of social connection, attachment avoidance employees may be less so). Thus, although we focus on attachment anxiety for our primary theorizing, we develop post hoc hypotheses for attachment avoidance and test its main and interactive effects in supplemental analyses (see our OSF repository).

Figure 1
Hypothesized Model



Simpson et al., 1992). In so doing, we add specificity to what had previously been hinted at—that sensitivity to social interactions (or, their absence) plays an important role in the social affiliation process (Hall, 2017; O'Connor & Rosenblood, 1996). In this way, our model and theory explain both *why* and *for whom* work interactions with AI may affect employee behaviors in both work and nonwork contexts (Whetten, 1989). This is important practically as well, as applied psychologists have been increasingly interested in understanding the organizational implications of attachment styles (McClean et al., 2021; Richards & Schat, 2011), and our results suggest this may be even more important given the increased pairing of employees and AI systems as we enter the Fourth Industrial Revolution (Brynjolfsson & McAfee, 2017; Jarrahi, 2018). Thus, our research provides timely insights for managers seeking to better understand the effects of augmenting employee jobs with AI.

Theory and Hypotheses Development

Interaction With AI in the 21st Century Workplace

Generally speaking, AI refers to "a broad collection of computer-assisted systems for task performance, including machine learning, automated reasoning, knowledge repositories, image recognition, and natural language processing" (von Krogh, 2018, p. 405). Although myriad forms of AI are used in organizations worldwide, a commonality among them is that they use machine learning and other forms of algorithmic reasoning to interpret data and augment employee decision-making processes (Brougham & Haar, 2018; Brynjolfsson & McAfee, 2014; Davenport & Kirby, 2016; Donald, 2019).[2] These systems leverage AI's ability to process large quantities of data and distill it into an interpretable and actionable form (Jarrahi, 2018). For example, using machine learning, AI systems make a series of microdecisions (largely outside of the awareness of human employees) about which pieces of information to emphasize and which it uses to make suggestions or recommendations. In contrast to traditional technologies that operate on a "fixed set of preprogrammed instructions," AI systems "have the capacity to learn and can therefore improve and adapt based on experience" autonomously (Chalmers et al., 2021, p. 3). In this way, AI and employee ideally form a connection that speeds up and streamline the data-gathering and decision-making process (Glaser, 2014; Gregory et al., 2021; Reeves, 2015). For this reason, AI is seen as having large economic and organizational significance (The Economist, 2018).

Yet, with this said, the relationship between employees and AI is complex (Cerulo, 2009; Newell & Card, 1985; Waytz et al., 2014). As noted, these systems are quite intelligent and sophisticated, which allows them to autonomously make decisions and suggestions (Davenport, 2018; Webster & Ivanov, 2020). Some employees find this aversive and feel that these systems are inauthentic (Dietvorst et al., 2018; Jago, 2019), but at the same time, there is evidence that people treat AI as a "social agent," in that they hold them to the same social expectations as they would to another person (Epley et al., 2007). This may be in part because these systems are designed to mimic the types of interactions that occur between coworkers (i.e., these systems communicate with employees and maintain "relational dynamics"; Guzman & Lewis, 2020, p. 70). Put differently, while interactions with traditional technology (i.e., phones, websites, or word processing software) are unidirectional—users provide input to which the technology responds in a predictable manner—interactions with AI systems are bidirectional (Tang, Koopman, McClean, et al., 2022). That is, AI systems engage employees in a manner that attempts to mimic how employees would interact with their human coworkers (Anderson et al., 2018; Borges et al., 2021; Li & Du, 2016).

These dynamics of employee–AI interactions explain why we expect employees will find these interactions to be socially isolating and devoid of the types of feedback that they would obtain when interacting with human colleagues. Given the above, we expect interactions with AI to activate the social regulatory process we

[2] Our Appendices (see OSF) provide pictures from our data collection sites across the field studies of the typical type of human-AI collaboration (Brynjolfsson & McAfee, 2017).

described earlier in much the same way as would occur with a human coworker. Yet, unlike interactions with a coworker, employees likely do not obtain the expected social feedback when interacting with AI. For this reason, interactions with AI may leave employees feeling deprived of social affiliation at work (Wirtz et al., 2019).

Interaction Frequency With AI and Research on Social Affiliation

A point of consensus across many different theories is that humans evolved to require social interaction to both thrive and survive (e.g., Leary, 2000; Leary & Baumeister, 2000; Sussman et al., 2005; Williams, 1997). Leveraging this work, O'Connor and Rosenblood (1996) proposed what they called the "social affiliation model" (p. 513), which describes an internal regulatory process through which people monitor their affiliation with others. This process is activated by social interactions with others, at which point people (automatically and outside of conscious awareness) search for signals that provide information on the quality of those interactions and their general social standing. For example, social interactions involve both verbal and nonverbal signals that may suggest that a person is accepted and valued by the other. Those signals (or lack thereof) provide an assessment of a person's current level of affiliation, which, per O'Connor and Rosenblood (1996), activate regulatory processes that drive subsequent behavior to redress the situation (see also Leary, 2010). Although this system developed millennia ago, the basic social context (and, operation of these internal processes) remains intact in modern organizations (i.e., people engage in social interactions at work to perform work tasks, and internal social affiliation processes monitor those interactions; Weick, 1979; Weiss, 1973).

Bridging back to our study context, the increasing augmentation of employee work with AI upends this traditional social structure by coupling employees with intelligent machines with whom they also interact (Wilson & Daugherty, 2018). As we noted, these systems have features that may lead employees to also see them as a coworker (D'Haussy, 2018; De Cremer, 2020; Mittal et al., 2019; Tang, Koopman, McClean, et al., 2022). As a consequence, we submit that the primitive social regulatory processes are similarly activated during these interactions. Yet, because AI systems cannot replicate the social and organic features of social interactions with other humans (e.g., Brynjolfsson & McAfee, 2017; Dietvorst et al., 2018; Lawless et al., 2017), those regulatory processes are left searching for signals that are not present. Thus, employees do not receive the social feedback they would otherwise expect (e.g., Carrigan & Porpora, 2021; Lazega, 2021).[3]

Thus, an unintended consequence of the increased frequency with which some employees interact with AI (i.e., an employee's involvement, usage, or engagement with AI systems in the course of assigned work duties; Kacmar et al., 2003; McAllister, 1995; Webster & Ivanov, 2020) is the potential to become deprived of social affiliation at work. With this as a backdrop, we draw from O'Connor and Rosenblood's (1996) work on social affiliation and their identification of the underlying regulatory process. To explain the behavioral consequences of this process, we integrate this with the broad social affiliation literature (Reissmann et al., 2021; Revenson & Lepore, 2012), which has identified two mechanisms that transmit the effects of social deprivation.

Adaptative Reaction—Increased Need for Affiliation and Helping Behavior

O'Connor and Rosenblood's (1996) social affiliation model exists within a broader constellation of theories and research pertaining to social affiliation, deprivation, and consequent coping. Over the years, much of this research has focused on the more adaptive ways in which people may cope with socially depriving situations (Reissmann et al., 2021). Building from this, interactions with AI may instantiate within employees a recognition that their social affiliation needs are unmet, which may drive compensatory behavior. People have a need to connect with others (e.g., Brewer & Hewstone, 2004; O'Connor & Rosenblood, 1996), and this need is unlikely to be met by interacting with AI systems (Nomura et al., 2006). That is, while AI can reproduce words and meaning, it is generally unable to reproduce various aspects of social interaction that foster affiliation (e.g., facial expressions, eye contact, body posture, and gestures; Dodds et al., 2011; G. H. Graham et al., 1991; Phutela, 2015). Further, AI is unable to form meaningful social connections with employees (Banerjee et al., 2018). While employees may observe a smile that crosses a coworker's face when they stop by to chat, typical AI systems are ill-equipped to respond in unique and customized ways to different interaction partners. That is, most AI can only "interact with humans in a uniform way" (Wirtz et al., 2019, p. 607)—a uniformity that contrasts with the more personalized interactions to which employees are used with coworkers (Tanaka & Kobayashi, 2015). Interactions with AI may thus create a discrepancy between employees' desired level of affiliation at work and their actual state, resulting in an increased need for affiliation (O'Connor & Rosenblood, 1996). Thus, we hypothesize:

> *Hypothesis 1:* AI interaction frequency is positively related to employee's need for affiliation.

There are reasons to suspect possible adaptive consequences of this increased need for affiliation—for example, Leary (2010) suggested that individuals in this situation may be more eager and motivated to connect with others. This dovetails with theory from O'Connor and Rosenblood (1996, p. 513) that suggests such deviations from desired levels of social affiliation may trigger a "social drive" that motivates individuals to seek out social contact as a means of coping. Indeed, one of the functions of this social regulatory process is to ensure that people maintain adequate levels of social contact that are necessary for survival (Hall, 2017).

In particular, psychologists have posited that increased prosocial behavior (i.e., helping) is a key means by which individuals connect with others (Crisp & Turner, 2014; Simpson & Beckes, 2010). Helping (i.e., discretionary behavior involving actions oriented toward assisting others at work; Organ, 1988) is an inherently social act that strengthens connections among coworkers (Koopman et al., 2016). This behavior provides a context in which an employee can

[3] An anonymous reviewer acknowledged that the arguments we develop around "unmet expectations" may be one explanation for our findings, but also argued that a plausible alternative is that employees not interacting with their human colleagues. While we attempted to rule this explanation out both theoretically as discussed above, as well as (to foreshadow our study designs) controlling for both the frequency and quality of interactions with coworkers, we acknowledge we cannot definitively tease-apart these micromechanisms. We return to this in our discussion.

both be in the presence of others as well as contribute meaningfully to their relationship. Notably, indirect evidence supports this argument, as scholars have noted that when individuals feel the need to develop social connections with others, they are often motivated to seek social contact and go the extra mile for others, as doing so serves as a form of social validation for their contributions (Baumeister & Leary, 1995). For example, both Gest et al. (2005) and Pavey et al. (2011) found that when individuals feel a greater need to affiliate with others, they tend to display more prosocial behavior. On this basis, we hypothesize:

> *Hypothesis 2:* The relationship between AI interaction frequency and employee's help behavior is mediated by employee's need for affiliation.

Maladaptive Reaction—Increased Loneliness and After-Work Alcohol Consumption and Insomnia

While there may be adaptive outcome of social deprivation stemming from interactions with AI as described above, other (particularly recent) research has articulated a likelihood that there may be an alternative mechanism that results in more maladaptive effects outcomes as well (Reissmann et al., 2021, p. 2)—specifically, these authors noted that when there is a difference "between a person's desired and actually attained levels" of affiliation, one possible reaction may be loneliness—a passive response to socially unfulfilling interactions (Cacioppo & Patrick, 2008; Rokach & Brock, 1996). While interactions with AI should activate social regulatory processes, these interactions are mechanical and inorganic in nature (Ackerman & Kanfer, 2020; Huang & Rust, 2021), which may lead the social regulatory process to signal a sense of social isolation that manifests as loneliness (Ozcelik & Barsade, 2018; Reissmann et al., 2021). Indeed, it seems likely that interacting with AI may be a lonely endeavor in the workplace—for example, previously routine activities such as seeking a second opinion on a proposed solution for a client can now be provided instantaneously (and more accurately) by an AI system (Ransbotham et al., 2017). Therefore, more frequent interactions with AI may lead employees to feel socially disconnected from others, which should increase feelings of loneliness. Thus, we hypothesize:

> *Hypothesis 3:* AI interaction frequency is positively related to employee's loneliness.

In turn, this sense of loneliness may lead to a host of maladaptive consequences for employees. This is due to what scholars have referred to as the "self-reinforcing cycle of loneliness" (Cacioppo & Patrick, 2008; Gabriel et al., 2021, p. 3). That is, the experience of loneliness is sufficiently distasteful that it may not only have negative implications for well-being but also may lead employees to cope with the experience by engaging in further isolating behaviors. Importantly, as Gabriel et al. (2021, p. 4) note, the effects of loneliness may be particularly likely to occur during "after work" hours. Thus, we examine two outcomes of loneliness after work: alcohol consumption and insomnia.

First, clinical observations and findings across more than 60 years reveal that lonely people are more likely to consume alcohol (Bell, 1956; Zwerling, 1959). To this point, Bryan et al. (2017, p. 606) conclude that lonely individuals are likely to fall prey to a "downward spiral," wherein these people may resort to consuming alcohol in order to "help them escape awareness of their lack of social connections" (see also Åkerlind & Hörnquist, 1992). Put differently, lonely employees are more likely to see themselves negatively, which can then spillover to other negative behaviors (e.g., alcohol use) in an attempt to escape from those feelings (Hawkley et al., 2008). For this reason, scholars from multiple disciplines have highlighted the role of alcohol consumption as a means of "coping with feelings of [social] isolation" (Segal, 1987, p. 303).

Second, we suspect loneliness may also lead to insomnia among employees. Indeed, a long-standing stream of research suggests lonely individuals are more likely to have problems sleeping at night (Mikulincer, 1990; Peplau & Perlman, 1979; Perlman & Peplau, 1981; Sermat, 1978). As recent organizational research suggests, loneliness may be accompanied by recurring thoughts about employees' lack of social connection at work, which render employees to be "mentally activated" after work (Gabriel et al., 2021, p. 4). More specifically, this mental activation may contain negative reflections on the self and the reasons for their detachment and loneliness at work. These reflections are problematic, as they may mentally preoccupy employees at night, which gives rise to the problem of insomnia. Taken all the above together, along with our theorizing in the prior hypotheses, we thus propose that:

> *Hypothesis 4a:* The relationship between AI interaction frequency and employee's after-work alcohol consumption is mediated by employee's loneliness.

> *Hypothesis 4b:* The relationship between AI interaction frequency and employee's after-work insomnia is mediated by employee's loneliness.

The Moderating Role of Attachment Anxiety and Insights From Attachment Theory

Our arguments thus far highlight that because interactions with AI can be devoid of the meaningful components of social interaction that foster social connection between employees (e.g., Kaplan & Haenlein, 2020; Wirtz et al., 2019), such interactions should trigger employees' social affiliation systems to respond in both adaptive and maladaptive manners. In articulating the social affiliation model, O'Connor and Rosenblood (1996, p. 514) further highlighted the likelihood of "individual differences" in the nature of this system—specifically noting that some individuals have a greater sensitivity to the absence of social connections in the workplace. This directly connects with attachment theory, which is predicated on the notion that individuals differ in the extent to which they desire social connections with others (Simpson et al., 1992). We, therefore, extend the social affiliation model by integrating it with attachment theory.

Attachment theory posits that experiences and relationships during infancy, childhood, and adolescence contribute to the development of relatively stable preferences regarding the desire for social connection in daily life (Bowlby, 1969, 1973). This theory primarily identifies two forms of attachment style: anxious and avoidant. Those with an avoidant attachment style generally place less emphasis on social connections with others (Simpson et al., 1992), whereas those with an anxious attachment style are seen as being sensitive to the nature and quality of their social interactions.

Plus, in the absence of these interactions, those with an anxious attachment style tend to be more insecure about losing their connection with others (Simpson & Rholes, 2010). Based on this logic, our focus in this article is on the anxious attachment style.[4]

Our examination of attachment anxiety also dovetails well with the nature of our focus on interactions with AI at work, given our arguments that these interactions are largely distant and devoid of social connection. For employees with higher levels of attachment anxiety, the absence of social information during interactions with AI should be particularly salient. That is, these employees may be sensitive to their inability to meaningfully relate to modern AI systems during interactions and thus may feel as if they risk losing important social connections (Brennan et al., 1998). Moreover, attachment-anxious employees may be prone to underestimating their social worth (Simpson & Rholes, 2010). This is problematic, as the inability of AI to provide social validation should further heighten the extent to which attachment-anxious employees see their interactions with AI systems at work as socially depriving (Ainsworth et al., 1978).

In contrast, those employees with low levels of attachment anxiety not only have more confidence in their ability to develop social connections with others (Ainsworth, 1985), but also these employees have a more stable sense of their own social worthiness. As a result, compared to their higher attachment-anxious counterparts, they should be less sensitive to instances in which they are unable to obtain strong signals of social connectedness (Simpson et al., 1992). Given this, the absence of social information from interactions with AI should be less concerning to these employees (Brennan et al., 1998). Overall, the sense of social loss, deprivation, and isolation that may accompany interactions with AI should be greater for those with higher levels of attachment anxiety, compared to those with lower levels. Taken these together, along with the mediating hypotheses that we proposed earlier, we hypothesize:

Hypothesis 5: Employee's attachment anxiety moderates the indirect effect of AI interaction frequency on employee's helping behavior via employee's need for affiliation, such that this indirect effect will be stronger when attachment anxiety is higher compared to when attachment anxiety is lower.

Hypothesis 6a: Employee's attachment anxiety moderates the indirect effect of AI interaction frequency on employee's after-work alcohol consumption via employee's loneliness, such that this indirect effect will be stronger when attachment anxiety is higher compared to when attachment anxiety is lower.

Hypothesis 6b: Employee's attachment anxiety moderates the indirect effect of AI interaction frequency on employee's after-work insomnia via employee's loneliness, such that this indirect effect will be stronger when attachment anxiety is higher compared to when attachment anxiety is lower.

Overview of Studies

We conducted four studies that (a) employ different research methodologies (i.e., field and experimental designs), (b) recruit participants from different industries, and (c) recruit participants from different geographical regions. In this way, our research fits what Chatman and Flynn (2005) term a "full cycle research approach" (p. 774)—examining a phenomenon in field and experimental settings to enhance both the internal and external validity of the findings (e.g., Koopman et al., 2023; Tang, Yam, et al., 2022). Studies 1 and 2 provide an initial test of our model with employees in a Taiwanese biomedical company (Study 1) and an Indonesian real-estate company (Study 2). Both studies incorporate multiple waves of surveys as well as obtain reports from two additional sources (i.e., a coworker and a member of the focal employee's family). Studies 3 and 4 then extend the generalizability of these two studies by assessing a broader spectrum of working adults—working in a range of industries in the United States (Study 3) and working in multiple business functions in a Malaysian technology services company (Study 4). Together, these four studies robustly test our hypotheses across employees working in different jobs, industries, and national cultures (Yam et al., 2022). Our studies were approved by the National Sun Yat-sen University's Departmental Review Committee (200604; 1110414-02), as well as Texas A&M University's Institutional Review Committee (IRB2021-0093M).

Transparency and Openness

We affirm that our study methods adhered to the *Journal of Applied Psychology* methodological checklist. All measurement items and Supplementary Materials are available on the Open Science Foundation website at https://osf.io/acym6/?view_only=6dac73046224421c8af6781f733b3f95. Data were analyzed using SPSS Version 28, R Studio, and Mplus Version 7.4. Study designs were not preregistered.

Study 1: Method

Sample and Procedure

We collected data in Spring 2021 from engineers in a Taiwanese biomedical company whose primary responsibilities include working with AI systems to design, test, and implement new procedures and equipment (e.g., Park et al., 2018; Zhu, 2020). All engineers received an announcement describing the study (including the need for a cohabiting family member to participate in the study as well). Data were collected data over three time points each separated by 1 week. In the first week (T1), employees reported their interaction frequency with AI, interaction frequency and quality with coworkers (controls), and their attachment anxiety and avoidance (controls). In the second week (T2), employees reported their need for affiliation and loneliness (mediators) and their belongingness and relatedness needs (controls). In the third week (T3), a coworker reported the focal employee's helping behavior (coworkers reported only one employee and were chosen for their work proximity to the focal employee; Tang et al., 2020), and a cohabiting family member reported the employee's after-work alcohol consumption and insomnia. Overall, 166 engineers (53% male)

[4] Although we focus on the moderating effect of attachment anxiety, a reviewer highlighted that opposing arguments could potentially be made for attachment avoidance based on the notion that these individuals may have greater tolerance for an absence of social connections in the workplace. As such, although we focus on attachment anxiety for our primary theorizing, we also develop post hoc hypotheses for attachment avoidance (please see the arguments and results in the materials available in OSF).

completed the study. Average age was 34.3 years old (SD = 5.75), average tenure was 2.96 years (SD = 1.62), and average years of using AI systems at work was 2.14 years (SD = 0.91). Most (88%) were tertiary educated.

Measures

Measures were translated into participants' native language using recommended back-translation procedures (Brislin, 1980). All measures, except attachment anxiety and avoidance, asked employees to respond as appropriate "over the last week." Anchors and wording for all measures are in open science framework (OSF) and reliabilities are given with our descriptive statistics. At T1, we measured *attachment anxiety and avoidance* (five items each; Simpson et al., 1996), *interaction frequency with AI and coworkers* (three items each, adapted for the particular referent; Shi et al., 2013), and interaction quality with coworkers (three items; Mallett et al., 2008). At T2, we measured *need for affiliation* (three items; Hill, 1987; Wiesenfeld et al., 2001), *loneliness* (three items; Gabriel et al., 2021), *need for belongingness* (five items; Puranik et al., 2021), and *need for relatedness* (three items; La Guardia et al., 2000). At T3, the focal employee's *helping* was rated by a coworker (three items; Yue et al., 2017) and *alcohol consumption* (multiplying two items that assess how many [a] days alcohol was consumed and [b] drinks were consumed; Bacharach et al., 2010) and *insomnia* (four items; Greenberg, 2006) were rated by a family member.[5]

Analytic Strategy

We tested our model with and without control variables (Becker, 2005). Primary results for all studies reflect models without control variables. The OSF repository shows results with controls as well as other post hoc analyses conducted following recommendations from the review team. A confirmatory factor analysis (CFA) on our primary model (attachment anxiety, interaction frequency with AI, need for affiliation, loneliness, helping, and insomnia—alcohol consumption was not included because it is a discrete number) indicated adequate model fit (χ^2 = 272.03, df = 174, comparative fit index [CFI] = .95, root-mean-square error of approximation [RMSEA] = .06, standardized root-mean-square residual [SRMR] = .05). We used the Mplus default maximum likelihood estimator for our model and tested all hypotheses simultaneously.[6] Mediation and moderated mediation were tested with a parametric bootstrap (with 20,000 replications to form 95% bias-corrected confidence intervals (CIs); Preacher et al., 2010; Selig & Preacher, 2008).

Study 1: Results

Table 1 presents descriptive statistics for study variables, and Table 2 provides path-analytic results of our primary model. In support of Hypothesis 1, interaction frequency with AI was positively associated with need for affiliation (B = .34, p < .001). Need for affiliation was positively associated with helping behavior (B = .35, p < .001), and the indirect effect confidence interval excluded zero (indirect effect = .119, 95% CI [.061, .202]), supporting Hypothesis 2. Supporting Hypothesis 3, interaction frequency with AI was positively associated with loneliness (B = .28, p = .004). Loneliness was positively associated with after-work alcohol consumption (B = 1.28, p = .033) and after-work insomnia (B = .34, p < .001). Hypotheses 4a (indirect effect = .363, 95% CI [.073, .866]) and 4b (indirect effect = .097, 95% CI [.030, .198]) were supported.

Attachment anxiety moderated the relationship between AI interaction frequency and need for affiliation (B = .07, p = .037; Figure 2A). Specifically, the relationship between AI interaction frequency and need for affiliation was stronger at higher (+1 SD) levels of attachment anxiety (B = .44, p < .001), compared to lower (−1 SD) levels (B = .23, p = .002). The difference between those slopes was also significant (difference = .21, p = .045). On this basis, Hypothesis 5 was supported, as a confidence interval for the indirect effect of AI interaction frequency on employee's helping behavior via need for affiliation excluded zero at higher levels (conditional indirect effect = .155; 95% CI [.076, .271]) of attachment anxiety but the confidence interval included zero at lower levels (conditional indirect effect = .082; 95% CI [.033, .158]). A confidence interval for the difference also excluded zero (95% CI [.003, .059]). Attachment anxiety did not moderate the relationship between AI interaction frequency and loneliness (B = .06, p = .367), so we do not report confidence intervals as these hypotheses are unsupported.

Discussion of Study 1 Findings

Results from Study 1 support most of our study hypotheses. Specifically, we found that interacting with AI at work leads to heightened experiences of need for affiliation and loneliness, which trigger a series of adaptive (i.e., helping at work) and maladaptive behaviors (i.e., alcohol consumption and insomnia after work). However, we only found support for the moderating role of attachment anxiety on the adaptive mechanism (i.e., need for affiliation). Notably, our model was robust to the inclusion or exclusion of a number of control variables (interaction frequency and quality with coworkers, need for belongingness and relatedness, and attachment avoidance). Yet, despite these positive aspects, there are important limitations of Study 1 as well.

First, while the field design of Study 1 is useful for establishing external validity, it is limited in its ability to establish internal validity. Although we employed time separation for the measures and obtained other reports, an experimental design may allow us to further draw causal inferences from our model (Hekman et al., 2017; Liang et al., 2018). Second, we have only assessed employees in a single job who work with one type of AI software (biomedical engineers based in Taiwan), which may limit the generalizability of our findings. Third, attachment anxiety did not moderate the relationship between interaction frequency with AI and loneliness, which necessitates further examination (and further, the moderation effect of attachment anxiety on the relationship between interaction frequency with AI and need for affiliation had some instability, as the results weakened when the interactive effect of attachment

[5] Please see our OSF repository for a series of content validation studies conducted for several of these measures.

[6] The company's structure places employees in different units, which results in a nested data structure. We therefore used the "COMPLEX" analysis in Mplus 7.4 (L. K. Muthén & Muthén, 2015) to account for nonindependence at the unit level. This approach allows intercepts to vary across clusters (Hofmann, 1997) and uses a sandwich estimator (B. O. Muthén & Satorra, 1995) to calculate robust standard errors (see Frieder et al., 2018; Yoon et al., 2021, for a recent example).

Table 1
Descriptive Statistics and Correlations Among Study Variables (Study 1)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Interaction frequency with AI	4.59	1.18	(.93)													
2. Interaction frequency with coworkers (control)	5.16	1.31	−.03	(.89)												
3. Interaction quality with coworkers (control)	4.78	1.32	−.14	.66*	(.82)											
4. Need for affiliation	4.71	1.10	.32*	.37*	.25*	(.82)										
5. Loneliness	3.29	1.40	.24*	−.09	−.16*	.03	(.84)									
6. Need for belongingness (control)	5.82	.74	.27*	.21*	.15	.29*	.00	(.84)								
7. Relatedness need (control)	5.03	1.24	.09	.10	−.03	.22*	.11	.30*	(.87)							
8. Helping behavior	4.40	1.38	.10	.29*	.41	.29*	−.07	.12	.02	(.88)						
9. Alcohol consumption	4.22	8.48	.19*	−.02	−.01	.04	.25*	−.05	−.07	.03	—					
10. Insomnia	3.97	1.40	.20*	.02	−.02	.16*	.37*	.09	−.02	.01	.10	(.86)				
11. Attachment anxiety	3.60	1.46	.11	−.29*	−.29*	−.25*	.09	−.17*	−.01	−.25*	.05	.07	(.90)			
12. Attachment avoidance (control)	3.99	1.78	.04	−.39*	−.38*	−.35*	.08	−.05	.00	−.33*	−.02	−.07	.41*	(.96)		
13. Age (years)	34.30	5.75	−.10	.042	−.05	−.10	−.01	−.05	−.08	.02	−.10	−.07	−.05	.00	—	
14. Gender (1 = male; 0 = female)	.53	.50	.11	.042	.03	.09	.03	−.01	−.03	−.05	.06	.08	−.11	−.09	.03	—
15. Tenure (years)	2.96	1.62	.19*	.093	.10	.08	.16*	.06	−.02	.05	.04	.22*	.02	−.02	.30*	.08

Note. $N = 166$. Scale reliabilities are reported along the diagonal in parentheses. AI = artificial intelligence.
* $p < .05$.

avoidance was added in the post hoc hypothesis test). Thus, we conducted a field experiment with employees in another industry who use another type of AI system (Dvir et al., 2002; M. K. Lee et al., 2012).

Study 2: Method

Sample and Procedure

We collected data in Spring 2021 from real estate consultants in an Indonesian property management company whose primary responsibilities include working with AI systems to perform customer portfolio matching (i.e., find the perfect match for people looking to buy, rent, or sell their properties) and property price estimation (Mather, 2019). All 142 consultants were given a briefing to describe the study (including the need for a cohabitating family member as in Study 1). The 126 participating employees completed a survey (T1) with measures of attachment anxiety and avoidance. Participants were then randomly assigned to two conditions. For 3 consecutive days, we instructed employees to either collaborate with AI systems as much as possible (AI condition) or not to use AI when performing their job duties (control condition).

After 3 work days, we sent a postmanipulation survey (T2) with measures of need for affiliation and loneliness, interaction frequency and quality with coworkers, and need for belongingness and relatedness needs. Employees also rated manipulation check items regarding interaction frequency with AI. At the same time, a coworker assessed the employee's helping behavior, and a cohabiting family member assessed the focal employee's after-work alcohol consumption and insomnia. Overall, 120 consultants (61.7% male) completed the study. Average age was 30.7 years old (SD = 6.20), average tenure was 3.03 years (SD = 1.61), and average years using AI systems at work was 1.95 years (SD = 4.03). Most (80.9%) were tertiary educated.

Measures

We followed the same back-translation procedures as in Study 1. All measures, except attachment anxiety and avoidance, asked employees to respond as appropriate "over the last three days." Anchors and wording for all measures are in OSF, and reliabilities are given with our descriptive statistics. *Attachment anxiety* and *avoidance* were measured at T1 as in Study 1. At T2, we used the items from Study 1 to measure *interaction frequency with AI*, *interaction frequency and quality with coworkers*, *need for affiliation*, *loneliness*, *need for belongingness*, and *relatedness needs*. We used the items from Study 1 to measure the focal employee's *helping behavior* from a coworker and both *alcohol consumption* and *insomnia* from a family member.

Analytic Strategy

A CFA on our primary model (attachment anxiety, need for affiliation, loneliness, helping, and insomnia—our independent variable was not included as it is an experimental condition, and alcohol consumption was not included as it is a discrete number) indicated adequate model fit (χ^2 = 164.97, df = 125, CFI = .98, RMSEA = .05, SRMR = .05). We thus proceeded with model testing following the same procedures as in Study 1.

Table 2
Path Analysis (Primary Hypotheses; Study 1)

Variable	Need for affiliation		Loneliness		Helping		Alcohol consumption		Insomnia	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Intercept	4.69*	.07	3.27*	.11	3.00*	.59	.23	3.27	2.11*	.57
Independent variable										
Interaction frequency with AI (IF)	.34*	.07	.28*	.10	.03	.13	1.00*	.47	.10	.10
Mediator										
Need for affiliation	—	—	—	—	.35*	.09	−.04	.75	.16	.10
Loneliness	—	—	—	—	−.08	.10	1.28*	.60	.34*	.07
Moderator										
Attachment anxiety (AAN)	−.22	.04	.06	.10	—	—	—	—	—	—
Interaction (AAN × IF)	.07*	.03	.06	.07	—	—	—	—	—	—

Note. $N = 166$. *SE* = standard error; AI = artificial intelligence.
* $p < .05$.

Study 2: Results

Table 3 presents the means, standard deviations, and correlations of our study variables, and Table 4 provides path-analytic results of our primary model. First, we conducted a one-way analysis of variance (ANOVA) to examine the effect of our manipulation. Responses to the manipulation check items differed significantly between the AI condition ($M = 5.29$, $SD = 1.29$) and the control condition ($M = 3.06$, $SD = 1.58$; $t[118] = 8.47$, $p < .001$, $d = 1.56$). Overall, our manipulation was deemed effective, and thus we next proceeded to perform hypotheses testing.

Supporting Hypothesis 1, AI condition was positively associated with need for affiliation ($B = 2.24$, $p < .001$). Supporting Hypothesis 2, the indirect effect between AI condition and helping via need for affiliation was positive and significant. That is, need for affiliation was positively associated with helping behavior ($B = .37$, $p = .002$), and the indirect effect confidence interval excluded zero (indirect effect = .826, 95% CI [.301, 1.457]). Supporting Hypothesis 3, AI condition was positively associated with loneliness ($B = 2.10$, $p = .004$). Hypotheses 4a predicted that the relationship between AI condition and after-work alcohol consumption is mediated by loneliness. Loneliness was not significantly associated with after-work alcohol consumption ($B = .27$, $p = .159$), and a confidence interval for the indirect effect included zero (indirect effect = .558, 95% CI [−.209, 1.380]), so Hypothesis 4a was not supported. Supporting Hypothesis 4b, the indirect effect between AI condition and after-work insomnia use via loneliness was positive and significant. That is, loneliness was positively associated with after-work insomnia ($B = .42$, $p < .001$), and a confidence interval excluded zero (indirect effect = .886, 95% CI [.404, 1.451]).

Attachment anxiety moderated the effect between AI interaction frequency and need for affiliation ($B = .83$, $p < .001$; Figure 2B). This relationship was stronger at higher (+1 *SD*) levels of attachment anxiety ($B = 3.15$, $p < .001$), compared to lower (−1 *SD*) levels ($B = 1.33$, $p = .002$). The difference between those slopes was also significant (difference = 1.82, $p < .001$). On this basis, Hypothesis 5 was supported—the indirect was stronger at higher levels of attachment anxiety (conditional indirect effect = 1.161; 95% CI [.452, 2.001]) compared to lower levels (conditional indirect effect = .491; 95% CI [.171, 1.013]). A confidence interval for the difference in these indirect effects excluded zero (95% CI [.106, .639]). Attachment anxiety also moderated the relationship between AI interaction frequency and loneliness ($B = .85$, $p < .001$; Figure 3A). This relationship was stronger at higher levels of attachment anxiety ($B = 3.04$, $p < .001$) compared to lower levels ($B = 1.17$, $p = .002$). The difference between those slopes was also significant (difference = 1.86, $p < .001$). As loneliness was not associated with alcohol consumption, Hypothesis 6a was not supported, so we do not report the confidence intervals.

However, Hypothesis 6b was supported. For Hypothesis 6b, the indirect effect of AI condition on employee's after-work insomnia via loneliness was stronger at higher levels of attachment anxiety (conditional indirect effect = 1.278; 95% CI [.603, 2.095]) compared to lower levels (conditional indirect effect = .493; 95% CI [.188, .988]). A confidence interval for the difference in these indirect effects excluded zero (95% CI [.147, .679]).

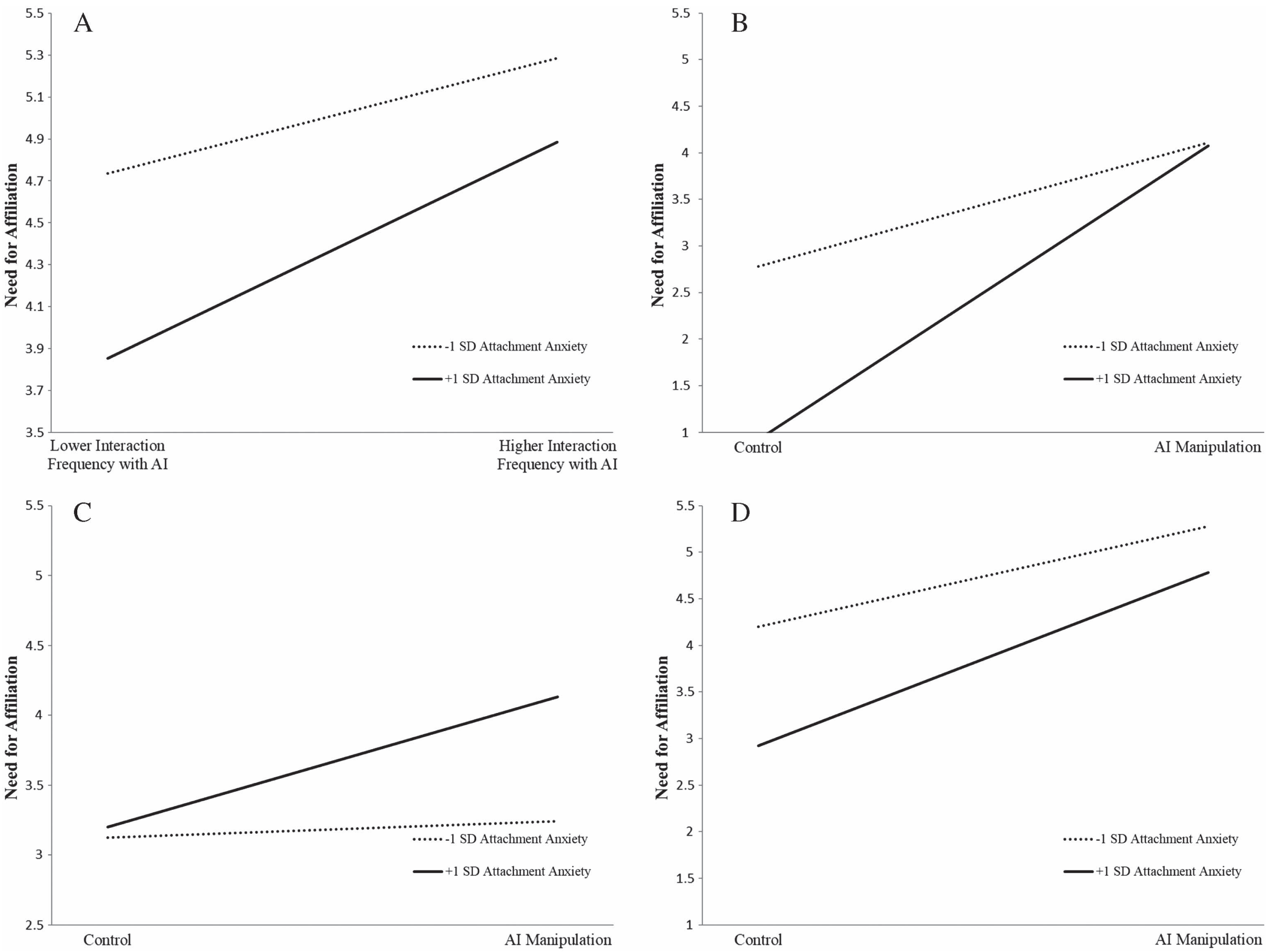
Discussion of Study 2 Findings

Study 2 constructively replicated our findings from Study 1 in a more controlled field experimental setting with employees working in another industry (real estate industry) and another country (Indonesia). The results of this study—combined with that of Study 1—provide further evidence with regard to (a) the robustness of our findings (by taking various confounding variables into account—though we note the nonsignificant link between loneliness and alcohol consumption); (b) completeness of our hypothesized model (examining two separate mechanisms by which interacting with AI influences a range of work and nonwork outcomes); (c) the generalizability of our findings to employees working in a different type of job, with a different type of AI, in a different country; and (d) validity of our findings via collecting reports from three different sources (i.e., focal employees, coworkers, and family members). That said, there are some remaining concerns that both Studies 1 and 2 are not able to thoroughly address.

First, despite the evidence for generalizability that we have provided from the convergent findings in two very different samples, a commonality among them is that we obtained a report of alcohol consumption and insomnia from a family member living with the employee. While not intentional, our results are thus implicitly constrained only to employees who cohabitate with a family member (and thus it is unclear whether we can generalize to

Figure 2

Attachment Anxiety Moderates the Relationship Between Interaction Frequency With AI and Need for Affiliation



Note. Panel A—Study 1; Panel B—Study 2; Panel C—Study 3; Panel D—Study 4. AI = artificial intelligence.

employees who live alone). Further, although the experimental design of Study 2 allows us to exert more control over the sample, both Studies 1 and 2 are conducted in the field. There are inherently some idiosyncratic issues that may arise for a given employee on a given period of time over which we do not have control. Thus, further evidence for both internal and external validity could be obtained by replicating our findings in a highly controlled laboratory design, as this would allow us to rule out any potential idiosyncratic confounds across people and jobs (as well as again show that our model can be applied to an entirely different form of AI). Another benefit of this approach is that we can recruit a sample of employees from a broad spectrum of jobs and industries, which would further highlight the generalizability of our findings (and by not restricting the sample to those employees who cohabitate with a family member, we can address the issue noted previously).

Second, a component of our theorizing that rests on an assumption that employees view AI as a coworker. This perspective is widely held in AI research across a number of different literature (e.g., Gerrish, 2018; Kelly & Hamm, 2013; Kujala & Saariluoma, 2018; Shadbolt & Hampson, 2019)—organizational scholarship included (D'Haussy, 2018; Kolbjørnsrud et al., 2016; Nyholm & Smids, 2020). Specifically, as Tang, Koopman, McClean, et al. (2022) recently note, "in the modern workplace, however, intelligent machines [e.g., AI] are increasingly seen as coworkers of human employees" and thus AI can be regarded as "both independent and co-dependent interaction partners at work" (p. 1023). Practitioners acknowledge this as well, as several publications in this space have noted the increasing trend that AI becomes the "new colleague" of employees (i.e., Mittal et al., 2019; Wilson & Daugherty, 2018). With this said, we felt that we should control for employee attitudes toward AI as a way to further increase the robustness of our findings. Thus, to address these two limitations, we conducted an online simulation-based study.

Study 3: Method

Sample and Procedure

We collected data in Spring 2022 from 214 full-time working adults (32.7% male) in the United States through Prolific who work

Table 3

Descriptive Statistics and Correlations Among Study Variables (Study 2)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Condition (1 or 0)	.50	.50	—													
2. Interaction frequency with coworkers (control)	5.24	1.37	.10	(.88)												
3. Interaction quality with coworkers (control)	5.28	1.12	.09	.56*	(.91)											
4. Need for affiliation	4.17	1.78	.63*	.11	.12	(.94)										
5. Loneliness	3.96	1.72	.64*	.11	.03	.68*	(.94)									
6. Need for belongingness (control)	4.60	1.27	.24*	.39*	.52*	.25*	.25*	(.94)								
7. Relatedness need (control)	3.15	1.43	.10	−.20*	.40*	−.08	−.06	−.57*	(.93)							
8. Helping behavior	4.90	1.66	.12	.20*	.26*	.26*	.08	.25*	−.12	(.95)						
9. Alcohol consumption	2.67	2.58	.32*	.13	.02	.27*	.32*	.09	−.01	.02	—					
10. Insomnia	3.36	1.72	.38*	.10	.04	.35*	.49*	−.02	.09	−.09	.17	(.87)				
11. Attachment anxiety	3.00	1.10	.17	.09	−.06	.09	.22*	−.15	.24*	.08	.08	.27*	(.92)			
12. Attachment avoidance (control)	4.22	.99	.07	−.16	−.27*	−.15	.01	−.30*	.32*	−.16	−.09	.09	.35*	(.74)		
13. Age (years)	30.68	6.20	.22*	−.04	−.06	.17*	.06	.05	.12	.15	.14	−.01	−.05	.07	—	
14. Gender (1 = male; 0 = female)	.62	.49	.27*	.17	.19*	.16*	.21*	.10	.00	.09	.09	.12	.26*	.21*	.06	—
15. Tenure (years)	3.03	1.61	.11	.17	.21*	.09	.12*	.18	−.12	.03	−.06	.05	−.01	−.05	.21*	.07

Note. $N = 120$. 1 = AI condition; 0 = control condition. Scale reliabilities are reported along the diagonal in parentheses. AI = artificial intelligence.
* $p < .05$.

in a broad spectrum of industries and job positions (see Table 5). Overall, 105 participants were randomly assigned to the interaction with AI condition, while 109 were assigned to the control condition. Average age was 33.97 years ($SD = 11.91$), and average tenure was 9.71 years ($SD = 11.41$). Participants, on average, spent 27.81 min on the study. Before beginning the study, participants reported their attachment anxiety and avoidance, along with their attitude toward AI (a new control in this study). Participants then proceeded to a business simulation experiment (adapted from Ederer & Manso, 2013; e.g., see Tang, Koopman, Yam, et al., 2022), wherein they were informed that they were going to provide consulting services for a lemonade stand business. In this study, the simulation involved three different rounds. In each round, participants made recommendations to the client on how to run a lemonade stand in terms of its location, the sugar and lemon content, the color, the price of the lemonade, and so forth. Participants had three choices for location, two for color, 10 each for sugar and lemon content, and 125 for price (i.e., \$0 to \$12.50 in increments of \$.10).

In the *interaction with AI condition*, participants interacted with an AI that provided additional information to help develop their recommendations. The AI interacted conversationally with participants through an embedded video in the survey powered by an AI-based text-to-voice service—Amazon Polly. As participants went through the task, the AI assisted by offering information about different aspects of the lemonade (e.g., the implications of different levels of sugar and lemon content). Once participants made recommendations, the AI combined its knowledge of the lemonade business with participants' choices to provide further advice (using formulas from Ederer & Manso, 2013). Finally, participants submitted their final proposal.

In the *control condition*, everything was the same as in the AI condition, except participants completed the task themselves without interacting with AI. Of note, in both conditions, participants completed the first three rounds wherein they provided advice to their client. At the end of the third round, they reported their current need for affiliation, loneliness, need for belongingness (control), relatedness need (control), intention to help colleagues at work, intention to consume alcohol after work, as well as the likelihood of having difficulty of sleeping after work. Finally, participants rated items pertaining to manipulation checks as well as psychological realism.

Measures

All measures, except attachment anxiety and avoidance, asked participants to respond as appropriate "right now." Anchors and wording for all measures are in OSF, and reliabilities are given with our descriptive statistics. *Attachment anxiety* and *avoidance* were measured as in the prior studies. At the same time, we measured *attitudes toward AI* (12 items; Schepman & Rodway, 2020). After the task, we used the same items from the prior studies to measure *need for affiliation*, *loneliness*, *belongingness needs*, *need for relatedness*, and *interaction frequency with AI*. Given the experimental nature of this study, in the posttask survey, we were only able to assess participants' intentions to (a) *help coworkers* in the rest of the workday and (b) *consume alcohol* after work, as well as (c) the likelihood that participants would have *insomnia* that evening.

Table 4
Path Analysis (Primary Hypotheses; Study 2)

Variable	Need for affiliation		Loneliness		Helping		Alcohol consumption		Insomnia	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Intercept	2.97*	.17	2.83*	.16	4.09*	.42	.95	.64	1.53*	.40
Independent variable										
AI condition (AI)	2.24*	.24	2.10*	.23	−.05	.40	.95	.61	.38	.38
Mediator										
Need for affiliation	—	—	—	—	.37*	.12	.05	.18	−.01	.11
Loneliness	—	—	—	—	−.18	.12	.27	.19	.42*	.12
Moderator										
Attachment anxiety (AAN)	−.43*	.15	−.23	.14	—	—	—	—	—	—
Interaction (AAN × AI)	.83*	.22	.85*	.21	—	—	—	—	—	—

Note. $N = 120$. *SE* = standard error; AI = artificial intelligence.
* $p < .05$.

We used the same items as in the previous studies to measure these constructs.[7]

Analytic Strategy

A CFA on our primary model (identical to Study 2) indicated adequate fit ($\chi^2 = 226.10$, $df = 125$, CFI = .96, RMSEA = .06, SRMR = .06). We thus tested our model as in prior studies.

Study 3: Results

Table 6 presents the means, standard deviations, and correlations of our study variables, and Table 7 provides path-analytic results of our primary model. First, we conducted a one-way ANOVA to examine the effect of our manipulation. Responses to the manipulation check items differed significantly between the AI condition ($M = 5.37$, $SD = 1.50$) and control condition ($M = 2.14$, $SD = 1.11$; $t[212] = 17.97$, $p < .001$, $d = 2.46$). Overall, our manipulation was deemed effective, and thus we next proceeded to perform hypotheses testing.

Supporting Hypothesis 1, AI condition was positively associated with need for affiliation ($B = .82$, $p < .001$). Supporting Hypothesis 2, the indirect effect between AI condition and helping via need for affiliation was positive and significant. That is, need for affiliation was positively associated with helping behavior ($B = .28$, $p < .001$), and the indirect effect confidence interval excluded zero (indirect effect = .226, 95% CI [.106, .387]). Supporting Hypothesis 3, AI condition was positively associated with loneliness ($B = .53$, $p = .001$). Supporting Hypothesis 4a, the indirect effect between the AI condition and after-work alcohol consumption use via loneliness was positive and significant. That is, loneliness was positively associated with after-work alcohol consumption ($B = .40$, $p < .001$), and a confidence interval excluded zero (indirect effect = .213, 95% CI [.082, .402]). Supporting Hypothesis 4b, the indirect effect between AI condition and after-work insomnia use via loneliness was positive and significant. That is, loneliness was positively associated with after-work insomnia ($B = .33$, $p < .001$), and a confidence interval excluded zero (indirect effect = .171, 95% CI [.064, .341]).

Attachment anxiety moderated the effect between AI interaction frequency and need for affiliation ($B = .29$, $p = .005$; Figure 2C). This relationship was stronger at higher (+1 *SD*) levels of attachment anxiety ($B = 1.18$, $p < .001$), compared to lower (−1 *SD*) levels ($B = .45$, $p = .015$). The difference between those slopes was also significant (difference = .74, $p = .005$). On this basis, Hypothesis 5 was supported, as the indirect was stronger at higher levels of attachment anxiety (conditional indirect effect = .328; 95% CI [.153, .570]) compared to lower levels (conditional indirect effect = .124; 95% CI [.030, .282]). A confidence interval for the difference in these indirect effects excluded zero (95% CI [.024, .171]).

Attachment anxiety also moderated the relationship between AI interaction frequency and loneliness ($B = .32$, $p = .008$; Figure 3B). This relationship was stronger at higher levels of attachment anxiety ($B = .93$, $p < .001$) compared to lower levels ($B = .12$, $p = .575$). The difference between those slopes was also significant (difference = .814, $p = .008$). Hypothesis 6a was supported, as the indirect effect of AI condition on after-work alcohol consumption was stronger at higher levels of attachment anxiety (conditional indirect effect = .377; 95% CI [.177, .680]) compared to lower levels (conditional indirect effect = .048; 95% CI [−.116, .240]). A confidence interval for the difference in these effects excluded zero (95% CI [.037, .268]). Hypothesis 6b was also supported, as the indirect effect of AI condition on after-work insomnia via loneliness was stronger at higher levels of attachment anxiety (conditional indirect effect = .303; 95% CI [.130, .572]) compared to lower levels (conditional indirect effect = .039; 95% CI [−.091, .200]). A confidence interval for the difference in these effects excluded zero (95% CI [.028, .226]).

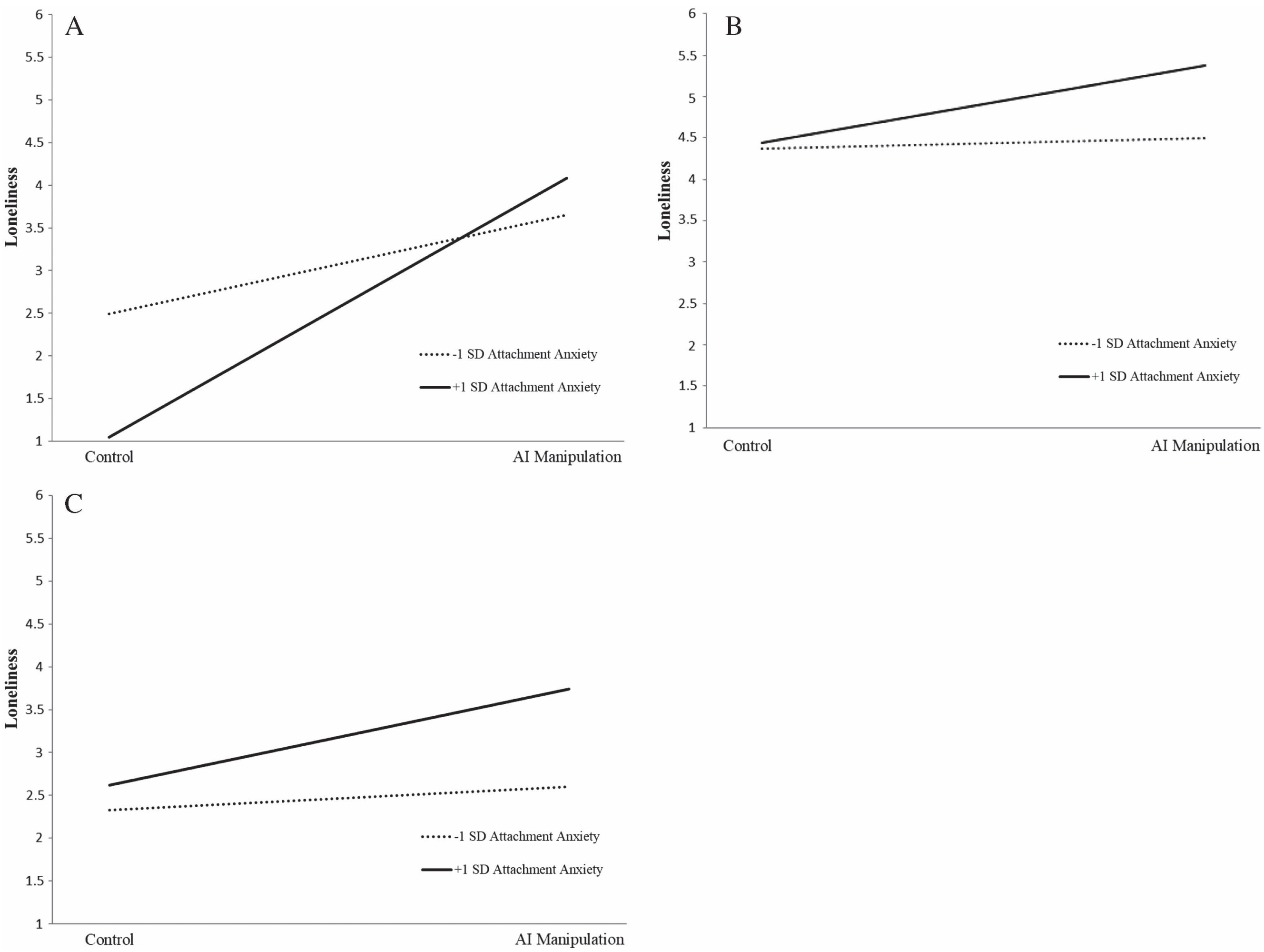
Discussion of Study 3 Findings

Study 3 provided further evidence for our hypotheses in a controlled online sample of working adults in the United States working in a wide spectrum of jobs and industries (Table 7). Further, this study added an important control variable—attitudes toward AI—and again used a different form of AI, thus adding more evidence for the generalizability

[7] Following Tang, Koopman, McClean, et al., 2022, we assessed the psychological realism of the simulation by asking participants several questions. Specifically, participants assigned to the AI interaction condition were asked to evaluate the psychological realism of the task with three items from Farh et al. (2017). Approximately 52.4% participants at least somewhat agreed (i.e., rating 5, 6, or 7; 1 = *strongly disagree*, 7 = *strongly agree*) with the item "It is realistic that I might work with the AI in this task." ($M = 4.14$, $SD = 1.80$), 55.2% at least somewhat agreed with the item "It is realistic that I might experience similar interactions with the AI that I just experienced in the task" ($M = 4.26$, $SD = 1.65$), and 46.7% at least somewhat agreed with the item "At some point during my career, I will probably encounter a situation like I just experienced in the task" ($M = 4.02$, $SD = 1.64$).

Figure 3

Attachment Anxiety Moderates the Relationship Between Interaction Frequency With AI and Loneliness



Note. Panel A—Study 2; Panel B—Study 3; Panel C—Study 4. AI = artificial intelligence.

of our model (along with not restricting the sample to employees who cohabitate with a family member, which addresses that lingering concern from Studies 1 and 2). In this study, all hypotheses received support. However, we want to be cautious with regard to the dependent variables. That is, given the experimental nature of our study, we could only assess these as intentions (Brutus et al., 2010). Notably, intentions are one of the most powerful predictors of subsequent behavior (Ajzen & Fishbein, 1977; Eagly & Chaiken, 1993). However, this remains a limitation. For this reason, we returned to the field to conduct an experiment with employees from different functional units (i.e., multiple areas of the business that use different forms of AI). As with Study 3, we do not restrict this sample to those who cohabitate with a family member, and we measure all controls.

Study 4: Method

Sample and Procedure

We collected data in Spring 2022 from employees in different business functions (finance, operations, marketing, and accounting) in a Malaysian technology company whose primary responsibilities include working with AI systems (of note, different across the different functions) to execute various job duties associated with their respective roles. For example, employees in the finance unit interact with AI systems to forecast financial performance and develop budgets, while employees in the operation unit interact with AI systems to coordinate resource allocation processes. All 316 employees were given a briefing to describe the study (which, unlike Study 2, did not require a cohabitating family member). The 294 participating employees completed a survey (T1) with measures of attachment anxiety and avoidance as well as attitudes toward AI. As in Study 2, participants were randomly assigned to two conditions and instructed to either collaborate with AI systems as much as possible (AI condition) or not to use AI when performing their job duties (control condition) for three consecutive days.

After 3 work days, we sent a postmanipulation survey (T2) with measures of need for affiliation and loneliness, interaction frequency and quality with coworkers, and need for belongingness and relatedness needs. Employees also rated manipulation check items

Table 5
Industries and Examples Job Titles of Participants (Study 3)

Industries	Percentage of participants (N = 214)	Example job titles
Educational services	13.1%	Teaching assistant, science teacher, senior lecturer
Finance and insurance	9.3%	Finance manager, financial analyst, accountant, broker
Health care and social assistance	9.3%	Nurse, massage therapist, pharmacist
Information	9.3%	Software developer, digital marketing, web designer
Retail and service	6.5%	Retail assistant, customer service manager, cashier
Accommodation and food services	4.7%	Bartender, waitress, baker
Arts, entertainment, and recreation	4.7%	Graphic designer, blog writer, producer
Professional, scientific, and technical services	4.7%	Lawyer, electrical engineer, consultant
Management	3.7%	Operation manager, project manager, assistant manager
Public administration	3.7%	Civil servant, procurement manager, human resources
Administration	2.8%	Administrator, proofreader
Transportation	2.8%	Crew scheduler, logistic and transport specialist
Construction	2.3%	architect, senior site manager
Others	23.1%	Dog trainer, homemaker, research fellow

Note. The categorization of industries was based on 2017 North American Industry Classification System (NAICS): https://www.census.gov/naics/.

regarding interaction frequency with AI as well as their own after-work alcohol consumption and insomnia. At the same time, a coworker assessed the employee's helping behavior. Overall, 294 consultants (47.3% male) completed the study. Average age was 37.9 years old (SD = 7.77), average tenure was 3.18 years (SD = 1.85), and average years of using AI systems at work was 1.63 years (SD = .78). Most (62.3%) were tertiary educated.

Measures

We followed the same back-translation procedures as in Study 1. All measures, except attachment anxiety and avoidance, asked employees to respond as appropriate "over the last three days." Anchors and wording for all measures are in OSF and reliabilities are given with our descriptive statistics. *Attachment anxiety* and *avoidance*, as well as *attitudes toward AI*, were measured at T1 as in Study 1. At T2, we used the items from Study 1 to measure *interaction frequency with AI*, *interaction frequency and quality with coworkers*, *need for affiliation*, *loneliness*, *need for belongingness*, and *relatedness needs*. We used the items from Study 1 to measure the focal employee's *helping behavior* from a coworker and employees self-reported their *alcohol consumption* and *insomnia*.

Analytic Strategy

A CFA on our primary model (identical to Study 2) indicated adequate fit (χ^2 = 375.48, df = 125, CFI = .95, RMSEA = .08, SRMR = .04). We thus tested our model as in prior studies.

Study 4: Results

Table 8 presents the means, standard deviations, and correlations of our study variables, and Table 9 provides path-analytic results of our primary model. First, we conducted a one-way ANOVA to examine the effect of our manipulation. Responses to the manipulation check items differed significantly between the AI condition (M = 5.09, SD = .83) and control condition (M = 3.52, SD = 1.45; t[292] = 11.46, p < .001, d = 1.34). Overall, our manipulation was deemed effective, and thus we next proceeded to perform hypotheses testing.

Supporting Hypothesis 1, AI condition was positively associated with need for affiliation (B = 1.47, p < .001). Supporting Hypothesis 2, the indirect effect between AI condition and helping via need for affiliation was positive and significant. That is, need for affiliation was positively associated with helping behavior (B = .10, p = .010), and the indirect effect confidence interval excluded zero (indirect effect = .153, 95% CI [.037, .285]). Supporting Hypothesis 3, AI condition was positively associated with loneliness (B = .70, p < .001). Supporting Hypothesis 4a, the indirect effect between the AI condition and after-work alcohol consumption use via loneliness was positive and significant. That is, loneliness was positively associated with after-work alcohol consumption (B = .53, p = .001), and a confidence interval excluded zero (indirect effect = .368, 95% CI [.149, .693]). Supporting Hypothesis 4b, the indirect effect between AI condition and after-work insomnia use via loneliness was positive and significant. That is, loneliness was positively associated with after-work insomnia (B = .39, p < .001), and a confidence interval excluded zero (indirect effect = .273, 95% CI [.146, .441]).

Attachment anxiety moderated the effect between AI interaction frequency and need for affiliation (B = .27, p = .013; Figure 2D). This relationship was stronger at higher (+1 SD) levels of attachment anxiety (B = 1.86, p < .001) compared to lower (−1 SD) levels (B = 1.07, p < .001). The difference between those slopes was significant (difference = .79, p = .013). On this basis, Hypothesis 5 was supported, as the indirect was stronger at higher levels of attachment anxiety (conditional indirect effect = .194; 95% CI [.051, .359]) compared to lower levels (conditional indirect effect = .112; 95% CI [.030, .229]). A confidence interval for the difference in these indirect effects excluded zero (95% CI [.005, .071]). Attachment anxiety also moderated the relationship between AI interaction frequency and loneliness (B = .29, p = .006; Figure 3C). This relationship was stronger at higher levels of attachment anxiety (B = 1.12, p < .001), compared to lower levels (B = .27, p = .208). The difference between those slopes was also significant (difference = .85, p = .006). Thus, Hypothesis 6a was supported, as the indirect relationship of AI condition on employee's after-work

Table 6
Descriptive Statistics and Correlations Among Study Variables (Study 3)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Condition (1 or 0)	0.49	0.50	—													
2. Need for affiliation	5.11	1.04	.35*	(.91)												
3. Loneliness	3.73	1.25	.29*	.07	(.81)											
4. Need for belongingness (control)	4.82	1.05	.00	.17*	−.27*	(.86)										
5. Relatedness need (control)	4.80	1.11	.05	.27*	−.24*	.46*	(.71)									
6. Helping behavior	5.61	1.14	−.06	.21*	−.25*	.50*	.36*	(.90)								
7. Alcohol consumption	2.85	1.74	−.19*	−.07	.21*	−.07	−.08	.01	—							
8. Insomnia	3.29	1.62	−.03	−.14*	.22*	−.15*	−.20*	−.00	.21*	(.87)						
9. Attachment anxiety	2.77	1.28	.21*	−.11	.42*	−.32*	−.26*	−.28*	.11	.17*	(.91)					
10. Attachment avoidance (control)	3.84	1.55	−.52*	−.37*	.08	−.27*	−.18*	−.14*	.22*	.22*	.18*	(.85)				
11. Attitudes toward AI (control)	4.44	1.13	−.28*	−.00	−.08	.06	.05	.06	.17*	−.11	−.03	.16*	(.94)			
12. Age (years)	33.97	11.91	.32*	.12	−.06	.11	.06	.20*	−.20*	−.01	−.08	−.23*	−.20*	—		
13. Gender (1 = male; 0 = female)	.67	.47	.19*	.12	.06	.13	.09	.09	−.05	.08	.06	−.11	−.26*	.04	—	
14. Tenure (years)	9.71	11.41	.24*	.09	.01	.09	.01	.15*	−.11	.07	−.11	−.18*	−.09	.73*	−.10	—
15. Race	1.49	1.19	−.17*	−.06	−.12	.06	−.06	−.02	.14*	.01	−.11	.09	.15*	−.20*	−.07	−.14*

Note. $N = 214$. 1 = AI condition; 0 = control condition. Scale reliabilities are reported along the diagonal in parentheses. AI = artificial intelligence. For race, it is coded as "1 = White; 2 = Black American; 3 = American Indian; 4 = Asian; 5 = Native Hawaiian or other pacific islander; 6 = other."
$^* p < .05$.

alcohol consumption was stronger at higher levels of attachment anxiety (conditional indirect effect = .592; 95% CI [.242, 1.106]) compared to lower levels (conditional indirect effect = .145; 95% CI [−.054, .457]). The confidence interval for the difference in these effects excluded zero (95% CI [.045, .339]). Hypothesis 6b was also supported, as the indirect effect of AI condition on after-work insomnia via loneliness was stronger at higher levels of attachment anxiety (conditional indirect effect = .438; 95% CI [.249, .634]) compared to lower levels (conditional indirect effect = .107; 95% CI [−.055, .294]). A confidence interval for the difference in these effects excluded zero (95% CI [.035, .214]).

Discussion of Study 4 Findings

All study hypotheses were supported in Study 4. Moreover, the design of this study comprehensively addresses many of the issues previously brought up (i.e., employees came from multiple units of the company, all used different types of AI systems, and were not selected based on whether they cohabited with a family member or not). Overall, this study (combined with the three prior) provides consistent, robust, and generalizable evidence for our hypotheses.

General Discussion

Anthropologists and evolutionary psychologists have long theorized that people evolved to require social interactions to survive and thrive in their communities (Horsfall & Arensberg, 1949). These interactions, scholars argue, were critical for individuals to gain social information about themselves and their place within the group (Levinson, 2006). For this reason, individuals developed an internal social affiliation process that helps to regulate these interactions (Leary & Baumeister, 2000). Until recently, the design of modern organizations mirrored those early communities, as organizations were social systems wherein people came together to collectively pursue goals (Barnard, 1938). However, as society enters the Fourth Industrial Revolution, digital transformations in companies worldwide are altering the workplace and the nature of social interactions among coworkers, as AI systems are increasingly coupled with employees in the course of their work (Murray et al., 2021). From an organizational point of view, this shift is critical to increase efficiency and competitiveness in the digital age (Gregory et al., 2021). Yet, the human element has been somewhat overlooked during this period. That is, people's social affiliation processes may be sensitive to the increasing frequency of interaction with nonhuman AI systems, which may have consequences for employees (O'Connor & Rosenblood, 1996).

Our purpose was to shed light on this phenomenon by testing a model built by integrating research on social affiliation (Hall, 2017; Leary, 2010; O'Connor & Rosenblood, 1996) and attachment theory (Simpson, 1990; Simpson & Rholes, 2015; Simpson et al., 1992). Based on this theoretical perspective, we argued that employees may respond to increasing interaction with AI at work in an (a) adaptive manner (enacting more affiliative behaviors [i.e., helping] due to increased needs for affiliation) or (b) a maladaptive manner (enacting behaviors that are more isolating in nature [alcohol consumption and insomnia after work] due to increased loneliness). We extend this research further by integrating theory on attachment styles. In so doing, we show employees with higher levels of anxious attachment are more sensitive to the experience of interacting with AI, which

Table 7
Path Analysis (Primary Hypotheses; Study 3)

Variable	Need for affiliation		Loneliness		Helping		Alcohol consumption		Insomnia	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Intercept	4.67*	.09	3.42*	.11	5.12*	.43	1.72*	.66	3.24*	.63
Independent variable										
AI condition (AI)	.82*	.13	.53*	.15	−.18	.16	−.96*	.25	−.19	.24
Mediator										
Need for affiliation	—	—	—	—	.28*	.08	.02	.12	−.21	.11
Loneliness	—	—	—	—	−.22*	.06	.40*	.09	.33*	.09
Moderator										
Attachment anxiety (AAN)	−.32*	.08	.19*	.09	—	—	—	—	—	—
Interaction (AAN × AI)	.29*	.10	.32*	.12	—	—	—	—	—	—

Note. $N = 214$. *SE* = standard error; AI = artificial intelligence.
* $p < .05$.

heightens subsequent feelings of both need for affiliation as well as loneliness. While we generally find support for our hypotheses across the four studies, it is important to be mindful of these findings when considering the implications of our findings for the future of human–AI integration in organizations worldwide (Murray et al., 2021; Tang, Koopman, Elfenbein, et al., 2022; Wilson & Daugherty, 2018), as well as research on affiliation and attachment.

Overall, the results of the four studies that we have conducted provide robust evidence for the validity of our hypothesized relationships. That is, we examined our model with employees who (a) come from a variety of jobs and industries, (b) work with different types of AI systems, and (c) come from both Eastern and Western cultures. Moreover, our research (d) employs different methodologies and operationalizations of interactions with AI, and (e) obtains multiple sources of data (i.e., from focal employees, coworkers, and family members). The largely consistent findings from the four studies should provide strong confidence in the theory we develop in this research. We now turn to discuss the implications of our findings.

Theoretical Implications and Avenues for Future Research

First, we broaden the scope of research on the incorporation of AI into organizations by taking a balanced approach to understanding the variety of outcomes that accrue to employees based on their interactions with AI at work. That is, while organizational research tends to focus on either the work-related benefits (e.g., Gregory et al., 2021; Raisch & Krakowski, 2021) or the aversive consequences (Dietvorst et al., 2018; Yam et al., 2022) of working with AI, the social affiliation lens that we apply helps us to simultaneously understand both perspectives. In so doing, we not only identify a positive outcome (increasing helping behavior) that aligns with research on the benefits accompanying AI-augmented jobs (e.g., von Krogh, 2018), but we also show several concomitant downsides in the form of impaired well-being.

The second implication of our work is that we stitch together research on social affiliation that is presently scattered throughout the scholarly literature. Importantly, bringing this research together revealed that scholars have theorized about, but never simultaneously examined, both adaptive and maladaptive mechanisms that transmit the effects of social deprivation. Thus, we contribute to research on social affiliation by juxtaposing these mechanisms and examining their implications for subsequent coping responses among employees following their interactions with AI systems. In so doing, we paint a fuller picture of the breadth of outcomes that may be driven by the social regulatory system suggested by social affiliation scholars (O'Connor & Rosenblood, 1996). Extending this point, we make an additional contribution to research on social affiliation. Typically, research regarding social affiliation looks at outcomes in a single (nonwork) domain. We extend this research by not only showing that they can be applied to explain psychobehavioral consequences after interacting with AI at work but also that this predicts outcomes across domains (i.e., helping at work and alcohol consumption and insomnia at home).

Third, our integration of attachment theory with the social affiliation research extends this theory even further. That is, we add specificity to what was previously only hinted at in terms of the role of individual differences as influencing people's sensitivity to the absence of social connection in their daily interactions (Hall, 2017; O'Connor & Rosenblood, 1996). As our results reveal, attachment-anxious employees may be particularly sensitive to interactions that are more socially distant (e.g., those with AI). To this end, the affiliation systems of those individuals may react more vigorously. It is also noteworthy that our results consistently reveal that attachment–avoidance is not associated with outcomes of these types of interactions. This is an important point of departure for organizational scientists seeking to address calls for further examinations of theory on attachment styles in applied scholarship (e.g., McClean et al., 2021).

Practical Implications

The Fourth Industrial Revolution has arrived (Davenport, 2018; Makridakis, 2017), so our research provides timely insights for decision-makers to enhance their understanding of how AI impacts employees. Managers must recognize that, while performance is an important metric (e.g., Raisch & Krakowski, 2021), interactions with AI may be linked (for better or for worse) with a variety of performance- and well-being-related employee outcomes. As interactions with AI are not going away (Wilson & Daugherty, 2018), managers should focus on a holistic set of employee outcomes. One way to mitigate some of the consequences of our model is to try and combat the potential for employees to be lonely—for example,

Table 8

Descriptive Statistics and Correlations Among Study Variables (Study 4)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Condition (1 or 0)	0.50	0.50	—														
2. Interaction frequency with coworkers (control)	5.00	1.21	.00	(.81)													
3. Interaction quality with coworkers (control)	5.11	1.06	−.06	.64*	(.88)												
4. Need for affiliation	5.03	1.58	.47*	.01	.08	(.98)											
5. Loneliness	3.17	1.48	.23*	−.28*	−.32*	.11	(.93)										
6. Need for belongingness (control)	4.45	1.19	−.27*	.42*	.48*	−.04	−.34*	(.88)									
7. Relatedness need (control)	4.65	1.11	.09	.28*	.29*	.11	−.35*	.32*	(.71)								
8. Helping behavior	5.45	1.03	−.08	.42*	.43*	.09	−.32*	.37*	.29*	(.86)							
9. Alcohol consumption	2.53	3.93	−.00	.06	.01	.01	.19*	.04	−.04	.08	—						
10. Insomnia	3.51	1.66	.04	−.15*	−.17*	−.12*	.34*	−.14*	−.30*	−.16*	.08	(.90)					
11. Attachment anxiety	4.33	1.47	−.03	−.08	−.05	−.18*	.37*	−.19*	−.32*	−.08	.09	.29*	(.91)				
12. Attachment avoidance (control)	4.65	1.34	−.05	−.14*	−.20*	.04	.22*	−.22*	−.31*	−.12*	.04	.14*	.14*	(.83)			
13. Attitudes toward AI (control)	4.80	1.04	−.08	.08	.11	−.04	−.04	.07	.01	.09	.03	.04	.05	.16*	(.92)		
14. Age (years)	37.92	7.77	−.05	−.00	−.01	−.02	−.04	−.02	−.08	−.03	.00	−.11	.08	−.00	−.02	—	
15. Gender (1 = male; 0 = female)	.47	.50	−.05	−.01	−.03	.12*	.02	−.01	.04	−.04	.08	−.05	.02	−.01	−.01	−.05	—
16. Tenure (years)	3.18	1.85	−.07	.09	.02	.01	−.08	−.00	.05	−.06	.06	−.04	.01	−.03	−.12*	.21*	.08

Note. $N = 294$. 1 = AI condition; 0 = control condition. Scale reliabilities are reported along the diagonal in parentheses. AI = artificial intelligence.
* $p < .05$.

managers could consider the appropriate density of AI systems in the work environment (Graetz & Michaels, 2018; Zhao et al., 2012), such that employees can maintain desirable levels of social interactions with others as well. Relatedly, managers can arrange other opportunities for socializing (Chong et al., 2020).

We further offer a word of caution regarding our finding that interactions with AI led to increased levels of helping. While this is a desirable outcome from a managerial standpoint (Podsakoff et al., 2009), this behavior is still a reaction to what employees viewed as a socially deficient work situation. As such, we do not suggest that the way to encourage greater levels of helping among employees is to otherwise deprive them of social interactions. To this point, it is important to note that the same experience that led to greater levels of helping also led to greater levels of alcohol consumption and insomnia after work (which might jeopardize employees' mental well-being and result in a negative spiral; Berryman et al., 2018; Pereira et al., 2013). In this way, our point is analogous to research on citizenship pressure (Bolino et al., 2010). While pressure to engage in citizenship is associated with greater levels of citizenship, it can also harm well-being and increase deviant behavior (Koopman et al., 2020; Vigoda-Gadot, 2006).

Limitations and Future Research

Importantly, each study has notable weaknesses, though many are offset by the design of another study (Hekman et al., 2017; Liang et al., 2018). For example, in Study 1, the interaction effect of attachment anxiety predicting need for affiliation weakened when adding the interaction of attachment avoidance (despite this added term itself being not significant). Also, the path between loneliness and alcohol consumption was not significant in Study 2. Both studies also have limitations associated with the generalizability of their findings, as they share a common feature that the assessments of alcohol consumption and insomnia come from a family member living with the employee. Further, although both Studies 1 and 2 were conducted in two different organizations, it makes sense that there are some inherent job differences associated with the experience of interacting with AI. These issues might call into question the generalizability of their findings. In order to address these concerns, Study 3 recruited a sample of employees from a broad spectrum of jobs and industries, whereas Study 4 recruited a sample of employees coming from different business units who interact with different types of AI systems. Overall, the four studies, when viewed holistically, should complement the limitations of the others.

Moreover, there are caveats associated with the interpretation of our findings pertaining to the adaptive pathway of the model and the associated construct—need for affiliation. Research on psychological needs differentiates between (a) need elicitation and (b) need satisfaction. For the former, scholars tend to focus on situational or personal factors that instantiate a particular need. For example, as per de Bloom et al.'s (2020) model, situational factors (e.g., work events or culture) make needs salient, which then drive subsequent behavior to address those needs. In a similar vein, other scholars have argued that some work experiences may deprive employees of certain needs (e.g., Vogel et al., 2020). In contrast, the latter stream of research focuses on how certain work experiences or interactions may satisfy or fulfill needs. For example, Foulk et al. (2019) found various forms of motivational striving at work can satisfy basic

Table 9
Path Analysis (Primary Hypotheses; Study 4)

Variable	Need for affiliation		Loneliness		Helping		Alcohol consumption		Insomnia	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Intercept	4.30*	.11	2.82*	.11	5.71*	.22	.91	.88	3.14*	.35
Independent variable										
AI condition (AI)	1.47*	.16	.70*	.15	−.17	.13	−.44	.52	.16	.21
Mediator										
Need for affiliation	—	—	—	—	.10*	.04	.03	.16	−.19*	.06
Loneliness	—	—	—	—	−.22*	.04	.53*	.16	.39*	.06
Moderator										
Attachment anxiety (AAN)	−.30*	.07	.24*	.07	—	—	—	—	—	—
Interaction (AAN × AI)	.27*	.11	.29*	.11	—	—	—	—	—	—

Note. $N = 294$. *SE* = standard error; AI = artificial intelligence.
* $p < .05$.

employee needs. Similarly, Lin et al. (2021) found that some out-of-work positive events may lead to need satisfaction at home. Our conceptualization is more aligned with the former research stream, as our theoretical arguments imply that interactions with AI instantiate a need to socially affiliate with others at work. However, this leads to another issue we must discuss.

As we highlighted earlier, an anonymous reviewer questioned whether our findings were indeed driven by the sense of "unmet expectations" about which we theorize, or instead whether they were driven by a corresponding lack of interactions with human colleagues. While the former argument derives from the theoretical lens of social affiliation that we apply to this research question, our study designs were not designed in such a way to directly test these competing explanations (note that we did control for both the frequency and quality of interactions with coworkers in an effort to speak to this point). Although this question does not threaten the validity of our findings, it has implications for understanding why those findings were observed. Thus, we think future research could benefit from zooming more closely into the micromechanism linking AI interactions with our two mediators. For example, scholars could compare our social affiliation framework against an alternative such as social baseline theory (Coan & Sbarra, 2015). From this competing perspective, interactions with AI at work might be considered as a kind of "relationship disruption" phenomenon (Coan & Sbarra, 2015, p. 87), such that it will trigger a social–regulatory process of heightened uncertainty and risk—the result of which would be efforts to maintain social relationships.

There is also a potential limitation associated with our need for affiliation measure. The original scale is quite long (Hill, 1987), and so we adapted three items for our studies. Doing so can create concerns over content validity, which we sought to address in two ways. First, we assessed the convergence of our items (and, the original items) with the definition of need for affiliation. Second, we conducted an additional study that follows a procedure from Rosen et al. (2019), in which we administered our scale and the original to a sample of working employees to evaluate the correlation between the two measures. The results from both studies (reported at OSF) provide reasonable basis from which to conclude that our shortened measure captures the core essence of this construct and is thus a valid operationalization. However, we recommend that scholars evaluating this construct in the future further examine the items used to measure this construct, and perhaps undertake additional efforts to refine them further.

We do also want to highlight the limitation of measuring our dependent variables as intentions in Study 3. Despite (as we highlighted earlier) the appropriateness and necessity of such measures for experimental studies, we do think that future research could go a step further with the study design to identify a way to capture a behavioral outcome that can proxy for those of interest to the current research. For example, participants could be asked to provide written responses to a scenario in which a colleague requested assistance, which could then be coded for evidence of prosocial behavior (e.g., Twenge et al., 2007). To assess the likelihood of socially isolating behavior, participants could be asked to write a narrative about what they plan to do over the upcoming weekend—responses to which could again be coded accordingly.

Meanwhile, there are some potential limitations associated with the specific design of each of the studies that warrant some further discussion. For example, in Study 1 (i.e., the multiwave and multisource field study), we adopted a 1-week interval between each of the surveys. This design choice follows prior research that also used this time frame as a way to capture the proximal responses that follow certain work experiences (e.g., Johnson et al., 2015; Lian et al., 2014; Ong, 2022; Rosen et al., 2014; Yoon et al., in press). Yet, this time interval is not without limitation, as it could be too long of a window and thus allow for other unmeasured influences on our downstream variables. Yet, here, Studies 2 and 4 (which use an interval of 3 days) and Study 3 (for which all variables were measured in the experimental setting) should alleviate this concern. Yet, with this said, there are other processes that may occur at work that take longer than a week to develop (e.g., turnover processes are theorized to unfold over much longer time periods; Lee & Mitchell, 1994). Thus, we recommend future research examine models such as ours over a variety of time intervals—both shorter and longer—to capture the effects of interacting with AI.

Following from the above, another potential limitation comes from the design of the simulation-based experiment (Study 3). While participants did tend to see the experience as at least somewhat realistic and a possible experience they may have in their work at some point, there is a need to enhance the quality of this (and other; Efendić et al., 2020) experimental tasks that involve interactions with AI. While it may not be surprising that participants who do not work with AI at work right now cannot imagine how they may in the future, it may behoove researchers to educate participants about the ways in which work is changing to improve the realism of the task. Along similar lines, it would be good to enhance the interaction experience as well. For example, scholars can consider incorporating aspects of open AI systems (e.g., ChatGPT; Pavlik, 2023) in developing a collaboration task with AI. In short, we recommend future research to augment the simulation paradigm to increase the realism of the study.

Conclusion

Across millennia, people evolved internal systems to gauge the quality of relationships with others. These systems have remained effective in a workplace that, just as in primitive tribal communities, prioritized social interactions with coworkers. Yet, the advent of digital, asocial AI systems and their incorporation into employee work, threatens to upend the operation of these systems. We show how employee interactions with their new AI colleagues may lead to an increased need for affiliation as well as loneliness. The mixed consequences of these states paint an important, but sobering, picture of the future of AI augmentation efforts. While this future continues apace, managers must pay heed to outcomes experienced by their human employees.

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