Abstract

Purpose - We examine how employees adopt beliefs about artificial intelligence (AI) with respect to career and employment prospects. Specifically, we demonstrate the importance of employees and organizations being in alignment in regards to the status they confer upon AI.

Design/methodology - We test our hypotheses via polynomial regression and response surface analysis using a study of 243 working adults from a variety of industries.

Findings - We find support for our model and demonstrate that congruency in AI status perceptions between the employee and the organization has important implications for how employees respond to AI.

Originality - We are among the first to examine how (in)congruency of AI attitudes between the employee and the organization jointly influence employee AI attitudes.

Keywords artificial intelligence, status, psychological safety, conservation of resources

Paper Type Research paper

I like the bots but my employer doesn't! An examination of AI status incongruence

Swedish fintech company Klarna made international news by claiming its new AI assistant was performing the equivalent work of 700 full-time employees, a move celebrated for boosting efficiency yet also sparking anxiety among workers who feared job loss (Mukherjee, 2024; Scheiber, 2025). Elsewhere, other organizations report the opposite dynamic: employees feel stifled by prohibitions on AI use and quietly adopt the technology in secret to keep pace with their work (McManus, 2025). These contrasting reactions suggest a deeper tension—employees' experiences with AI may depend not only on their own attitudes but also on how they perceive their organization's stance.

While scholars and practitioners increasingly recognize that employee attitudes toward AI matter (Braganza et al., 2021; Saad, 2023), less attention has been given to how alignment or misalignment between employee and organizational views shapes workplace outcomes. This is important as research suggests employee attitudes, such as increased job satisfaction and commitment (Ostroff et al., 2005), can be shaped by perceptions of congruence between the employee and the organization (Kristof-Brown & Jansen, 2007). Given that employees hold their own, individual views about AI (Park et al., 2024) and also commonly assess their organization's views about AI (Presbitero & Teng-Calleja, 2022), these factors likely work together to influence workplace attitudes.

In the present study, we explore how the alignment between employee and organizational AI attitudes influences beliefs about organizational obstruction (i.e., career goal stymie) and employment insecurity (i.e., fear of job loss). We suggest the congruency of employee and organization status afforded to AI prompts employees to feel psychologically safe at work - one's perception that it is safe to take interpersonal risks at work (Edmondson, 1999). We focus

on status afforded to AI as status generally entails one's feelings about another entity's prominence, prestige, and respect (Djurdjevic et al., 2017), capturing one's belief about AI's place and value at work. Drawing from conservation of resources theory (COR; Hobfoll, 1988, 2001), we suggest congruence regarding AI's status at work is itself a resource (see Hobfoll, 2001), leading to psychological safety which then encourages employees to invest energy into their work to accumulate future resources (Frazier, et al., 2017; Ng & Feldman, 2012), resulting in decreased perceptions of organizational obstruction and employment insecurity.

Our research expands current nascent understanding of how to mitigate employee AI apprehension (Bradford, 2024; Kim & Lee, 2025) by proposing employee and organization AI status (in)congruence serves as an important element influencing employee attitudes. We also expand the burgeoning conversation (e.g., Edmonson & Bransby, 2023) regarding how organizations can foster employee psychological safety beyond the predominant view focusing on social exchange or social learning processes. Instead, we draw from COR theory to suggest that psychological safety emerges from the perception one has about their future resources (Newman, et al., 2017), thus expanding our understanding of COR Theory application to AI in the workplace (Bankins, et a., 2024). Finally, we further explain the nuances involved with employee reactions to AI. By examining employee-organization AI status congruency, organizations can gain greater clarity regarding AI impact on resource gain/loss percepts and subsequent organizational outcomes.

Literature Review and Hypothesis Development

Information technology in the workplace has driven technological advancements that enhance decision-making, automate tasks, and improve productivity (Furman & Seamans, 2019). With the 2022 release of OpenAI's ChatGPT, generative artificial intelligence entered the

managerial zeitgeist. We use "AI" to refer to generative artificial intelligence - systems that can "generate new content that resembles human-created output, such as images, text, audio, and videos" (Grimes, et al., 2023, p. 1617). AI aids in the workplace in regards to problem-solving initiatives (Dell'Acqua et al., 2023) and may especially benefit less-experienced workers (Noy & Zhang, 2023).

Employees regularly attribute a certain level of workplace status to themselves and co-workers. Workplace status refers to one's "relative standing in an organization, as characterized by the respect, prominence, and prestige he or she possesses in the eyes of other organizational members" (Djurdjevic et al, 2017, p. 1125) and ranges from low-status to high-status (Sessions, et al., 2021). High-status may entail positive attention and influence (Anderson et al., 2001), perceptions of high skillset (Djurdjevic et al., 2017), or favorable reputation (Hochwater et al., 2007). Conversely, low status represents a lack of these attributes.

We suggest status conferment to AI emerges for multiple reasons. First, individuals frequently accord status to non-human entities, such as respecting a governmental office (Rossiter, 1960) or ranking higher education institutions (Johnes, 2018). Moreover, individuals often imbue a certain level of human characteristics to AI (Pelau et al., 2021), such as ascribing personality characteristics to AI (e.g., Evans & Kortum, 2010), sharing vulnerable and emotional information with AI (Laestadius et al., 2022), or referring to AI as an assistant or partner (Maeda & Quan-Haase, 2024). Lastly, AI's heightened performance capabilities (e.g., Von Krogh, 2018) and prominent place in modern society (Gallego & Kurer, 2022) are two key elements of status (Djurdjevic et al., 2017) that afford the potential to situate AI within a status hierarchy. Thus, employees likely develop individual perceptions about and confer status upon AI, referred to here as *employee AI status*. An individual who affords high status to AI may regularly and

openly use AI for work tasks or share the benefits of AI with coworkers. Alternatively, an individual who affords low status to AI may regularly warn of potential unethical uses for AI or demonstrate pride in publicizing shortcomings in AI output.

Organizations also likely signal to employees the status level the organization affords to AI, possibly by relying on the technology to improve task performance (Marikyan et al., 2022), information processing (Von Krogh, 2018), problem solving and decision making (Liboni et al., 2019), and automation efficiencies (Bessen et al., 2019). Organizational leaders may frequently speak positively about AI or encourage AI training and integration into daily work tasks. Conversely, leaders may warn of AI deficits or enact policies prohibiting AI use. Given that status is socially constructed (e.g., Pearce, 2011), employees likely form an impression of their organization's assessment of AI in the workplace via these signals, irrespective of their own status conferred to AI. We refer to this concept as *organizational AI status*.

COR Theory and Psychological Safety

Because AI status perceptions rest with both an employee and the organization at large, these perceptions may be either congruent or incongruent, leading to impactful organizational outcomes. To explicate these organizational implications, we draw from conservation of resources theory (Hobfoll, 1988), which contends employees protect and seek resources such as objects, personal characteristics, conditions, or energies they perceive as valuable and aiding in goal attainment (Halbesleben et al., 2014; Hobfoll, 1989). For example, family-supportive workplace policies (Payne et al., 2012), self-esteem (Xanthopoulou et al., 2009), and job autonomy (Chen et al., 2009) have all been characterized as resources within a COR framework as they bring value to employees.

Congruency between an employee's own AI status and the employee's perception of the organization's AI status likely serves as an important employee resource. Research suggests employees' perceptions of alignment with their organization on a range of outcomes can lead to increased resources. For example, Song & Chathoth (2011) demonstrated that employee-organization values alignment was positively associated with self-esteem. Similarly, we suggest that congruency between one's own employee AI status and perceived organizational AI status leads to increased psychological safety at work.

Psychological safety refers to one's perception that it is safe to take interpersonal risks at work (Edmondson, 1999). We position psychological safety as a key resource stemming from employee-organizational AI status congruency for multiple reasons. First, with AI changing the workplace at a rapid pace (Gallego & Kurer, 2022), psychological safety likely plays a prominent role in helping employees adjust to changing AI advancements in the workplace (Edmondson & Lei, 2014). Second, psychological safety promotes a positive cognitive state that compels employees to invest energy and risk-taking into their work (Frazier et al., 2017), likely increasing the accumulation of resources (e.g., Ng & Feldman, 2012; Sonnentag et al., 2008). Finally, psychological safety has been suggested to reduce perceived resource threats caused by changes in the workplace (Schein & Bennis, 1965), e.g. AI introduction. A central tenet of COR Theory is that even the perceived threat of losing resources is psychologically harmful (Hobfoll, 1988), making psychological safety an important mechanism affecting perceived levels of resource attainment at work.

COR theory suggests individuals are motivated to acquire new resources to achieve goals, and those with current resources are better positioned to accumulate future resources (Hobfoll, 2001). Drawing from COR, we propose congruency between high employee AI status

and high organizational AI status should instill perceptions that resource gain is possible. For example, in the case of high-high AI status, both parties likely afford AI the characteristics of high competence (Djurdjevic et al., 2017), favorable reputation (Hochwater et al., 2007), or social endorsement (Anderson, et al, 2001). Employees likely view AI as a tool increasing productivity and resources (Marikyan, et al., 2022); the organization likely promotes AI as a beneficial asset and facilitates its use, increasing psychological safety perceptions through greater resource availability (Edmondson, 1999). Employees in a high-high AI status scenario likely view being in alignment with their organization's view on AI as an important condition by which they can continue to use AI to accumulate resources in the form of enhanced productivity, problem solving, or automation (Liboni et al., 2019; Marikyan, et al., 2022; Bessen et al., 2019). Indeed, COR suggests employees are well- positioned to accumulate additional resources when current resources fit with their organizational environment (Hobfoll, 1988; Kaplan & Gangestad, 2005). We suggest employees in a high-high AI status scenario with their organization will feel psychologically safe to invest energy and take risks at work in an attempt to gain resources (Campbell et al., 2013; Paustian-Underdahl & Halbesleben, 2014).

Similarly, congruency between low employee AI status and low organizational AI status should reduce employee perceptions of potential resource loss as both parties see AI as less valuable and less influential (Magee & Galinsky, 2008). However, because the employee and organization are congruent in their views on AI status, conflict is reduced and employees should feel less threatened by AI. Because the organization sends low-status cues regarding AI status, employees who also view AI as low status fear no AI impact on their day-to-day work or threat to their current resources as their organization signals low intentions to implement AI in the

workplace. Employees feel psychologically safe to make resource investments in accordance with their employer's AI status view.

However, incongruence between employee AI status and organizational AI status may emerge. If so, we expect psychological safety to decrease. For example, if employee AI status is high and organizational status is low, the employee views AI as a means to accrue further resources in the form of enhanced productivity, decision making, and efficiency (Bessen et al., 2019; Liboni et al., 2019; Marikyan, et al., 2022), while the organization views AI as either generating no new resources or as a threat to existing resources. This incongruence likely leads employees to perceive lower psychological safety as they assess using the AI resource to be risky behavior (Carmeli & Gittell, 2009; Edmondson, 2004); organization leaders may punish attempts to use or promote AI. The employee likely recognizes that efforts to invest energies and resources into AI will not garner additional resources.

Similarly, we expect psychological safety to be low in cases where employee AI status is low and organizational AI status is high. The employee perceives AI as generating no resources or perhaps even threatening existing resources due to job loss (e.g., Dorn, 2015). Moreover, the organization and its members signal that AI is beneficial and should be incorporated into regular work tasks. Thus, the employee may fear AI will threaten or diminish resources as the organization and its other members push for AI inclusion in the workplace. Employees may view their organization as impeding upon them and feel less psychologically safe (Frazier et al., 2017). Taken together, we suggest the following:

> *H1*. Congruent employee AI status and organizational AI status is associated with higher psychological safety than incongruent employee AI status and organizational AI status.

We suggest psychological safety stemming from AI status congruence should alleviate concerns of organizational obstruction - "an employee's belief that the organization obstructs,

hinders or interferes with the accomplishment of his or her goals and is a detriment to his or her well-being" (Gibney et al., 2009, p.667). Applying COR reasoning, employees who are psychologically safe due to a congruent employee-organizational AI status should expect to experience resource gain as opposed to resource loss. Employees will feel psychologically safe at work, allowing them to take risks and invest energy in efforts to accumulate further resources. In this regard, employees should perceive that their organization is not thwarting their efforts to garner future resources (or is not threatening current resources), representing a decrease in perceived organizational obstruction. COR's primary tenets suggest employees' goals are to maintain current resources and gain future resources (Hobfoll, 1988). Employees who feel psychologically safe as a result of congruent AI status perceptions should perceive that resource investment attempts will not be impeded by the organization. Therefore, we suggest the following:

H2. Psychological safety is negatively related to organizational obstruction.

We also examine the concept of employment insecurity, defined as one's fear of being unable to consistently engage in paid labor (Cheng et al., 2011), including both obtaining and maintaining employment (Wilthagen & Tros, 2004). Employment insecurity is important to our research for multiple reasons. Popular press and academic research both suggest AI has the potential to prompt concerns related to increased job loss at one's current organization (e.g., Tong et al., 2021), as well as difficulty obtaining future employment (e.g., Frank et al., 2019; Marr, 2024). Indeed, many workers who lose their jobs due to technological advancements remove themselves from the labor force completely (Kurer & Gallego, 2019).

We expect psychological safety to be negatively related to employment insecurity; individuals with more socioeconomic resources feel more confident in their employment security

(Virtanen, et al., 2003). Similarly, those with higher psychological resources should feel more secure about their ability to invest current resources to garner additional resources. Indeed, employees who have greater psychological resources (e.g., less job pressure) and job resources (e.g., autonomy) feel more secure about their employment (Cheng et al., 2011). Individuals who feel psychologically safe and possess psychological resources perceive a sense of control and optimism about the future (Taylor et al., 2000), believing they are better able to adapt to changes (Carter & Cook, 1995) and are more secure in their chances of maintaining and obtaining employment. Thus, we suggest the following:

H3. Psychological safety is negatively related to employment insecurity.

Considering the hypothesized relationships between our focal variables, we propose that psychological safety is the mechanism through which AI status congruency impacts organizational obstruction and employment insecurity. When an employee and their organization differ in their perception of AI status, the employee likely perceives their organization as hindering their ability to achieve work goals by creating fear of potential loss of resources. This fear represents a decrease in psychological safety. Second, psychological safety explains the AI status congruency-employment insecurity relationship in a similar fashion. When employees disagree with their organization regarding AI status, they fear regarding how AI might jeopardize their employment.

Therefore, we posit that AI status congruency leads to lower organizational obstruction and lower employment insecurity due to higher levels of psychological safety. COR theory (Hobfoll, 1988, 2001) supports our supposition as high organizational obstruction and employment insecurity likely represent manifestations of a perceived threat to the acquisition and/or maintenance of resources necessary to reach work goals. Thus, we offer the following:

H4. Psychological safety mediates the negative indirect relationship between congruent employee-organizational AI status and organizational obstruction.

H5. Psychological safety mediates the negative indirect relationship between congruent employee-organizational AI status and employment insecurity.

Method

Data and Sample

Our sample consists of participants on the Prolific research platform. Participants worked full-time (excluding Prolific), lived in the United States, and were fluent in English. Participants received $1.45 for completing a Time 1 survey and $1.45 for completing a Time 2 survey. The Time 2 survey was completed approximately one week later to mitigate concerns regarding same source variance (Podsakoff et al., 2003). Participants were from various industries (e.g., data analyst, nurse, staff accountant) to enhance generalizability of the research model.

Two hundred seventy-five individuals completed the Time 1 survey. Two hundred forty-nine participants completed the Time 2 survey (91% retention). After listwise deletion, our final sample consisted of 243 individuals. The average age of the sample was 36.21 years (*SD* = 8.51). The sample was predominantly White (62.6%). Participants worked at their current job for 6.95 years (SD = 5.11) and worked 41.65 hours (*SD* = 6.69) per week.

Procedure and Measures

Prior to the study, participants were provided the definition of generative AI and example AI programs. All ratings are on a 7-point Likert-type scale (1 = *strongly disagree*; 7 = *strongly agree*).

Employee AI status was measured in Time 1 via a 5-item measure adapted from Djurdjevic et al. (2017). We modified the referent to reflect the status of AI, rather than individuals. An example item is “In general, I believe AI possesses high status.” (α = .97).

Organizational AI status was measured in Time 1 using the same five-item measure developed by Djurdjevic et al. (2017). However, the stem asked participants to indicate their agreement that the items reflected their organization's view of AI. An example item is "My organization believes AI has a great deal of prestige." ($\alpha = .97$).

Psychological safety was measured during Time 2 using a seven-item measure developed by Edmondson (1999). An example item is "No one in this organization would deliberately act to undermine my efforts." ($\alpha = .88$).

Organizational obstruction was measured in Time 2 by a five-item scale developed by Gibney et al. (2009). An example item is "My organization obstructs the realization of my professional goals." ($\alpha = .95$).

Employment insecurity was measured in Time 2 by a six-item scale developed by Cheng et al. (2011). An example item is "My job security is not good" such that higher scores reflect higher insecurity. ($\alpha = .85$).

The more one is exposed to an object or idea, the more likely the acceptance of the object or idea (e.g., Cooke, 2007). We controlled for AI use via a one-item measure: "Which best describes the frequency with which you use some form of AI at work?" (1 = *never*; 5 = *always*).

Analytical Strategy

Because our hypotheses involve congruency, we applied polynomial regression and response surface methodology (Edwards, 2002; Edwards & Cable, 2009). Research (e.g., Shanock et al., 2010) has demonstrated polynomial regression and response surface methodology has more explanatory potential than other congruence approaches (e.g., difference scores) as it affords the examination of whether (in)congruences along the continuum are divergent (Edwards & Cable, 2009). We estimated the following equation (omitting control variables for simplicity):

$$M = b_0 + b_1(\text{Employee AI Status}) + b_2(\text{Organizational AI Status}) + b_3(\text{Employee AI Status})^2 + b_4(\text{Employee AI Status} * \text{Organizational AI Status}) + b_5(\text{Organizational AI Status})^2 + e \quad (1)$$

where M represents the mediator, psychological safety. For the quadratic terms, we mean-centered the independent variables to reduce multicollinearity and ease interpretation. The regression coefficients were then used to plot the three-dimensional response surface (Edwards & Parry, 1993; Cole et al., 2013).

Results

To assess the factor structure of our measures, we performed a five-factor confirmatory factor analyses (CFA) using maximum-likelihood estimation (employee AI status, organizational AI status, psychological safety, organizational obstruction and employment insecurity). The results provided an adequate fit to the data (χ^2 = 700.33, *df* = 340, RMSEA = .07, CFI = .94, TLI = .94, SRMR = .05) and demonstrated better fit indices than an alternative four-factor model that allowed employee AI status and organizational AI status items to load onto the same factor (χ^2 = 2,129.29, *df* = 344, RMSEA = .15, CFI = .72, TLI = .69, SRMR = .10).

The means, standard deviations, and intercorrelations among the study variables can be found in Table I. See Figure I for the response surface plot. Figure II displays the results of the mediation analysis.

Insert Table I, Figure I and Figure II here.

For hypothesis 1, we first inspected the curvature along the incongruence line. The curvature of the incongruence line ($b_3 - b_4 + b_5$) was significant and negative (b = -0.18, *SE* = 0.09, p = .04), satisfying the first condition for a congruency effect. Subsequently, we examined

the first principal axis of the response surface to determine if the slope p_{11} = 1.0 and the intercept p_{10} = 0.0. We performed 10,000 bootstrap samples to calculate the 95% bias-corrected confidence intervals for p_{11} and $p_{10,}$ (Edwards, 2002; Cole et al., 2013). The first principal axis showed a slope (p_{11}) that was not statistically and significantly different from 1.0 (b = 1.27, 95% CI [0.23, 5.51]) and the intercept (p_{10}) was -0.73 and not statistically and significantly different from zero (95% CI [-12.59, 0.43]). Therefore, we satisfied the second condition for determining a congruence effect. Thus, we find support for hypothesis 1 in that psychological safety is highest when employee AI status and organizational AI status are congruent in that the ridge of the response surface runs along the congruence line.

To test hypotheses 2-5, we followed the block variable approach (Cole et al., 2013; Edwards & Cable, 2009). To create a single coefficient representing the joint effect of the five polynomial terms (E, O, E^2, E x O, and O^2), we combined the five terms into one "block" variable, weighting each term by the corresponding regression coefficient gained from equation 1. The block variable was subsequently used in the mediation analyses. We tested the statistical significance of the indirect effect using a bias-corrected bootstrapping method of 5,000 samples (Efron & Tibshirani, 1993). The results supported hypothesis 2, showing a statistically significant relationship between psychological safety and organizational obstruction (b = -0.71, SE = 0.09, $p < .001$). Similarly, the results support hypothesis 3 as a statistically significant relationship between psychological safety and employment insecurity emerged (b = -0.54, SE = 0.07, $p < .001$).

For hypothesis 4, we examined the indirect effect of the block variable on organizational obstruction via psychological safety. Supporting hypothesis 4, a statistically significant, negative indirect effect of employee AI status and organizational AI status congruency on organizational

obstruction through psychological safety was found (b = -0.71, 95% LCI, UCI = -1.28, -0.20). Supporting hypothesis 5, a statistically significant, negative indirect effect of employee AI status and organizational AI status congruency on employment insecurity through psychological safety was found (b = -0.54, 95% LCI, UCI = -0.95, -0.18).

Discussion

As the workplace continues to evolve with AI integration, researchers urge for the continued understanding of "fit" in organizational contexts (e.g., Kristof-Brown et al., 2023). Our study moves beyond individual beliefs about AI by introducing employee-organization AI status congruency as critical to understanding subsequent employee attitudes. This advances practitioners' and academics' calls to understand AI trepidation mitigation strategies at work (Bradford, 2024; Kim & Lee, 2025).

Theoretical Implications

Drawing from COR theory, we positioned psychological safety as both a resource and an indicator of future resource acquisition regarding AI status at work. This suggests the anticipation of resource gain or loss shapes job and career perceptions related to AI. Through this lens, we show that individual and organizational views on AI status jointly influence perceptions of resource gain or loss. Consequently, our study answers calls to champion COR theory as critical to understanding AI in the workplace (Bankins et al., 2023).

Additionally, we demonstrated that psychological safety serves as a key mechanism in explaining how AI congruency influences workplace attitudes, advancing our nascent understanding of how organizations can foster employee psychological safety beyond the predominant views of social exchange or social learning processes (Edmonson & Bransby,

2023). Instead, we highlight how COR theory explains how resource perceptions prompt the emergence of psychological safety.

Practical Implications

Building on these theoretical insights, managers should establish a clear, organization-wide AI stance and align their messaging with employee perceptions during implementation. Our data shows that when employee and organizational AI status views align – whether low or high – psychological safety is higher than under misalignment. Mismatches create problems: when employees view AI positively but the organization does not, employees perceive career obstruction; when employees are AI-skeptical but organizations embrace AI, employees feel job insecurity threats.

To operationalize these findings, a single, well-articulated AI policy developed collaboratively with employees can accelerate returns on AI investments. Given that status congruence drives psychological safety, managers should sequence training and communication before policy enforcement. Organizations should audit congruence gaps by training managers to spot AI-related anxiety and holding open Q&A sessions during adoption. Tailoring the approach further, AI-receptive organizations with AI-skeptical employees may benefit from a measured, gradual approach to AI adoption, while AI-skeptical organizations with AI-receptive employees might benefit from empowering enthusiasts to run small pilot projects.

Limitations

Our data comes from one source – the employee – raising common source variance concerns. However, temporal separation of surveys and the fact that our constructs are predicated on employee perceptions support self-report measures as appropriate. Future scholarship could collect variables from different sources (e.g., supervisor-rated measures of organizational AI

status) for additional insight. Additionally, our cross-sectional design limits causal determination. Future research may benefit from longitudinal designs or pre/post-test AI implementation to further examine the causal nature of the study variables.

Future research

Future research could examine other resources that may stem from AI congruency perceptions. The COR framework includes several relevant constructs such as job autonomy, social support, and professional development opportunities (Halbesleben et al., 2014). Rather than positioning psychological safety as the primary mechanism, future studies could investigate whether specific resources are enhanced or threatened by AI status congruency. Expanding the scope of congruency, it would also be interesting to examine congruency with other sources – direct supervisors, coworkers, work units, or industry AI status. Particularly intriguing, our data suggests no significant difference in psychological safety between high and low levels of AI status congruency. This finding indicates that negative AI perceptions still allow for psychological safety when organizations share their views. Given AI's predicted workplace prominence, researchers may benefit from tracking experiences of those who afford low status to AI (Bankins et al., 2023).

Conclusion

We contribute to emerging research on employee reactions to workplace AI and the literature on psychological safety at work. We demonstrate that employee-organization AI status congruency significantly impacts employees' perceptions of organizational obstruction and employment insecurity, with psychological safety as the key mechanism. We hope our study spurs future research on how employees evaluate AI in the rapidly evolving workplace.

References

Anderson, C., John, O. P., Keltner, D., & Kring, A. M. (2001). Who attains social status? Effects of personality and physical attractiveness in social groups. *Journal of Personality and Social Psychology*, *81*(1), 116-132.

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, *45*(2), 159-182.

Bessen, J. E., Goos, M., Salomons, A., & van den Berge, W. (2019). *Automatic Reaction: What Happens to Workers at Firms that Automate? Boston Univ. School of Law, Law and Economics Research Paper No. 19-2 (2019).*

Bradford, N. (2024, February 5). *HR trends for 2025: AI comes to a crossroads*. SHRM.

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research, 131*, 485–494.

Campbell, N. S., Perry, S. J., Maertz, C. P., Allen, D. G., & Griffith, R. W. (2013). All else equal: Are preferences in the job attribute selection process stable? *Journal of Management, 39*(2), 517–541. https://doi.org/10.1177/0149206310394187

Carmeli, A., & Gittell, J. H. (2009). High-quality relationships, psychological safety, and learning from failures in work organizations. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *30*(6), 709-729.

Carter, M. A. T., & Cook, K. (1995). Adaptation to retirement: Role changes and psychological resources. *The Career Development Quarterly*, *44*(1), 67-82.

Chen, S., Westman, M., & Eden, D. (2009). Impact of enhanced resources on anticipatory stress and adjustment to new information technology: A field-experimental test of conservation of resources theory. *Journal of Occupational Health Psychology*, *14*(3), 219-230.

Cheng, Y., Huang, H. Y., Li, P. R., & Hsu, J. H. (2011). Employment insecurity, workplace justice and employees' burnout in Taiwanese employees: A validation study. *International Journal of Behavioral Medicine, 18*, 391-401.

Cole, M. S., Carter, M. Z., Zhang, Z. (2013). Leader-team congruence in power distance values and team effectiveness: The mediating role of procedural justice climate. *Journal of Applied Psychology 98*(6), 962–973.

Cooke, L. (2007). The importance of exposure for healthy eating in childhood: A review. *Journal of Human Nutrition and Dietetics, 20*(4), 294-301.

Dell'Acqua, F., McFowland III, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. *Harvard Business School Technology & Operations Mgt. Unit Working Paper*, (24-013).

Djurdjevic, E., Stoverink, A. C., Klotz, A. C., Koopman, J., da Motta Veiga, S. P., Yam, K. C., & Chiang, J. T. J. (2017). Workplace status: The development and validation of a scale. *Journal of Applied Psychology, 102*(7), 1124.

Dorn, D. (2015). The rise of the machines: How computers have changed work. UBS Center Public Paper.

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly, 44*(2), 350-383.

Edmondson, A. C. (2004). Learning from failure in health care: frequent opportunities, pervasive barriers. *BMJ Quality & Safety*, *13*(suppl 2), ii3-ii9.

Edmondson, A. C., & Bransby, D. P. (2023). Psychological safety comes of age: Observed themes in an established literature. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 55-78.

Edmondson, A. C., & Lei, Z. (2014). Psychological safety: The history, renaissance, and future of an interpersonal construct. *Annual Review of Organizational Psychology and Organizational Behavior*, 1(1), 23–43.

Edwards, J. R. (2002). Alternatives to difference scores: Polynomial regression analysis and response surface methodology. In F. Drasgow & N. W. Schmitt (Eds.). *Advances in Measurement and Data Analysis* (pp. 350–400). Jossey-Bass.

Edwards, J. R., Cable, D. M. (2009). The value of value congruence. *Journal of Applied Psychology* 94(3), 654–677.

Edwards, J. R., Parry, M. E. (1993). On the use of polynomial regression equations as an alternative to difference scores in organizational research. *Academy of Management Journal* 36(6), 1577–1613.

Efron, B., Tibshirani, R. J. (1993). *An introduction to the bootstrap*. Boca Raton, FL: Chapman & Hall/CRC.

Evans, K., & Kortum, P. (2010). The impact of perceived personality traits on trust in human-robot interaction. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 54*(14), 1245–1249. https://doi.org/10.1177/154193121005401406

Frank, A. G., Mendes, G. H., Ayala, N. F., & Ghezzi, A. (2019). Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting and Social Change*, *141*, 341-351.

Frazier, M.L., Fainshmidt, S., Klinger, R.L., Pezeshkan, A. and Vracheva, V. (2017), Psychological safety: A meta-analytic review and extension. *Personnel Psychology*, 70: 113-165. https://doi.org/10.1111/peps.12183

Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation policy and the economy*, *19*(1), 161-191.

Gallego, A., & Kurer, T. (2022). Automation, AI, and the future of work: How are workers reacting? *Annual Review of Political Science, 25*, 401–419. https://doi.org/10.1146/annurev-polisci-051120-102620

Gibney, R., Zagenczyk, T. J., & Masters, M. F. (2009). The negative aspects of social exchange: An introduction to perceived organizational obstruction. *Group & Organization Management*, *34*(6), 665-697.

Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F., & Gruber, M. (2023). From scarcity to abundance: Scholars and scholarship in an age of generative artificial intelligence. *Academy of Management Journal*, *66*(6), 1617-1624.

Halbesleben, J. R., Neveu, J. P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR" understanding the role of resources in conservation of resources theory. *Journal of Management*, *40*(5), 1334-1364.

Hobfoll, S. E. (1988). *The ecology of stress*. Taylor & Francis.

Hobfoll, S. E. (1989). Conservation of resources: a new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513-524.

Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. *Applied Psychology*, *50*(3), 337-421.

Hochwarter, W. A., Ferris, G. R., Zinko, R., Arnell, B., & James, M. (2007). Reputation as a moderator of political behavior-work outcomes relationships: A two-study investigation with convergent results. *Journal of Applied Psychology, 92*(2), 567–576. https://doi.org/10.1037/0021-9010.92.2.567

Johnes, G. (2018). University rankings: What do they really show? *Scientometrics*, 115(1), 585–595. https://doi.org/10.1007/s11192-018-2673-2

Kaplan, H. S., & Gangestad, S. W. (2005). Life history theory and evolutionary psychology. In D. M. Buss (Ed.), *The Handbook of Evolutionary Psychology* (pp. 68–95). Wiley.

Kim, B. J., & Lee, J. (2025). The dark sides of artificial intelligence implementation: Examining how corporate social responsibility buffers the impact of artificial intelligence-induced job insecurity on pro-environmental behavior through meaningfulness of work. *Sustainable Development*.

Kristof-Brown, A. L., & Jansen, K. J. (2007). Issues of person-organization fit. In C. Ostroff & T. A. Judge (Eds.), *Perspectives on Organizational Fit* (pp. 123–153). Lawrence Erlbaum Associates Publishers.

Kristof-Brown, A., Schneider, B., & Su, R. (2023). Person-organization fit theory and research: Conundrums, conclusions, and calls to action. *Personnel Psychology*, *76*(2), 375-412.

Kurer, T., & Gallego, A. (2019). Distributional consequences of technological change: Worker-level evidence. *Research & Politics*, *6*(1), 2053168018822142.

Laestadius, L. I., Bishop, L., Gonzalez, J., Illenčik, L., & Campos-Castillo, C. (2022). Sharing health data with digital assistants: Trust, concerns, and disclosure likelihood. *Digital Health, 8*, 1–12. https://doi.org/10.1177/20552076221083292

Liboni, L. B., Cezarino, L. O., Jabbour, C. J. C., Oliveira, B. G., & Stefanelli, N. O. (2019). Smart industry and the pathways to HRM 4.0: Implications for SCM. *Supply Chain Management: An International Journal*, 24(1), 124–146. https://doi.org/10.1108/SCM-03-2018-0150

Maeda, T., & Quan-Haase, A. (2024, June). When human-AI interactions become parasocial: Agency and anthropomorphism in affective design. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1068-1077).

Magee, J. C., & Galinsky, A. D. (2008). Social hierarchy: The self-reinforcing nature of power and status. *Academy of Management Annals*, *2*(1), 351–398. https://doi.org/10.1080/19416520802211628

Marikyan, D., Papagiannidis, S., Rana, O. F., Ranjan, R., & Morgan, G. (2022). "Alexa, let's talk about my productivity": The impact of digital assistants on work productivity. *Journal of Business Research*, *142*, 572-584.

Marr, B. (2024). *Generative AI in practice: 100+ amazing ways generative artificial intelligence is Changing Business and Society*. John Wiley & Sons.

McManus, S. (2025). *Why employees smuggle AI into work*. https://www.bbc.com/news/articles/cn7rx05xg2go

Mukherjee, S. (2024, August 27). *Sweden's Klarna says AI chatbots help shrink headcount*. Reuters.

Newman, A., Donohue, R., & Eva, N. (2017). Psychological safety: A systematic review of the literature. *Human Resource Management Review*, *27*(3), 521-535.

Ng, T. W., & Feldman, D. C. (2012). Employee voice behavior: A meta-analytic test of the conservation of resources framework. *Journal of Organizational Behavior*, *33*(2), 216-234.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 382(6668), 620–624. https://doi.org/10.1126/science.adh2586

Ostroff, C., Shin, Y., & Kinicki, A. J. (2005). Multiple perspectives of congruence: Relationships between value congruence and employee attitudes. *Journal of Organizational Behavior*, *26*(6), 591-623.

Park, J., Woo, S. E., & Kim, J. (2024). Attitudes towards artificial intelligence at work: Scale development and validation. *Journal of Occupational and Organizational Psychology*, *97*(3), 920-951.

Paustian-Underdahl, S. C., & Halbesleben, J. R. B. (2014). The role of social cues in resource acquisition: A social information processing perspective. *Journal of Organizational Behavior, 35*(4), 451–466. https://doi.org/10.1002/job.1890

Payne, S. C., Cook, A. L., & Diaz, I. (2012). Understanding childcare satisfaction and its effect on workplace outcomes: The convenience factor and the mediating role of work-family conflict. *Journal of Occupational and Organizational Psychology*, *85*(2), 225-244.

Pearce, J. L. (2011). Status in management and organizations. *Development and Learning in Organizations: An International Journal*, *25*(6).

Pelau, C., Dabija, D.-C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy, and perceived psychological anthropomorphism. *Psychology & Marketing, 38*(4), 627–645. https://doi.org/10.1002/mar.21456

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903.

Presbitero, A., & Teng-Calleja, M. (2022). Job attitudes and career behaviors relating to employees' perceived incorporation of artificial intelligence in the workplace: a career self-management perspective. *Personnel Review*, *52*(4), 1169-1187.

Rossiter, C. (1960). *Conservatism in America: The Thankless Persuasion*. New York: Vintage Books.

Saad, W. (2023). *AI—The good, the bad, and the scary*. Virginia Tech Engineering Magazine.

Scheiber, N. (2025, February 2). *Why is this C.E.O. bragging about replacing humans with A.I.?* The New York Times.

Schein, E. H., & Bennis, W. G. (1965). *Personal and organizational change through group methods: The laboratory approach*. New York: Wiley.

Sessions, H., Nahrgang, J. D., & Ramachandran, N. (2021). The Role of Job Admiration in Employee Engagement and Performance. *Journal of Organizational Behavior*, 42(3), 345–360. https://doi.org/10.1002/job.2489

Shanock, L. R., Baran, B. E., Gentry, W. A., Pattison, S. C., & Heggestad, E. D. (2010). Polynomial regression with response surface analysis: A powerful approach for examining moderation and overcoming limitations of difference scores. *Journal of Business and Psychology*, *25*, 543-554. https://doi.org/10.1007/s10869-010-9183-4.

Song, Z., & Chathoth, P. K. (2011). Intern newcomers' global self-esteem, overall job satisfaction, and choice intention: Person-organization fit as a mediator. *International Journal of Hospitality Management*, *30*(1), 119-128.

Sonnentag, S., Binnewies, C., & Mojza, E. J. (2008). " Did you have a nice evening?" A day-level study on recovery experiences, sleep, and affect. *Journal of Applied Psychology*, *93*(3), 674-684.

Taylor, S. E., Kemeny, M. E., Reed, G. M., Bower, J. E., & Gruenewald, T. L. (2000). Psychological resources, positive illusions, and health. *American Psychologist*, *55*(1), 99-109.

Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal*, *42*(9), 1600-1631.

Virtanen, P., Liukkonen, V., Vahtera, J., Kivimäki, M., & Koskenvuo, M. (2003). Health inequalities in the workforce: The labour market core–periphery structure. *International Journal of Epidemiology, 32*(6), 1015-1021

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, *4*(4), 404-409.

Wilthagen, T., & Tros, F. (2004). The concept of 'flexicurity': a new approach to regulating employment and labour markets. *Transfer: European Review of Labour and Research*, *10*(2), 166-186.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational behavior*, *74*(3), 235-244.